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# Urban Land Development in the Process of Urbanization

Edited by
Sheng Zheng, Yuzhe Wu and Ramesh P. Singh

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Guest Editors

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**Yuzhe Wu**
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*Article*

# Effects of Urban Form on Carbon Emissions in China: Implications for Low-Carbon Urban Planning

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**Abstract:** Carbon emissions are closely related to global warming. More than 70% of global carbon emissions have been generated in cities. Many studies have analyzed the effects of cities on carbon emissions, from the perspective of urbanization, economics, and land use, yet a detailed understanding of the relationship between urban form and carbon emissions is lacking due to the absence of a reasonable set of urban form metrics. The aim of this research is to explore the effects of urban form on carbon emissions through empirical research. By eliminating collinearity, we established a set of urban form landscape metrics comprising Class Area (CA), Mean Perimeter–Area Ratio (PARA-MN), Mean Proximity Index (PROX-MN), and Mean Euclidian Nearest Neighbor Distance (ENN-MN) representing urban area, complexity, compactness, and centrality, respectively. Through spatial autocorrelation analysis, the results show that there is a positive spatial autocorrelation of carbon emissions. The high–high agglomeration regions are located in the Beijing–Tianjin–Hebei and Yangtze River Delta, while the low–low agglomeration regions are concentrated in the Southwest and Heilongjiang Province. Based on a spatial error model, for the whole study area, CA, PARA-MN, and ENN-MN show a positive correlation with carbon emissions, but PROX-MN is the opposite. Based on ordinary least squares, PARA-MN in the Northeast and East, PROX-MN in the North and Mid-South, and ENN-MN in the North are significantly correlated with carbon emissions. These findings are helpful for low-carbon urban planning.

**Keywords:** carbon emissions; urban form; spatial error model; urban planning

## 1. Introduction

Since the Industrial Revolution, coal, oil, natural gas and other forms of fossil energy have become the main resources for human life. The utilization of fossil energy leads to increased carbon emissions, causing global warming [1]. China is the largest developing country in the world. Its industrialization and urbanization have developed rapidly, and its carbon emissions are also increasing. In 2006, China surpassed the United States to become the country with the highest carbon emissions in the world [2]. In 2020, China's carbon emissions accounted for 30% of global carbon emissions [3]. In the same year, China put forward the goals of peak carbon emissions in 2030 and carbon neutrality in 2060 [4,5].

As the center of human socio-economic activities, cities carry 85% of human production and economic activities [6], and generate more than 70% of global carbon emissions with 2% of the earth's land area [7,8]. From 1990 to 2018, China's urban population and construction land area grew significantly [9]. On the one hand, the rapid development of cities has expanded the scale of production activities and increased the consumption of fossil energy. On the other hand, the outward expansion of urban area continues to encroach on farmland and forests, resulting in a reduction in carbon sinks. In fact, as much as 50% of carbon emissions in cities are attributed to the choice of urban form [10]. For example, the increase in carbon emissions is affected by the intensity effect, expansion effect and economic effect

to different degrees [8]. Urban form affects residents' carbon emissions mainly through the housing market, losses in power transmission and the urban heat island effect [11]. Furthermore, urban form affects regional meteorological factors. For instance, urban form can influence the urban heat island effect through energy consumption, ultimately increasing carbon emissions [12]. In addition, carbon reduction, a priority for future development, requires an important foundation that can consolidate its achievements in order to achieve its sustainability. The urban form, as the physical foundation of cities, is relatively stable. It is also spatially integrated and interacts with economic and demographic factors, ultimately leading to a long-term effect of urban form on carbon emissions [13]. Thus, the urban form is not only an important factor in reducing carbon emissions but also an important vehicle for sustaining low-carbon sustainable development in the future. Exploring the effects of urban form on carbon emissions could provide a new perspective to achieve low-carbon sustainable development.

Due to the different connotations of urban form, there are many types of urban form measurement metrics. The first category is dominated by socio-economic metrics, including urbanization [14], economy [15], land use [13,16] and climate [5]. First, urbanization is an important metric affecting carbon emissions. In the early stage of urbanization, urban carbon emissions efficiency decreases with the growth of urban areas and their populations, but as the level of urbanization exceeds a certain point, carbon emissions efficiency increases instead. The impact of urbanization on carbon emissions shows a U-shaped trend [15]. Currently, the urbanization of Chinese cities shows large regional differences, with some cities growing while others are shrinking [4]. However, in general, China's level of urbanization is in the first half of a U-shaped line, with the huge pressures of population growth and the environment. Thus, urbanization shows a positive relationship with carbon emissions [17]. Second, different industrial distributions and structures can change the effects of the economy on carbon emissions. Therefore, a large number of studies have classified economic data. For example, per capita GDP [18], industrial $SO_2$ emissions per capita and the proportion of employees in the secondary sector are positively related to carbon emissions, while the proportion of employees in the three sectors and population density are negatively related to carbon emissions [19]. Third, influenced by urban density, community layout and building heights [20,21], specific land-use types can generate more carbon emissions. Retail trade and residential land have larger carbon emissions, while terrace houses produce more carbon emissions than other residential building categories [16]. Finally, climate shows a negative effect on carbon emissions [22]. This trend is mainly from the increase in temperature and precipitation [5]. Increased temperatures usually directly enhance autotrophic and heterotrophic soil respiration, and the increased precipitation can intensify soil erosion and lead to losses in soil nutrients, ultimately affecting ecosystem productivity and carbon sink functions. The second category of urban form measurement metrics is mainly based on the geometric characteristics of urban forms. Measures of the geometric characteristics are constantly changing as cities grow. In the early urbanization process, the population moved from rural to urban area, so urban areas became the most direct indicator of urban form [23]. With the expansion of cities, the ability of single-dimensional metrics to explain them is decreasing, and high-density land use is becoming the future direction of urban planning. Metrics such as compactness, complexity and centrality have been incorporated into the measurement dimensions of urban form. Compact development is associated with a high density of urban areas. The reduced distances between urban parts can reduce the need for transport and tourism, which directly reduces carbon emissions [24]. Complexity refers to the roughness of the urban patch perimeter. It has been proven that there is a positive correlation between complexity and carbon emissions [25]. Since landscape metrics can combine the characteristics of patch size, shape and quantity, they play an important role in the study of the spatiotemporal characteristics of urban land use [26] and the prediction of future morphological changes [27].

Since different urban forms have different effects on carbon emissions [28], it is important to analyze their relationship from an appropriate perspective. Although some studies have begun to focus on the relationship between landscape metrics and carbon emissions, most of them considered landscape metrics as a driving factor, and integrated them with other factors such as urbanization and economy in one metric set. However, the urban form landscape metric includes multiple subdivision concepts such as urban area, compactness and centrality, which can not only directly reflect the level of urbanization, but also reflect the economic development and policy orientation of the region. Considering the rich information of landscape metrics, we need to select appropriate metrics from a large number of landscape metrics for analyzing their effects on carbon emissions. Therefore, the following hypotheses are proposed: urban form landscape metrics affect carbon emissions, and the effect of each metric changes from region to region. In order to prove these hypotheses, this study selected 282 cities at the prefectural level and above in China as an example. The aim of the presented research was to construct a reasonable set of urban form metrics through stepwise linear regression, analyze the effects of the urban form on carbon emissions through the spatial error model and ordinary least squares, and propose relevant policy recommendations for low-carbon urban planning.

In detail, there are two main contributions of this study. On the one hand, a set of reasonable urban form landscape metrics was constructed by stepwise linear regression This metric set can help in the selection of metrics for future research. On the other hand, key urban form metrics, which are significantly associated with carbon emissions in each region, are found, providing a reference for empirical research on the effects of urban form on carbon emissions and helping to suggest targeted improvements for low-carbon city planning. The rest of this paper is organized as follows: the Section 2 includes the study area and data; the Section 3 presents the methods; the Section 4 contains the results and discussion; and the Section 5 provides conclusions.

## 2. Study Area and Data

### *2.1. Study Area*

Due to the lack of carbon emission data in the Tibet Autonomous Region, Hong Kong, Macau and Taiwan, 282 cities at the prefectural level and above in China were selected as the study area. Because of the vast size of China, carbon emissions vary greatly from region to region. In order to explore the impact of different urban forms on carbon emissions and provide more policy recommendations for low-carbon urban planning, cities need to be classified. This study classifies China's administrative regions according to traditional geographic locations. It has been proven that the geographical location of cities and regional policies affects the urban form [29]. The traditional geographical divisions divide China into six regions, which are the North, Northeast, East, Mid-South, Southwest, and Northwest [30]. This method can analyze the driving factors affecting carbon emissions and provide more specific suggestions. Figure 1 shows the classification results of the 282 cities, comprising 30 cities in the Northwest, 33 cities in the Southwest, 77 cities in the Mid-South, 76 cities in the East, 34 cities in the Northeast and 32 cities in the North.

### *2.2. Data*

There are mainly carbon emissions and urban form data in this study. The carbon emissions data were obtained from the carbon emissions inventory at the county level in China developed by Chen et al. [31] (https://www.ceads.net.cn/data/county/ (accessed on 1 April 2022)). This inventory is based on nighttime light data and uses the particle swarm optimization back-propagation (PSO-BP) algorithm to downscale the energy carbon emissions of each province. Finally, the carbon emissions of 2735 county-level energy sources from 1997 to 2017 were calculated. We summarized the county-level to city-level carbon emissions, and those of the 282 cities were obtained.

Urban form landscape metrics are based on the urban built-up area. Impervious surface data, as a typical representative of urban built-up areas, can be used directly in the

calculation of urban form [32]. The national 40-year urban impervious surface data released by Gong et al. [33] (http://data.ess.tsinghua.edu.cn (accessed on 1 April 2022)) was used as the basic remote sensing data source for calculating urban form metrics. This dataset comprehensively considers MODIS and nighttime light data, classifies urban and rural impervious surfaces, and finally derives the annual dynamic change data of impervious surfaces within the urban area from 1978 to 2017. In order to improve the efficiency of data, the spatial resolution of the impervious surface data in 2017 was resampled to 100 m. Then, the urban administrative map was used for cropping to obtain the impervious surface distribution map of 282 cities in 2017.

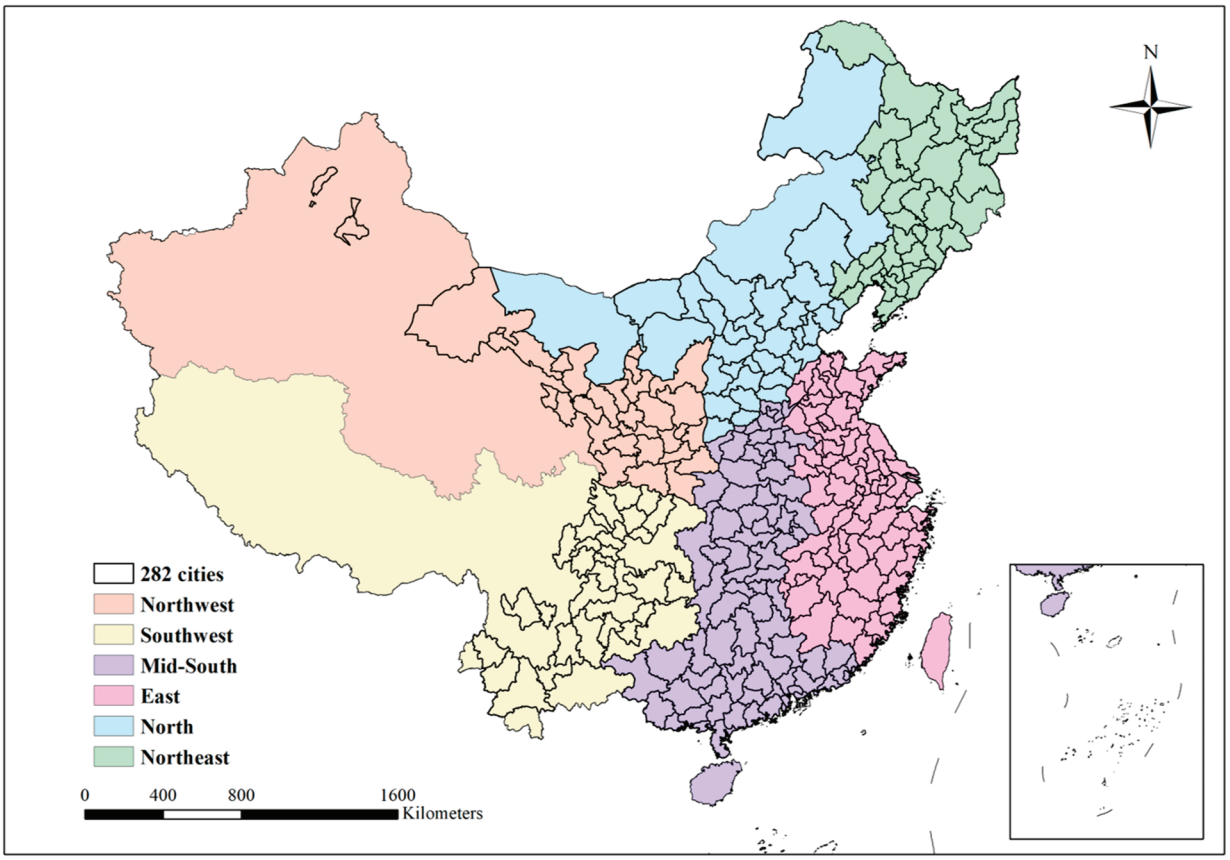


**Figure 1.** Distribution of 282 cities in six regions in China.

### *2.3. Urban Form Landscape Metrics*

In terms of urban area, patchiness, urban irregularity and urban compactness [28,34–36], 15 urban form landscape metrics were selected. We divided them into four categories: area, edge, shape and aggregation. (The equations and specific descriptions of the 15 metrics are shown in Table A1 in Appendix A).

For the metric of area, Class Area (CA) represents the total area of all urban patches. The Number of Patches (NP) can measure the urban fragmentation. The Largest Patch Index (LPI) is equal to the percentage of the total landscape area occupied by the largest urban patch.

For the indicator of edge, Edge Density (ED) is the sum of the lengths of all edge segments divided by the total landscape area.

For the metric of shape, the Area-weighted Mean Shape Index (AWMSI) at the patch level is equal to the sum of the perimeter-to-area ratio of each urban patch multiplied by the proportion of the entire urban patch area to the landscape area. Based on the AWMSI formula, the Area-weighted Mean Patch Fractal Dimension (AWMPFD) introduces a fractal dimension to weight all patches. However, the fractal dimension depends on the patch

size and the units used. Therefore, changing the cell size of the input image will affect the AWMPFD to a large extent. Mean Perimeter–Area Ratio (PARA-MN) is the ratio of the total perimeter of urban patches to the total area of the area.

For the indicator of aggregation, the Landscape Shape Index (LSI) measures the perimeter–area ratio of urban patches. The Clumpiness Index (CLUMPY) reflects the degree of aggregation between urban patches. The Percentage of Like Adjacencies (PLADJ) represents the degree of connectivity within the urban built-up area. The Patch Cohesion Index (COHESION) is the ratio of the area-weighted average perimeter–area ratio to the area-weighted average patch shape index. Its formula is similar to PARA, but the interpretation of changes is more robust. The Aggregation Index (AI) examines the connectivity between patches of each landscape type. Patch Density (PD) represents the urban patch area per unit area. The Mean Proximity Index (PROX-MN) refers to the sum of the ratios of the size of all urban patches to the edge-to-edge distances of their nearest neighbors within a specified search radius. The Euclidian Mean Nearest Neighbor Distance (ENN-MN) quantifies the average distance between the two closest urban patches.

Based on the impervious surface distribution in 282 cities in 2017, the above 15 urban form landscape metrics were calculated. To eliminate the effect of differences in data magnitude, we normalized all variables by extreme value normalization, and the equation is as follows:

$$X = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

## 3. Methods

Highly correlated metrics could lead to redundant information, so it is necessary to judge whether there is multicollinearity by analyzing the variance inflation factors (VIF) of the metrics. Stepwise linear regression was used to eliminate the multicollinearity of metrics. Then, to investigate the effects of the urban form on carbon emissions, spatial autocorrelation analysis was applied to determine the spatial dependence of carbon emissions. Finally, the spatial error model and ordinary least squares were used to analyze the effect of each urban form metric on carbon emissions.

### *3.1. Stepwise Linear Regression*

Stepwise linear regression is one of the most common methods of eliminating multicollinearity in variables. Its basic principle is to select the most important variables from a large number of variables. We used forward stepwise linear regression [37], adding one variable at a time until there were no new significant variables. The variables were introduced on the condition that they were statistically significant ($p < 0.1$) and to avoid multicollinearity (VIF < 10).

### *3.2. Spatial Autocorrelation Test*

Only if there is a spatial dependence on carbon emissions can the spatial regression method be used. The spatial autocorrelation is used to test spatial dependence, including global spatial autocorrelation and local spatial autocorrelation [38]. Moran's I is the most popular indicator to explore spatial autocorrelation. The calculation formula is as follows:

$$\text{Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(\text{CE}_i - \overline{\text{CE}})(\text{CE}_j - \overline{\text{CE}})\Big)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \quad (2)$$

where n is the total number of cities; $\text{CE}_i$ and $\text{CE}_j$ represent the carbon emissions of city i and j, respectively; $\omega_{ij}$ represents the spatial weight; $\overline{\text{CE}}$ is the mean carbon emissions and $S^2$ is the sample variance. Moran's I has a value between $-1$ and 1. If the value exceeds 0, it means that there is a positive spatial autocorrelation of carbon emissions; conversely, it means that there is a negative spatial autocorrelation. If the value is close to 0, it means that there is no spatial independence.

### *3.3. Spatial Error Model*

The spatial error model (SEM) is used to quantify the effects of the urban form on carbon emissions (for the choice of SEM, please see Appendix B). The SEM is different from the ordinary linear regression model, because its dependent variable is influenced not only by the independent variables in the region, but also by the independent variables in the neighboring regions. The SEM is expressed as follows [39]:

$$CE = \beta X + \lambda W_{\mu} + \varepsilon,\ \varepsilon\ \sim\ N\left[0,\ \delta^2 I_n\right], \tag{3}$$

where β is a coefficient vector, $X$ is a matrix of the independent variables, λ is the spatial error factor, $W_{\mu}$ is the spatial weight matrix and $\varepsilon$ is the stochastic error.

### *3.4. Ordinary Least Squares*

If there is no spatial dependence on carbon emissions in the spatial autocorrelation test, or if carbon emissions and the urban form do not pass the Lagrange Multiplier test, then the next step is to use ordinary least squares (OLS) for multiple regression analysis. The OLS is expressed as follows:

$$CE = \alpha + \beta X + \varepsilon \tag{4}$$

where α is the regression constant, β is the regression coefficient, $X$ is the independent variable and $\varepsilon$ is the stochastic error.

## 4. Results and Discussion

### *4.1. Urban Form Metrics Set*

The results of the multicollinearity test for the metrics are shown in Table 1. The VIF values of 10 metrics, comprising CA, NP, ED, AWMSI, AWMPFD, LSI, CLUMPY, PLADJ, AI and PD, are higher than 20, indicating that these metrics contain redundant information and ordinary linear regression is inappropriate. In the stepwise linear regression, the independent variables comprise 15 landscape metrics, and the dependent variable is carbon emissions. The results are shown in Table 2. The final five metrics remaining in the model are CA, PARA-MN, PROX-MN, ENN-MN and PLADJ. The $R^2$ of the model is 0.739, and the model passes the F-test (F = 155.968, $p < 0.05$).

**Table 1.** Multicollinearity test results statistics.

| Landscape Metrics | Collinearity Statistics | | Landscape Metrics | Collinearity Statistics | |
|---|---|---|---|---|---|
| | Tolerance | VIF | | Tolerance | VIF |
| CA | 0.041 | 24.658 | CLUMPY | 0.003 | 372.238 |
| NP | 0.023 | 43.959 | PLADJ | 0.000 | 8627.861 |
| LPI | 0.053 | 18.816 | COHESION | 0.072 | 13.827 |
| ED | 0.007 | 134.318 | AI | 0.000 | 9250.508 |
| AWMSI | 0.037 | 27.091 | PROX-MN | 0.102 | 9.769 |
| AWMPFD | 0.034 | 29.444 | ENN-MN | 0.263 | 3.802 |
| PARA-MN | 0.209 | 4.782 | PD | 0.029 | 34.254 |
| LSI | 0.015 | 67.847 | - | - | - |

Note: VIF: the variance inflation factors; CA: Class Area; NP: the Number of Patches; LPI: the Largest Patch Index; ED: Edge Density; AWMSI: the Area-weighted Mean Shape Index; AWMPFD: the Area-weighted Mean Patch Fractal Dimension; PARA-MN: Mean Perimeter–Area Ratio; LSI: the Landscape Shape Index; CLUMPY: the Clumpiness Index; PLADJ: the Percentage of Like Adjacencies; COHESION: the Patch Cohesion Index; AI: the Aggregation Index; PROX-MN: the Proximity Index; ENN-MN: the Euclidian Mean Nearest Neighbor Distance; PD: Patch Density.

Each VIF of the metric remaining in the stepwise linear regression model is less than 5, and the multicollinearity problem is statistically solved. However, due to the potential overlap between the metrics descriptions, we needed to optimize the metric set. First, CA, PARA-MN and ENN-MN depict different contents, but CLUMPY and PROX-MN both depict urban compactness. Second, CLUMPY requires patches to be adjacent. However,

PROX-MN considers the size and proximity of all patches within the specified search radius of the edge, and there is no requirement that there must be a neighboring relationship between urban patches. Thus, we eliminated CLUMPY. Finally, the set of urban form metrics included the four metrics of CA, PARA-MN, PROX-MN and ENN-MN.

**Table 2.** Stepwise linear regression model results statistics.

| Variable | Coefficient | VIF |
|---|---|---|
| Constant | −0.314 *** | - |
| CA | 0.796 *** | 1.534 |
| PROX-MN | −0.331 *** | 1.437 |
| PARA-MN | 0.350 *** | 3.055 |
| ENN-MN | 0.182 *** | 2.534 |
| CLUMPY | 0.093 *** | 1.871 |
| $R^2$ | 0.739 | |
| Adjusted $R^2$ | 0.734 | |
| F | F = 155.968, $p$ = 0.000 | |

Note: *** indicates significance at 1% level. F: F-test statistic value.

### *4.2. Analysis of Landscape Metrics and Carbon Emissions*

The results for the 282 cities' carbon emissions after extreme value normalization in 2017 are shown in Figure 2. Shanghai, Chongqing, Tianjin and Suzhou are the four cities with the highest grade. The high-carbon-emissions cities are mainly distributed in the North and East, and are concentrated in Henan, Jiangsu, Hebei, Shandong, Shanxi and Zhejiang Province.

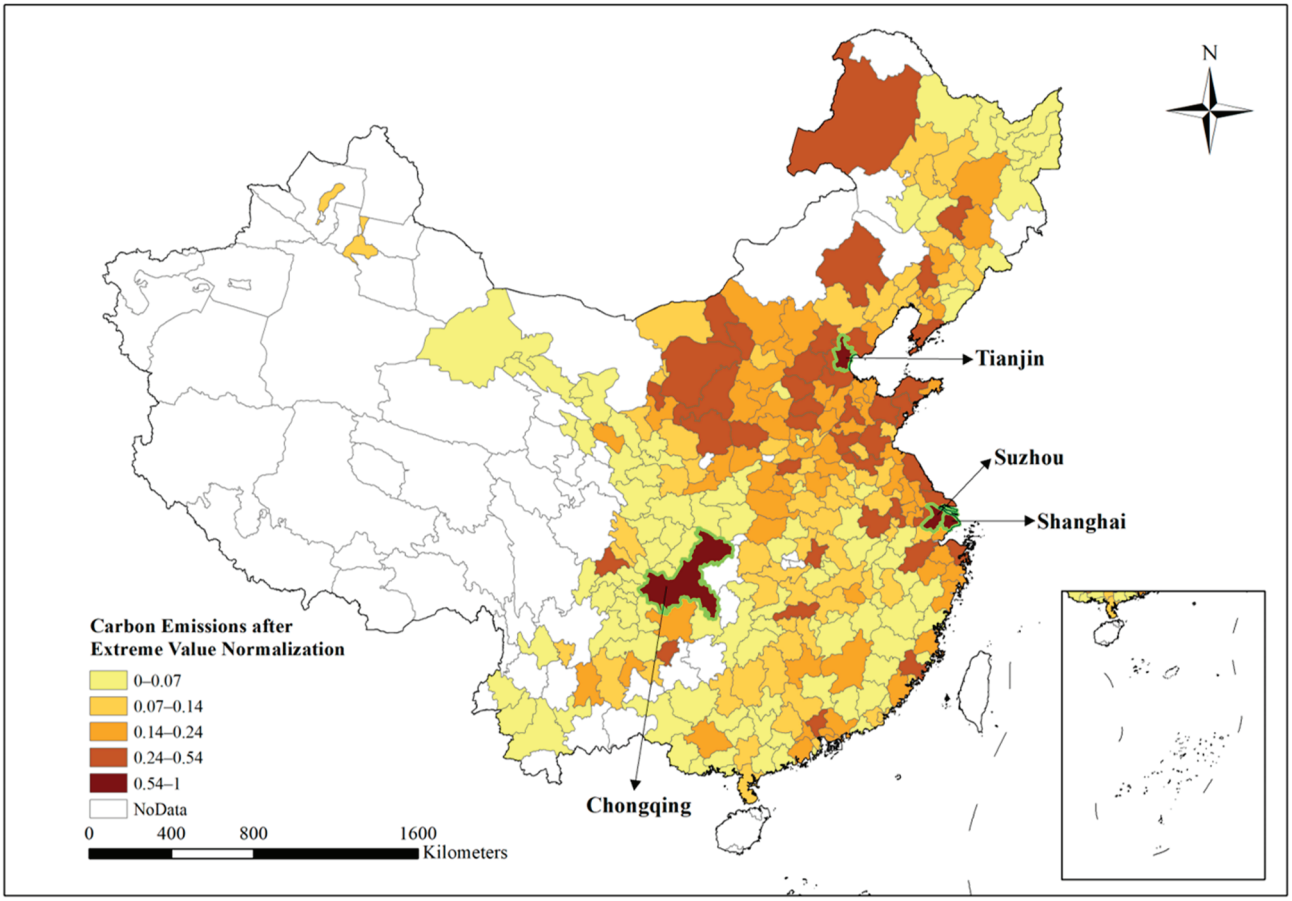


**Figure 2.** Distribution of carbon emissions in 282 cities.

The carbon emissions and landscape metrics statistics of the study area are shown in Table 3. The characteristics of each region are as follows.

**Table 3.** Result statistics of urban form metrics.

| Area | Statistics | Carbon Emissions | CA | PARA-MN | PROX-MN | ENN-MN |
|---|---|---|---|---|---|---|
| All Areas | Min | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | Max | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | Mean | 0.1402 | 0.1611 | 0.8222 | 0.0346 | 0.0500 |
| | Std | 0.1342 | 0.1654 | 0.1147 | 0.0858 | 0.1119 |
| North | Min | 0.0683 | 0.0593 | 0.5528 | 0.0016 | 0.0068 |
| | Max | 0.7741 | 1.0000 | 0.8638 | 0.2810 | 0.6036 |
| | Mean | 0.2668 | 0.2612 | 0.7808 | 0.0460 | 0.0467 |
| | Std | 0.1571 | 0.2132 | 0.0701 | 0.0683 | 0.1045 |
| Northeast | Min | 0.0092 | 0.0225 | 0.0000 | 0.0023 | 0.0150 |
| | Max | 0.4105 | 0.3548 | 0.9373 | 0.2960 | 1.0000 |
| | Mean | 0.1103 | 0.1086 | 0.7161 | 0.0328 | 0.1801 |
| | Std | 0.0882 | 0.0846 | 0.2484 | 0.0580 | 0.2569 |
| East | Min | 0.0150 | 0.0226 | 0.6903 | 0.0006 | 0.0023 |
| | Max | 1.0000 | 0.9553 | 0.9242 | 0.2351 | 0.0469 |
| | Mean | 0.1697 | 0.2380 | 0.8187 | 0.0315 | 0.0177 |
| | Std | 0.1479 | 0.1877 | 0.0457 | 0.0473 | 0.0107 |
| Mid-South | Min | 0.0016 | 0.0138 | 0.7048 | 0.0009 | 0.0000 |
| | Max | 0.4495 | 0.6562 | 0.9449 | 1.0000 | 0.0787 |
| | Mean | 0.1069 | 0.1363 | 0.8489 | 0.0485 | 0.0253 |
| | Std | 0.0833 | 0.1292 | 0.0591 | 0.1387 | 0.0139 |
| Southwest | Min | 0.0000 | 0.0000 | 0.8626 | 0.0000 | 0.0148 |
| | Max | 0.7938 | 0.5986 | 0.9498 | 0.0636 | 0.1121 |
| | Mean | 0.0987 | 0.0758 | 0.9090 | 0.0085 | 0.0409 |
| | Std | 0.1549 | 0.1199 | 0.0218 | 0.0153 | 0.0211 |
| Northwest | Min | 0.0060 | 0.0109 | 0.5396 | 0.0005 | 0.0013 |
| | Max | 0.3237 | 0.3576 | 1.0000 | 0.3294 | 0.3938 |
| | Mean | 0.0954 | 0.0766 | 0.8320 | 0.0253 | 0.0609 |
| | Std | 0.0857 | 0.0834 | 0.0937 | 0.0603 | 0.0799 |

Note: Min: minimum value; Max: maximum value; Std: standard deviation.

First, the average carbon emissions of the Norther region are nearly twice the national average, making it a high-carbon-emitting region. Influenced by carbon outflows from Beijing, Tianjin and other central cities, the North region contains more high-carbon-emissions cities than any other region. These central cities gather a large amount of resources, but the carbon emissions generated by its production resources are burdened by neighboring cities [40]. For example, urban-household-embedded carbon emissions in Shanxi, Hebei and Henan provinces increased from 37 Mt in 2002 to 97 Mt in 2012, while that for Beijing and Tianjin only increased from 9 Mt to 21 Mt [41]. The CA and PROX-MN of the cities in the North are higher than the national level, which indicates that these cities are larger and more compact. Benefitting from strategies such as the development of western China and the rise of central China, industrial transfer among cities in the North has become an important link in regulating regional carbon emissions [42]. However, it is not realistic to change the energy-intensive industries in the North in the short term. The more appropriate carbon reduction strategy should be to optimize the energy mix and improve the efficiency of energy use.

Second, the average carbon emissions of the East and Northeast regions are close to the national average, but the urban form between the two areas is completely different. The cities in the East have a higher CA, but their ENN-MN is the lowest among all regions. This suggests that there are many large and compact cities in the East. They have entered a period of orderly development and land-intensive development [43]. In the East, the carbon

emissions in the Yangtze River Economic Belt are mainly limited by energy consumption, carbon sinks and socio-economic development [44]. Because the core industries in the East are light industries, this region has a stronger ability to reduce carbon emissions and can easily transform into high-tech industries. The mean ENN-MN of the Northeast region is 0.1801, three times the national average, while the mean PARA-MN is 0.7161, the lowest among all regions. This is consistent with the characteristics of the Northeast's population outflow and resource-dependent cities.

Third, the mean carbon emissions of the Mid-South, Southwest and Northwest regions are each far below the national mean carbon emissions. The cities in the three regions have similarities: the average CA is lower than the national average, but the average PARA-MN is higher than the national average, indicating that these cities are in the early urbanization stage of sprawl. The poorer quality level and the restricted scale of urbanization lead to lower carbon emissions in the West and South than in the East and North [45]. The three regional cities also have differences. The mean PROX-MN of the cities in the Mid-South and Southwest are completely opposite, suggesting that the cities in the Mid-South are highly compact, and the cities in the Southwest are scattered. The Northwest region of China has a higher ENN-MN and a more dispersed urban distribution compared to the other regions. The cities in the Northwest are mostly close to the borderline and are unsuitable for concentrated distribution, influenced by land use and the military.

### *4.3. Spatial Effects of Carbon Emissions*

The value of Global Moran's I is 0.196, and $p = 0.001$ after randomization 999 times. There is a low-medium degree of spatial dependence of carbon emissions, and high-carbon cities are more likely to cluster with other high-carbon cities. The significance map and the clustering map could be obtained through calculating the Local Moran's I. In Figure 3, many cities are shown in red or blue in the local indicators of spatial autocorrelation (LISA) cluster map, indicating the high–high or low–low spatial clustering. A total of 132 cities show significant spatial dependence in the LISA significance map, while others are not significantly spatially dependent.

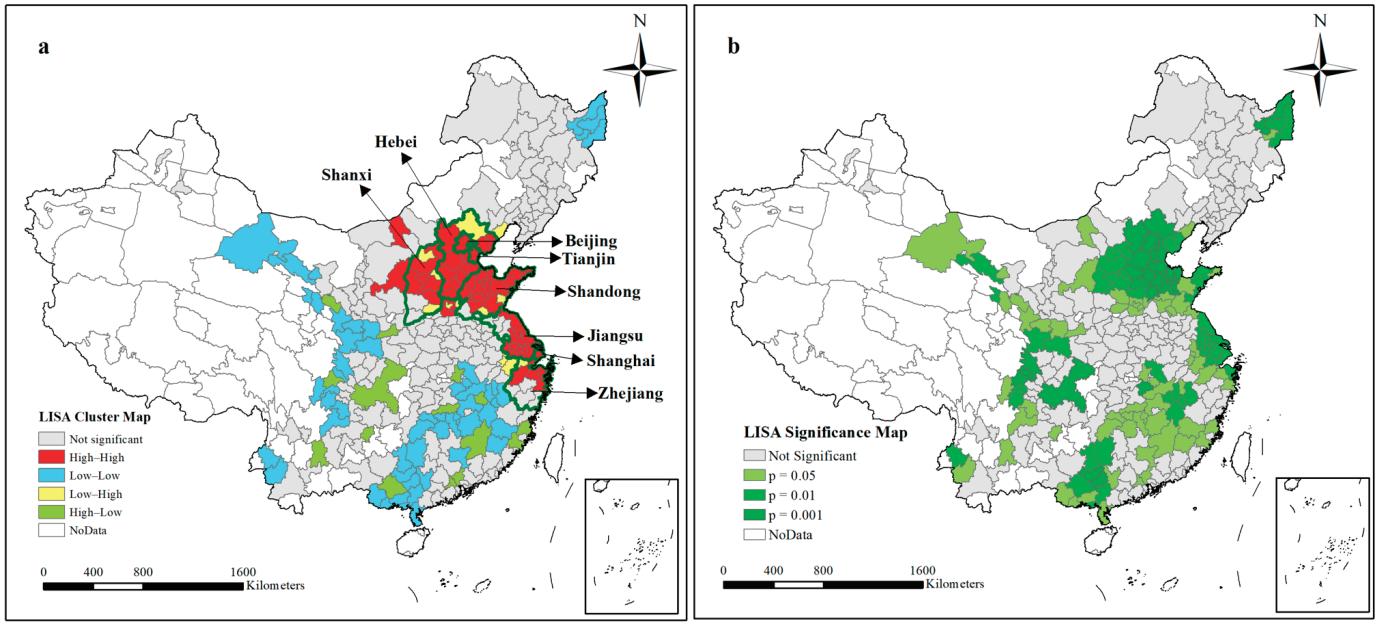


**Figure 3.** The local spatial autocorrelation of carbon emissions in 282 cities in 2017: (**a**) the local indicators of spatial autocorrelation (LISA) cluster map; (**b**) LISA significance map. Note: In the LISA significance map, $p = 0.001$ indicates significance at the 1‰ level, $p = 0.01$ indicates significance at the 1% level, $p = 0.05$ indicates significance at the 5% level. If the significance level is below 5%, the city passes the significance test.

First, the Beijing–Tianjin–Hebei region and the Yangtze River Delta region exhibit a significant high–high clustering. With Beijing and Shanghai as the two centers, the significance gradually decreases outwards. This suggests that the cities with high carbon emissions in China are mainly clustered in these two regions, and they have a stronger spatial dependence the closer they are to the two core cities. However, spatial dependence may change when the study area is narrowed from the national to regional scale. The carbon emissions of cities in the Yellow River Economic Belt showed significant clustering characteristics in the spatial autocorrelation analysis, but high–high clusters were mainly concentrated in Shandong Peninsula, while low–low clusters were distributed in the upstream and midstream of the Yellow River [46]. In Yangtze River Delta cities, the maximum Global Moran's I was only 0.071, implying a weak trend of spatial aggregation of urban carbon emissions [6]. The scope on a national scale is more conducive to highlighting regional characteristics and comparing differences between regions. In addition, the cities with low–low clusters are mainly concentrated in Southwest and Heilongjiang province. Panzhihua in Sichuan Province, Liuzhou in Guangxi Zhuang Autonomous Region, and Shuangyu and Jiamusi in Heilongjiang Province are highly significant, but do not form a clear center due to their fragmented distribution. This means that the cities with low carbon emissions are mainly clustered in the Southwest and Northeast and are evenly distributed, which is consistent with previous studies. Finally, cities with high–low and low–high clustering are mainly distributed at the edges of high- (low-) carbon-emissions-clustering city blocks, without forming significant spatial aggregation.

### *4.4. Results of SEM and OLS*

As shown in Table 4, for the 282 cities in the study area, SEM has a higher log likelihood and lower Akaike information criterion than OLS, which indicates that SEM fits the data better. Meanwhile, the $R^2$ of SEM and OLS is 76% and 73%, respectively, so SEM can explain carbon emissions better.

**Table 4.** Comparison between ordinary least squares (OLS) and spatial error model (SEM) results.

| Variable | OLS | SEM |
|---|---|---|
| Constant | −0.208 *** | −0.253 *** |
| CA | 0.777 *** | 0.800 *** |
| PARA-MN | 0.271 *** | 0.322 *** |
| PROX-MN | −0.289 *** | −0.293 *** |
| ENN-MN | 0.199 *** | 0.202 *** |
| LAMBDA | - | 0.557 *** |
| $R^2$ | 0.73 | 0.76 |
| Log likelihood | 351.532 | 365.674 |
| Akaike info criterion | −693.064 | −721.348 |

Note: *** indicates significance at the 1% level.

The coefficients of CA, PARA-MN and ENN-MN are 0.800, 0.322 and 0.202, respectively, showing a significant positive correlation with carbon emissions. This means that the growth in urban areas, irregularity of morphology and urban sprawl all increase carbon emissions, and the effect of urban areas on carbon emissions is much greater than irregularity and sprawl. In contrast, the coefficient of PROX-MN is −0.293, which shows a significant negative correlation with carbon emissions. This suggests that an increase in urban segregation and fragmentation will increase carbon emissions. At the same time, the results support the hypothesis that urban form landscape metrics affect carbon emissions.

In the spatial autocorrelation test for each region, there is no significant spatial dependence in the North, Southwest and Mid-South regions. There is significant spatial dependence in the East, Northwest and Northeast regions, but the Lagrange Multiplier (lag) and Lagrange Multiplier (error) of these regions are insignificant, indicating that OLS should be used to analyze the effects of urban form on carbon emissions in these regions. Therefore, OLS is more suitable for use in regional analysis than SEM.

The results of OLS for different regions are shown in Table 5. The variables that are significant in each region ($p \leq 0.05$), are selected for the next analysis. CA has a significant positive correlation with carbon emissions in all regions, with the highest coefficient of 1.253 in Southwest. As the sizes of cities increase, the influence of the area on carbon emissions decreases [13]. PARA-MN shows a significant positive correlation with a coefficient of 0.231 and 0.358 in the Northeast and East, respectively. PROX-MN shows a significant negative correlation with a coefficient of −0.752 and −0.241 in the North and Mid-South, respectively. Sha et al. [28] not only found this result by studying 232 cities in China during 2000–2010, but also concluded that this phenomenon is more obvious in coastal areas. However, it is worth noting that the value of PROX-MN in the East is 0.114, indicating an upward trend in carbon emissions as urban compactness grows in the East region. Considering this metric has no significant effect on carbon emissions, the phenomenon will not be discussed next. However, the results can provide a direction for future research, especially the impact of compact cities on carbon emissions. ENN-MN shows a significant positive correlation with a coefficient of 0.566 for urban carbon emissions in the North. The above results support the hypothesis that the effect of each metric varies from region to region.

**Table 5.** OLS results statistics based on administrative divisions.

| Variable | Northeast | North | East | Southwest | Northwest | Mid-South |
|---|---|---|---|---|---|---|
| Constant | −0.160 *** | −0.297 | −0.331 *** | −0.455 | −0.233 | −0.080 |
| CA | 0.946 *** | 0.680 *** | 0.730 *** | 1.253 *** | 0.928 *** | 0.724 *** |
| PARA-MN | 0.231 *** | 0.505 | 0.358 *** | 0.507 | 0.310 * | 0.112 |
| PROX-MN | −0.252 * | −0.752 ** | 0.114 | −0.570 | −0.451 * | −0.241 *** |
| ENN-MN | 0.059 | 0.566 ** | 0.581 | 0.059 | 0.187 | 0.185 |

Note: *** indicates significance at a 1% level, ** indicates significance at a 5% level, * indicates significance at a 10% level.

### *4.5. Discussion*

#### 4.5.1. Mechanisms of the Effects of Urban Form on Carbon Emissions

CA shows a positive correlation with carbon emissions in all 282 cities, implying that the expansion of urban areas can increase carbon emissions. Urban growth does not directly lead to the increase in carbon emissions, but it can increase economic opportunities, population growth and commuting distances, which have been closely linked to carbon emissions. Urban areas, economy and ecology are the core issues for achieving sustainable development in complex geographic areas, and the growth of urban areas has positive effects on economic development and carbon emissions [47]. However, as the city grows, the ecology in general moves in a positive direction. Wang et al. [48] found that urbanization plays a positive mediating effect in the impact of financial scale and financial efficiency on carbon emissions, and this mediating effect includes both chain and parallel effects. Then, although there is a U-type relationship between urbanization and carbon emissions intensity [14], China is currently in the process of rapid urbanization. The rate of urbanization in some developed cities is gradually slowing down, but more cities are still in the first half of the U-shape. Thus, we were able to establish that urban area affects urban carbon emissions through various factors.

PARA-MN shows a significant positive effect on carbon emissions in the Northeast and East, implying that irregular urban development can increase carbon emissions. Regional policies are the key factors contributing to this effect. After the 16th Communist Party Congress, the Northeast region began to revive the old industrial bases and enhance development efforts in specific regions, such as the Liaoning coastal economic belt, Shenyang economic zone and Hadazhi industrial corridor. During the implementation of the policy, the government strengthened infrastructure development and restructured the state-owned enterprises, but there were still a lot of land sales. On the one hand, this has exacerbated the low-density extension of some cities I then Northeast, leading to irregular urban expansion [49]. On the other hand, there are a large number of resource-dependent cities.

These resource-dependent cities are mainly located around capital cities and dominated by secondary industries. While the spatial distribution range expands, the population and economy shrink, generating more carbon emissions than other types of cities. Finally, the irregular shape of the city also affects the traffic road network in the East region. The irregular development of cities increases the development of inter-regional long-range transport situations and intensifies the emission of $CO_2$.

PROX-MN shows a significant negative effect on carbon emissions in the North and Mid-South, implying that compact urban development can reduce carbon emissions. The North and Mid-South regions of China are in the stage of rapid urban development. Influenced by urban planning, the cities in these regions are beginning to develop into compact cities. The compact city can improve land use efficiency and reduce commuting distances. It has been proven to be a more useful form to reduce carbon emissions compared to the scattered patterns of early urban development [50]. Thus, the focus of our compact city policy is to maximize the strengths and minimize the weaknesses to capture the best shape of compact cities. However, compact cities may not always be the best form for reducing carbon emissions according to the experience of foreign urban development. For example, the concentration of population beyond a certain level will consume a lot of resources and increase per capita carbon emissions [28].

ENN-MN shows a significant positive effect on carbon emissions in the North. Urban expansion has a deeper connotation than the growth in area, which means that cities gradually shift from outward expansion to inward development. Si et al. [51] also found that in the North, urbanization has the most significant impact on carbon emissions than other regions, followed by the consumption of fossil energy. The cities in the North have higher intra-urban land use, a large concentration of people and industries in a smaller land area, and high transportation density, which results in more significant carbon emissions from urban expansion than other regions. For example, Tianjin has been transformed from a production city to a consumption city since 2000, and investments in industrial infrastructure have generated the most carbon emissions [52]. An integrated model consisting of population, income and urbanization can better explain the growth in carbon emissions.

#### 4.5.2. Policy Implications for Low-Carbon Urban Planning

According to the effects of urban size, complexity, compactness and centrality on carbon emissions, the region-specific policy recommendations regarding low-carbon urban planning are as follows.

First, based on the significant positive effect of urban area on carbon emissions and the significant negative effect of urban compactness on carbon emissions in the North and Mid-South, the selection of appropriate urban development patterns is a key aspect of low-carbon urban planning in China. Currently, there is still a gap in the urbanization level between China and the developed countries, especially in some cities in the Northwest, Southwest and Mid-South. Therefore, the focus of urban development at this stage remains on compact development, improving the efficiency of land and public facilities utilization, and avoiding blind expansion. However, when urban compactness exceeds a certain threshold, we also need to consider the issues of traffic, population density and health. On the one hand, we need to develop specific measures for different cities to maintain urban compactness at an appropriate level, so as to achieve the goal of maintaining low carbon emissions while living in a livable environment, for example, by balancing the relationship between urban compactness, water bodies and green spaces to achieve the coexistence of regulated urban microclimates and compact cities [53]. On the other hand, future urban development can also shift towards other urban forms, such as polycentric development. It can improve carbon efficiency while reducing traffic pressure and is suitable for cities with large populations in China [28].

Second, based on the significant positive effect of urban expansion on carbon emissions and the spatial characteristics in the North, low-carbon urban planning should focus on optimizing the energy structure and improving energy use efficiency. Above all, population

and technology are prerequisites for improving energy efficiency. The North region should use its regional attractiveness and combine it with the national strategy of "One Belt, One Road" to increase the inflow of highly qualified personnel and the import of high technology. The development of a low-carbon transportation system is also an important aspect. Transportation carbon emissions caused by decentralized urban distribution should be reduced through rational transportation and road network planning. Transportation planning should shift from quantity to quality and from building more roads to optimizing the structure of the road system. Public transportation, as one of the main sources of carbon emissions from transportation, produces less carbon emissions than private cars. Thus, it is necessary to increase the number of public car and subway operating stations and reasonably limit the amount of private car ownership [54]. Finally, the North region is at the key node of domestic industrial transfers and needs to ensure that pollution does not occur again. To reduce the vicious competition in the process of industrial transfers, relevant planning is needed to restrict companies. Companies also need to optimize their development for energy-intensive industries, shifting from a focus on coal resources to cleaner energy sources and technological innovation. Cities need to seize the important opportunity period of industry shifts to eliminate outdated production equipment and develop a reasonable strategy for future industrial development.

Third, based on the significant positive effect of urban complexity on carbon emissions in the Northeast and East, the government should pay attention to urban development boundary control in its planning. In the context of China's current territorial spatial planning, the government needs to strengthen the control of urban development boundaries. The control of these boundaries mainly includes the formulation of growth boundaries and the delineation of urban areas. The growth boundary should be set with attention to both the rigid boundary of a reasonable scale and the flexible boundary of the reuse of the internal stock of land. Then, the cities should choose the appropriate development boundary orientation, combining their stage of development and existing problems. For example, Sargent et al. [55] detected changes in carbon emissions around Boston by combining $CO_2$ emissions inventories and Lagrangian particle dispersion models, which were used to assess carbon mitigation efforts in the surrounding area and establish buffer zones.

## 5. Conclusions

This study identified the set of urban form landscape metrics, then analyzed the characteristics and spatial correlation of carbon emissions in 282 cities in China and used a spatial error model to analyze the effects of urban form on carbon emissions. First, through stepwise linear regression, the set of urban form landscape metrics was determined to include the four metrics of CA, PARA-MN, PROX-MN and ENN-MN. In addition, there is a significant positive spatial autocorrelation within the study area. Through Local Moran's I, it was found that cities with high (low) carbon emissions are more likely to cluster spatially. The cities with high–high clustering are mainly clustered in the Beijing–Tianjin–Hebei region and the Yangtze River Delta region. The low–low clustering cities are mainly concentrated in the Southwest and Heilongjiang Province. Furthermore, the results of the spatial error model reveal that CA, PARA-MN and ENN-MN show a significant positive correlation with carbon emissions, and the most significant effect for urban areas among the three. In contrast, PROX-MN shows a significant negative correlation with carbon emissions. By dividing cities into administrative divisions, CA shows a significant positive correlation in all regions, and the highest coefficient in the Northwest, which is related to the economic growth and population increase that occurs as urban areas grow. PARA-MN has a significant positive correlation in the Northeast and East, which is related to regional planning and traffic. PROX-MN has a significant negative correlation in the North and Mid-South, which is related to the rapid urbanization development of these cities. ENN-MN has a significant positive correlation only in the North, which is related to the high land utilization rate and dense population resources of cities in the North. These results strongly support the validity of the hypotheses. Finally, based

on the effects of urban form on carbon emissions, we proposed recommendations for low-carbon urban planning, including selecting appropriate urban development patterns, strengthening energy structure optimization and utilization efficiency, and strengthening urban development boundary control.

This study has some research limitations. Firstly, limited by the availability of data, the data used only contain urban impervious surfaces and therefore do not allow for the identification of detailed land use types. By exploring the effects of the urban form on carbon emissions as influenced by different land use types, it can help to suggest low-carbon planning recommendations specific to the land use type. Future work will identify the different land use types. Secondly, this study classifies cities according to their geographical location and ultimately finds that PROX-MN in the East has the opposite effect on carbon emissions compared to other regions. For this particular result, we need to extend the time scale in future work and focus on the coefficient of PROX-MN in the East.

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**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

We selected 15 landscape metrics and described them briefly. The equations and specific descriptions of these metrics are given in Table A1 in order to improve comprehension of the metric selection.

**Table A1.** Urban form landscape metric system.

| Category | Variable | Equation | Description |
|---|---|---|---|
| Area | Class Area (CA) | $CA = \sum_{i=1}^{n} a_i \left(\frac{1}{10000}\right)$ | Urban area |
| | Number of Patches (NP) | $NP = n$ | Urban fragmentation |
| | Largest Patch Index (LPI) | $LPI = \frac{\max_{j=1}^{n}(a_{ij})}{CA} 100$ | Urban growth |
| Edge | Edge density (ED) | $ED = \frac{\sum_{i=1}^{n} e_i}{CA}$ | Urban shape complexity |
| Shape | Area-weighted Mean Shape Index (AWMSI) | $AWMSI = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\left(\frac{p_{ij}}{\min p_{ij}}\right)\left(\frac{a_{ij}}{CA}\right)\right]$ | Urban shape complexity |
| | Area-weighted Mean Patch Fractal Dimension (AWMPFD) | $AWMPFD = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\left(\frac{2\ln\left(0.25p_{ij}\right)}{\ln\left(a_{ij}\right)}\right)\left(\frac{a_{ij}}{CA}\right)\right]$ | Urban shape complexity |
| | Mean Perimeter–Area Ratio (PARA-MN) | $PARA\text{-}MN = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{p_{ij}}{a_{ij}}\right)}{mn}$ | Urban shape complexity |
| Aggregation | Landscape Shape Index (LSI) | $LSI = \frac{0.25 \sum_{k=1}^{m} e_{ik}^{*}}{\sqrt{CA}}$ | Urban shape complexity |
| | Clumpiness Index (CLUMPY) | $CLUMPY = \left[\frac{G_i - P_i}{P_i}\right]$ if $G_i < P_i < 0.5$ else $CLUMPY = \left[\frac{G_i - P_i}{1 - P_i}\right]$ | Urban compactness |
| | Percentage of Like Adjacencies (PLADJ) | $PLADJ = \left(\frac{\sum_{i=1}^{m} g_{ii}}{\sum_{i=1}^{m} \sum_{k=1}^{n} g_{ik}}\right)(100)$ | Urban compactness |
| | Patch Cohesion Index (COHESION) | $COHESION = \left[1 - \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij}^{*}}{\sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij}^{*} \sqrt{a_{ij}^{*}}}\right] \times \left[1 - \frac{1}{\sqrt{Z}}\right]^{-1} (100)$ | Urban compactness |
| | Aggregation Index (AI) | $AI = \left[\frac{g_{ii}}{\max(g_{ii})}\right](100)$ | Urban compactness |
| | Mean Proximity Index (PROX-MN) | $PROX\text{-}MN = \sum_{s=1}^{n} \frac{a_{ijs}}{h_{ijs}}$ | Urban compactness |
| | Mean Euclidian Nearest Neighbor Distance (ENN-MN) | $ENN\text{-}MN = h_{ij}$ | Centrality |
| | Patch Density (PD) | $PD = \frac{n}{CA}$ | Urban fragmentation |

## Appendix B

Before determining the spatial econometric model, it is necessary to diagnose the spatial dependence of urban form and carbon emissions. Comparing the spatial regression statistics in Table A2, both Lagrange Multiplier (lag) and Lagrange Multiplier (error) are significant ($p < 0.05$), but P (Robust LM (lag)) = 0.120 > 0.1, $p$ (Robust LM (error)) = 0.000 < 0.01, and value (Robust LM (lag)) < value (Robust LM (error)), so the spatial error model is the better choice.

**Table A2.** Diagnostics for spatial dependence of urban form and carbon emissions.

| Test | Degree of Freedom | Value | Probability |
|---|---|---|---|
| Lagrange Multiplier (lag) | 1 | 4.339 | 0.037 |
| Robust LM (lag) | 1 | 2.417 | 0.120 |
| Lagrange Multiplier (error) | 1 | 38.279 | 0.000 |
| Robust LM (error) | 1 | 36.358 | 0.000 |

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Article

# Towards Sustainable Management of Urban Ecological Space: A Zoning Approach Hybridized by Ecosystem Service Value and Ecological Risk Assessment

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**Abstract:** Massive growth is posing threat to the ecological security and sustainability of cities. Ecosystem service value (ESV) and ecological risk index (ERI) assessment can be conducted to enhance urban ecosystem management through the enhanced recognition of these values and risks in decision-making. This paper aimed to measure spatiotemporal ESV and ERI for Shizuishan City located in central China, and, based on this, how to zone urban ecological space using land cover data (for the years 2010, 2015, and 2020). The management options of different zones were suggested to mitigate and manage any potential negative impacts on urban ecological security. Results show that: (1) The spatial distribution characteristic of ESV is "high in the south and low in the north". The total ESV exhibited an upward tendency from 2010 to 2020. (2) The high-ERI areas were distributed in the peripheral region, while the low-ERI areas were concentrated in the central region. The ERI of water was in decline continuously, whereas the ERI of wetland maintained a high level. (3) The zoning approach integrating ESV and ERI assessment can truly reflect the status of the environment and better clarify the direction of ecological development for different areas. Among four different ecological zones, the high-ESV and low-ERI areas (I) have abundant ecological resources, and they are set as "Priority Development Areas". The low-ESV and low-ERI areas (II) are set as "Ecological Improvement Areas" because the area of ecological lands are confined. The low-ESV and high-ERI areas (III) have a fragile ecological environment, and they are set as "Exploitation-Prohibited Areas". The high-ESV and high-ERI areas (IV) are mainly distributed near water and wetland, and they are set as "Research-focused Areas".

**Keywords:** urban planning; ecological planning; urban sustainability; China

## 1. Introduction

Natural ecosystems perform fundamental life-support services upon which human civilization depends. A robust ecosystem can contribute to social and economic well-being by providing a stable base for a diverse set of urban activities. The spatial prioritization and optimization of urban ecological space is a nature-based solution to promote ecosystem services and maintain urban ecological security [1,2]. Urban ecological planning is the process of facilitating decision-making to carry out the spatial arrangements of urban ecological space with consideration given to the ecosystem service and ecological risk. Sustainable management aims to control urban development and improve the framework of life in the cities. To avoid putting unnecessary strain on the supporting ecosystem constitute the major objective of sustainable management [3]. It is about creating an equilibrium between consumerist human culture and the living world. In simple terms, sustainable management is the practice of interacting with the planet [4]. Sustainable management is essential because ecosystem services and their ecological process provide goods and services to human well-being and subsistence [5]. Nevertheless, these goods and services

were once mistakenly regarded as abundant and inexhaustible, which directly accelerated excessive consumption of their supply and increased their scarcity [6], ultimately resulting in the degradation of the ecosystem and the increased ecological risk. So, it is urgent to implement sustainable management to legitimately control the consumption of ecological resources by human activities and minimize the damage to the biodiverse ecosystem [7]. Meanwhile, there are spatio-temporal interactions between ecosystem service value and ecological risk. Thus, analyzing the ecological risk based on ecosystem service value, and then constructing ecological zones of different levels and managing them rationally will be an inevitable requirement for ecological civilization construction and sustainable management in the new era.

Human activities usually affect the process, structure, and functions of the ecological environment by altering land cover types [8], and these changes in the ecosystem can be reflected by ecosystem service value (ESV) changes [9]. Thus, ESV can be used to evaluate the potential of the regional ecosystem for human services and explore the changing impacts of human disturbances on the ecological environment [10]. According to the construction of the evaluation framework and pricing method, the approaches in ESV assessments can be roughly divided into two types. One is based on the unit service function price [11] (hereinafter referred to as the functional value method), and the other is based on the equivalent value factor per unit ecosystem area [12] (hereinafter referred to as the equivalent factor method). The functional value method is primarily employed in small-scale regions. Meanwhile, this approach requires multiple input parameters, and the calculation process is extremely cumbersome, which leads to difficulty in unifying the evaluation processes and parameter thresholds [13]. Therefore, this approach is not applicable for the assessment of ESV on a large scale. The equivalent factor method is an alternative market method, which is mainly built on the area of different landscape types and their corresponding value equivalents [14]. This method is intuitive and easy to use, requires relatively little data, and is highly comparable and comprehensive, making it a pervasive approach for evaluating ESV at regional and global scales [15]. The prototype of this method was proposed by Costanza et al. and was used to estimate the value of 17 ecosystem services by 16 land resources [16]. However, this prototype method had high requirements for data collection and processing, and the calculation is relatively complicated and is not generalized [17]. Hence, taking the findings of Constanza et al. as a reference, Xie et al. established a table of China's equivalents of ecosystem service value supplied per unit area of ecosystem grounded on the ecological questionnaire survey conducted by Chinese professionals and finally calculated the 11 types of ecosystem service value [5]. Compared with other methods, this method is considered more practical and has the advantages of low data requirements, high comparability of results, and the ability for comprehensive evaluation [18]. Subsequently, extensive studies on ecosystem service valuation have been carried out in terms of the pattern [19], process [20], and function [21]. Most recent attention has focused on the relationship between ESV and urbanization, and studies were performed on the changing trend of ESV in rapid urbanization areas [22], the synergies between ESV and economic development [23], and the driving mechanism of changes in ESV [24]. Moreover, a number of studies have directly focused on the changes in ESV of ecological lands, such as the spatial autocorrelation in land use type and ESV in rainforest national parks [15], and the effect of biological invasion on ESV [25]. Overall, these studies highlight the impact of human activities on regional ESV.

Ecological risk represents the likelihood of adverse ecological effects occurring as a consequence of anthropogenic activities and natural hazards [26], which reveals the ability of an ecosystem to maintain its self-stability under specific environmental pressures [27]. As an important means of ecological and environmental management [28], an ecological risk assessment is performed to evaluate the likelihood of adverse ecological effects occurring as a result of exposure to physical or chemical stressors. This helps us appreciate the fact that anthropogenic activities and natural environmental changes may be detrimental to regional ecosystems [29]. There are two chief approaches to ecological risk assessment.

One is based on the risk source–risk receptors–exposure and hazard assessment model [30]. The most original approach of ecological risk assessments focused on the environmental impacts of chemical contaminants or pollution events on ecosystems, mostly emphasizing a single risk source or a single risk receptor [31]. Risk assessment that follows this method has been carried out by taking water contaminants [32], toxic metal [33], landslides [34], and other sudden environmental events or specific objects as the risk sources. Currently, this approach is still used for analyzing particular site-specific hazards in small geographic areas, such as monitoring the impact of toxic chemicals on local human health [35]. Thus, this approach is susceptible to subjective factors in that it focuses on identifying the risk sources and receptors, while different scholars will have different views on their determination of them. The other group of literature mostly depends on RS, GIS, and Landscape metrics to construct the landscape ecological risk index (ERI) which combines multiple sources of risk generated by natural or human disturbances [36] to evaluate the ecological risk from the perspective of the land-cover change. River basins [37], protected areas [38], administrative districts [39], urban agglomerations [40], etc., are extensively examined. This approach takes account of scale effects, temporal changes, and regional spatial heterogeneity, which contributes to the spatial visualization of regional ecological management. Meanwhile, with the advancement of global change and ecological risk studies, this approach has become mainstream research and is widely applied. Most recent studies have focused on analyzing the spatiotemporal distribution of ecological risk, and the study areas were selected areas with intensive human activities, mainly in watersheds, urban territories [41], mining areas [42], and coastal areas [43]. Moreover, some studies have been conducted on exploring the driving forces of ecological risk [44] or constructing the ecological risk projection model [45]. In conclusion, the ecological risk assessment has changed dramatically, such as the evaluation elements have developed from single-risk source and single-risk receptor to multi-risk source and multi-risk receptors [46], and the evaluation scope has expanded from small-scale areas to the regional landscape [47], and the evaluation unit has been transformed from an administrative region to risk communities.

There is a growing body of research on ecosystem service evaluation and ecological risk evaluation. However, gaps remain: (1) the ESV and ERI remain relatively independent, and there have been infrequent studies that would combine these two assessment approaches and ecological zone to identify the priority of urban ecological area protection and propose targeted ecological management measures. (2) The study areas were mostly economically prosperous areas such as the Beijing–Tianjin–Hebei urban agglomeration and Yangtze River Delta in China and areas with special geomorphological characteristics in the southwest of China, while the northwest area of China has not received much attention.

Therefore, unlike previous studies, this research took Shizuishan City in northwest China as an illustration, based on land cover data in 2010, 2015, and 2020, and not only analyzed the temporal and spatial distribution of ESV and ERI in the study area but also established a zoning approach integrated the ESV and ERI to facilitate the proposal of targeted ecological management measures. To the best of our knowledge, few studies have comprehensively evaluated the regional ecological environment from human well-being and potential risks perspectives. Meanwhile, compared with previous work that applies a single ESV or ERI assessment, this zoning approach emphasizes the integrity of the ecosystem, which can reflect the ecological environment security status from positive and negative sides. Then the decision-making basis and theoretical guidance will be precisely provided for the ecological environment construction of the study area.

## 2. Materials and Methods

### *2.1. Study Area*

The area of the study is Shizuishan City, which is located in the north of Ningxia Hui Autonomous Region, China (Figure 1). It extends over an area of about 5309.5 $km^2$ with a population of 805,000 and encompasses two districts and one county: Dawukou, Huinong, and Pingluo. Topographically, the altitude ranges from 940–3411 m, and there

exist diversified landforms including mountains, alluvial plain, and platforms. It has a continental climate characterized by hot summers and cold winters and is a typical arid and semi-arid region with an annual average temperature of 8.4–9.9 °C and annual precipitation of 167.5–188.8 mm on average. As the most important river systems in Shizuishan City, Xinghai Lake, Sha Lake, and Yellow River play an irreplaceable role in regulating climate, purifying the environment, and preserving biodiversity.

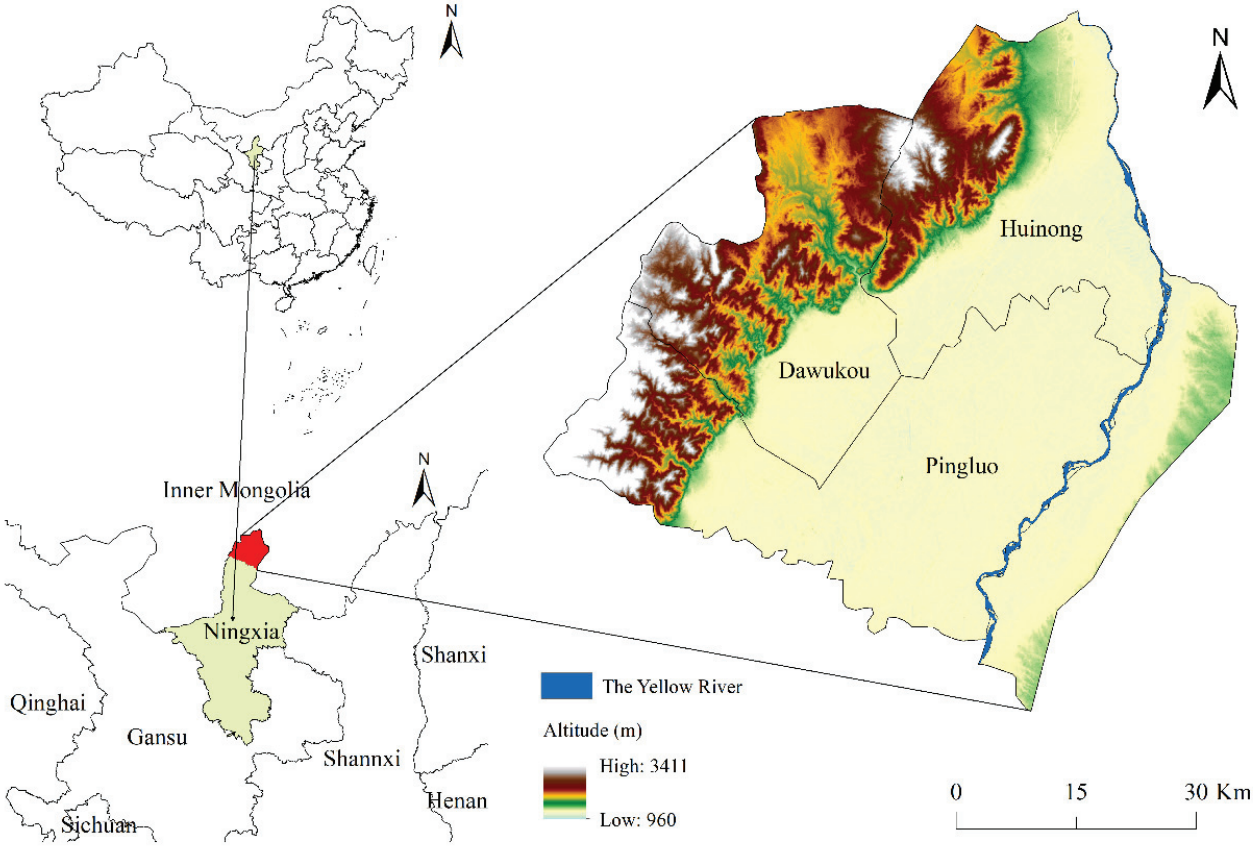


**Figure 1.** Overview of the study area.

This region was selected for two reasons: (1) Shizuishan City is one of the representative resource-based cities in Northwest China, which heavily depends on mineral exploitation and is vulnerable to the deterioration of the ecological environment. Some developing countries are also facing such urban development dilemma. Therefore, identifying the priority areas of ecological space in Shizuishan City will contribute to the scientific management and control of ecological lands, and research results will provide suggestions for the policy on green transformation development of resource-based cities in Northwest China. Meanwhile, it also has general value for the management of urban ecological space beyond China; (2) Shizuishan City is a typical arid and semi-arid region in the upper reaches of the Yellow River, where water bodies are particularly important for the improvement of the ecological environment in this region. Thus, carrying out ecological space research is effective in identifying the priority water protection zones, and the research results are excepted to provide a valuable reference for the preservation and restoration of watersheds in the arid and semi-arid regions of China and some desert cities around the world.

### *2.2. Data*

The data involved in this study include land use and statistical data. The land use grids of 2010, 2015, and 2020 with a spatial resolution of 30 m × 30 m were derived from GLC_FCS30-1985_2020 which is developed by the Aerospace Information Research

Institute of the Chinese Academy of Science [48] (http://www.aircas.ac.cn/, accessed on 18 May 2022). Produced from Landsat-TM, Landsat-ETM+, and OLI sensors, it covers 29 land-use types. The data were reclassified into eight types-: dry land, paddy field, forest land, grassland, water, wetland, bare land, and impervious surface (Table 1). The statistical data of main grain market price and grain yield per unit of farmland area (The statistical data were obtained to calculate the Ecosystem Service Value Index) were obtained from the Bureau of Statistics of Ningxia Hui Autonomous Region (http://tj.nx.gov.cn/, accessed on 20 April 2022), and the Food and Strategic Reserves Administration of Ningxia Hui Autonomous Region (http://lswz.nx.gov.cn/, accessed on 20 April 2022).

**Table 1.** Reclassified land-use types.

| Reclassification System | Original Classification System | Area ($km^2$) | | |
|---|---|---|---|---|
| | | 2010 | 2015 | 2020 |
| Dry land | Rainfed cropland | 1090.82 | 1104.95 | 1147.04 |
| Paddy field | Irrigated cropland | 502.49 | 518.56 | 539.64 |
| Forest land | Open deciduous broadleaved forest<br>Closed deciduous broadleaved forest<br>Open evergreen needle-leaved forest<br>Closed evergreen needle-leaved forest<br>Shrubland | 239.87 | 234.60 | 221.98 |
| Grassland | Grassland<br>Sparse vegetation<br>Herbaceous cover | 797.04 | 764.10 | 668.61 |
| Wetland | Wetland | 44.10 | 57.86 | 83.35 |
| Impervious Surface | Impervious Surface | 154.53 | 166.71 | 221.52 |
| Bare Land | Bare areas<br>Unconsolidated bare areas | 1192.12 | 1161.72 | 1111.02 |
| Water | Water body | 60.23 | 72.70 | 88.04 |

### *2.3. Methods*

#### 2.3.1. Ecological Zones

The zonation of urban ecological space is constructed on the basis of assessing ecosystem service value and ecological risk. To spatialize the ecosystem service value and ecological risk, the evaluation units were established. Building on the relevant studies, the area of landscape samples is supposed to reach 2–5 times the average, thus comprehensively reflecting the landscape pattern information around the sampling site [49]. The northwest of the study area is a mountainous region and the northeast is a plain region. The landscape features, such as forest land, grassland, and cultivated land, in this area, are relatively broken. Therefore, the study area was divided into plenty of 3 km $\times$ 3 km grids by comprehensively considering the calculation intensity, calculation accuracy, and the actual situation in the study area. Then a total of 516 evaluation units were obtained. What is more, the geometric center of the grid was taken as a sampling point of the ecosystem service value index and ecological risk index as calculated by Fragstats.

These indices of the 516 evaluation units were standardized by using the Z-score standardization method to build a scatter plot with ecosystem service value on *X*-axis and ecological risk on *Y*-axis. Finally, the four quadrants of the scatter plot were divided to represent different types of ecological zones. Among them, quadrant I represents a high value-low risk, quadrant II represents a low-ESV and low-ERI, quadrant III represents a low-ESV and high-ERI, and quadrant IV represents a high-ESV and low-ERI [50].

#### 2.3.2. Ecosystem Service Value Index

According to the ecosystem service value equivalence coefficients as proposed by Costanza et al. (1997) [16] and "China's equivalents of ecosystem service value supplied by

per unit area of an ecosystem (Table 2)" by Xie et al. (2015) [5], the calculation equation of ecosystem service value ($ESV_k$) is expressed as follows:

$$ESV_k = \sum_{j=1}^{m} A_{kj} \times VC_j \quad (1)$$

where $ESV_k$ represents the ecosystem service value of sample $k$ (RMB/ha), $A_{kj}$ indicates the area of landscape $j$ in sample $k$ (ha), $VC_j$ refers to the ecosystem service value per unit area of landscape $j$ (RMB/ha), and its calculation equation is expressed as follows:

$$VC_j = \frac{1}{7}\sum_{i=1}^{n} \frac{m_i p_i q_i}{M} \times V_j \quad (2)$$

where $m_i$ represents the average crop area of grain $i$ in the study area from 2010 to 2020 (ha), $p_i$ denotes the average price of grain $i$ in the study area from 2010 to 2020 (RMB), $q_i$ refers to the average yield per unit area of grain $i$ in the study area from 2010 to 2020, $M$ stands for the total crop area of all kinds of grain (ha) [51], and $V_j$ means the ESV equivalents of different landscape types, which can be obtained from Table 2.

**Table 2.** China's equivalents of ecosystem service value supplied by per unit area of ecosystem.

| Landscape Type | Dry Land | Paddy Field | Forest Land | Grassland | Wetland | Bare Land | Water | Impervious Surface |
|---|---|---|---|---|---|---|---|---|
| Provisioning services | | | | | | | | |
| Food production | 0.85 | 1.36 | 0.23 | 0.24 | 0.51 | 0.00 | 0.80 | 0.00 |
| Raw material production | 0.40 | 0.09 | 0.54 | 0.35 | 0.50 | 0.00 | 0.23 | 0.00 |
| Regulating services | | | | | | | | |
| Water supply | 0.02 | 2.63 | 0.28 | 0.20 | 2.59 | 0.00 | 8.29 | 0.00 |
| Climate regulation | 0.67 | 1.11 | 1.76 | 1.24 | 1.90 | 0.02 | 0.77 | 0.00 |
| Gas regulation | 0.36 | 0.57 | 5.27 | 3.28 | 3.60 | 0.00 | 2.29 | 0.00 |
| Purify environment | 0.10 | 0.17 | 1.57 | 1.08 | 3.60 | 0.00 | 2.29 | 0.00 |
| Hydrological regulation | 0.27 | 2.72 | 3.81 | 2.40 | 24.23 | 0.03 | 102.24 | 0.00 |
| Supporting services | | | | | | | | |
| Soil retention | 1.03 | 0.01 | 2.14 | 1.51 | 2.31 | 0.02 | 0.93 | 0.00 |
| Nutrient cycling | 0.12 | 0.19 | 0.16 | 0.12 | 0.18 | 0.00 | 0.07 | 0.00 |
| Biodiversity conservation | 0.13 | 0.21 | 1.95 | 0.37 | 7.87 | 0.02 | 2.55 | 0.00 |
| Cultural services | | | | | | | | |
| Aesthetic landscape | 0.06 | 0.09 | 3.86 | 0.61 | 4.73 | 0.01 | 1.89 | 0.00 |

2.3.3. Ecological Risk Index

The landscape ecological risk refers to the possible adverse consequences of the interactions between the landscape pattern and ecological processes under the influences of natural and or human factors, and it can be defined as the combined result of the different probabilities of the risk probability and landscape loss degree. The magnitude of regional ecological risk is related to the intensity of the external disturbance to which the local ecosystem is exposed and the internal resistance capacity of different landscape types within the ecosystem [52]. Different landscape types play different roles in protecting species, preserving biodiversity, and promoting ecosystem succession. Thus, based on previous research results and the practicalities in the study area, the spatial pattern characteristics of each landscape are converted into a composite representation of the relative scale of ecological risk and the degree of the potential loss. Then an evaluation model of the ecological risk ($ERI_k$) was constructed by using the landscape disturbance degree index ($U_i$), landscape vulnerability index ($F_i$), and the area of different landscape types [53], which can be expressed as follows:

$$ERI_k = \sum_{i=1}^{n} \frac{A_{ki}}{A_k} U_i \times F_i \quad (3)$$

where $n$ represents the number of landscape types, $A_{ki}$ indicates the area of landscape $i$ in sample area $k$, $A_k$ is the total area of sample $k$, $U_i$ refers to the landscape disturbance degree index, and $F_i$ stands for the landscape vulnerability index.

The landscape disturbance degree index can be adopted to measure the external disturbance caused to the urban ecosystem by the changes in resources and environment as a result of the changes in the population size and composition in the process of rapid urbanization [54]. To be specific, the activities that can disrupt the urban ecosystem include the expansion of construction land, the destruction of ecological lands, and the construction of urban roads [55]. Thus, the landscape disturbance degree index was constructed by integrating the landscape fragmentation degree index, landscape separation degree index, and landscape dominance degree index [56], which is expressed as follows:

$$U_i = aC_i + bN_i + cD_i \quad (4)$$

where $C_i$, $N_i$, and $D_i$ represent the landscape fragmentation index, landscape separation index, and landscape dominance index, respectively. Table 3 shows the formula used to calculate these indices and the ecological meaning. $\alpha$, $b$, and $c$ refer to the weights of the corresponding landscape indices. According to the previous research results and the characteristics of the study area, $\alpha$ = 0.5, $b$ = 0.3, and $c$ = 0.2 were assigned as weights [57].

**Table 3.** Ecological meaning and expression of the landscape pattern index.

| Index | Calculation | Ecological Meaning |
| --- | --- | --- |
| Landscape fragmentation degree index | $C_i = \frac{n_i}{A_i}$ | Represents the fragmentation of the landscape, the higher the value, the lower the stability of the landscape ecosystem [58]. |
| Landscape separation degree index | $N_i = \frac{A}{2A_i}\sqrt{\frac{n_i}{A}}$ | Represents the separation of patches in the landscape, the higher the value, the more complex the landscape spatial distribution [59]. |
| Landscape dominance degree index | $D_i = dL_i + eP_i$ | Represents the significance of patches in the landscape, which directly reflects the influence of patches on the formation and change in landscape patterns [60]. |

Note: $n_i$ is the number of patches in the $i$ the landscape type; $A_i$ is the area of the $i$th landscape type, $A$ is the total area; $L_i$ is the landscape relative density; $P_i$ is the landscape relative coverage; $d$ and $e$ are the weights of the corresponding indices, which are 0.6 and 0.4 respectively.

The landscape vulnerable index is an effective indicator that is applied to denote the resistance and the degree of loss of the stability of different landscape types due to external disturbance. The eight landscape types, including bare land, wetland, water area, paddy field, dry land, grassland, forest land, and impervious surface were assigned the values of 8-1, respectively. Then, they were normalized to obtain $F_i$ [61].

## 3. Results

### *3.1. Spatiotemporal Analysis of ESV*

#### 3.1.1. Distribution Characteristics of ESV

Kriging interpolation [62] was performed on the ecosystem service value index [63]. The spatial distribution of the ecosystem service value in the study area in 2020 was mapped (Figure 2). In previous studies, it was indicated that the natural breakpoint method achieves high grading accuracy by taking into account the balance of extreme differences in index intensity at all levels [64]. In this way, better-integrated mapping results can be achieved [65]. Therefore, this method was applied to classify ESV into five levels: low value, medium-low value, medium value, medium-high value, and high value.

In general, the ecosystem service value in the study area was high in the south but low in the north. The high-value areas were distributed mainly in the south of Dawukou District and the south of Pingluo County, where Xinghai Lake and Sha Lake were located,

respectively. These areas featured high vegetation coverage, favorable hydrothermal conditions, and strong adjustment capabilities. Therefore, these areas could provide various ecosystem services, creating a high ecosystem value. The medium-high-value areas were concentrated around the high-value areas, with a small number of them distributed near the Yellow River Basin in the east of Pingluo County. The medium-value areas included the south of Dawukou District, the east and west of Pingluo County, and the south of Huinong District. Notably, the medium-value areas in the east of Pingluo County were integrally and continuously distributed. These areas were found in the middle and upper reaches of the Shizuishan section of the Yellow River Basin, which suggests the increasing efforts made in Shizuishan City over recent years to preserve the Yellow River Basin. The medium-low-value areas were extensively distributed in Dawukou District, Huinong District, and Pingluo County. The landscape types in these areas were dominated by forest land and grassland. However, these areas were also interspersed with some bare land, which led to a highly fragmented landscape. Thus, the corresponding ecosystem service value was relatively low. The low-value areas accounted for the largest proportion and were distributed throughout the study area. They featured either dense population or low vegetation coverage. The disruption caused by human activities impeded vegetation growth. As a result, the ecosystem service value was the lowest in these areas [66].

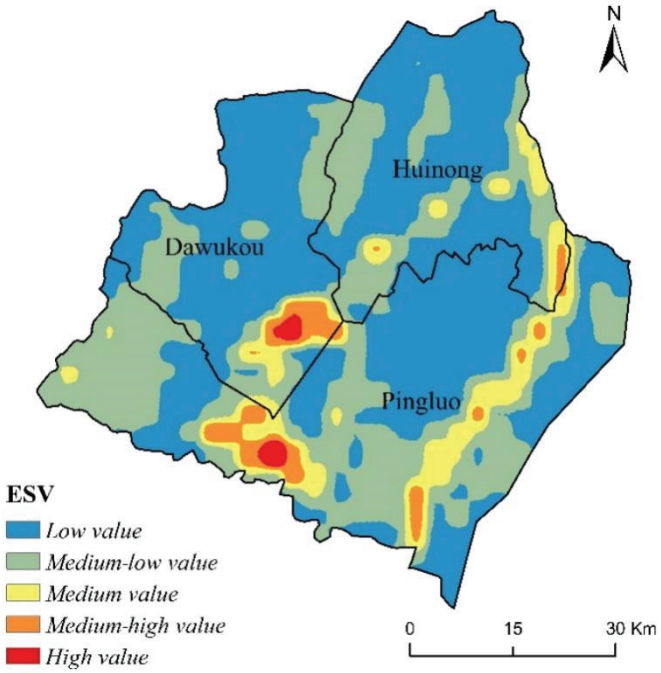


**Figure 2.** Distribution of ecosystem service value in Shizuishan City, 2020.

The total ESV of Shizuishan City in 2020 amounted to RMB 8.550 billion. Concerning landscape types, water had the largest ESV of RMB 2.479 billion, accounting for 28.99% of the whole. Water provides a major driving force for the evolution of the ecosystem [67], which deserves effective preservation. The ESV of grassland was lower than that of water, accounting for 20.48% of the total. The value of paddy fields, forest land, and arid land accounted for a similar proportion, reaching 13.29%, 12.89%, and 12.36%, respectively. Despite a confined area of wetland, its ESV accounted for 11.67%. Therefore, enhancing the protection and restoration of wetlands is considered effective in improving ESV for Shizuishan City [68]. The ESV of bare land was the lowest, accounting for barely 0.3% of the total. In terms of ecosystem services types, the ESV of regulating services reached RMB 6.227 billion. As the highest amount, it accouned for more than half of the total. Thus, water is essential for regulating the circulation of the ecosystem. The ESV of provisioning services was significantly lower than that of regulating services, accounting for only 13.97% of the

total. The ESV of supporting services and cultural services was the lowest, accounting for 7.96% and 5.25%, respectively (Table 4).

**Table 4.** Ecosystem service value (%) of landscape types and services types in Shizuishan City, 2020.

| | **ESV (RMB, Billion)** | **Proportion (%)** |
|---|---|---|
| Landscape Type | | |
| Arid Land | 1.059 | 12.38 |
| Paddy Field | 1.136 | 13.29 |
| Forest Land | 1.102 | 12.89 |
| Grassland | 1.751 | 20.48 |
| Wetland | 0.997 | 11.67 |
| Bare Land | 0.026 | 0.30 |
| Water | 2.479 | 28.99 |
| Impervious surface | 0.000 | 0.00 |
| Services Type | | |
| Provisioning Services | 0.680 | 7.96 |
| Regulating Services | 6.227 | 72.83 |
| Supporting Services | 1.194 | 13.97 |
| Cultural Services | 0.449 | 5.25 |

3.1.2. Variation among Landscape Types and Services Types in ESV

The total ESV in the study area exhibited an upward tendency from 2010 to 2020, amounting to RMB 7.594 billion in 2010, RMB 8.043 billion in 2015, and RMB 8.550 billion in 2020, respectively. It suggests that a satisfactory performance has been achieved over recent years in enforcing environmental protection policies in Shizuishan City, with the ecological environment considerably improved. As for landscape types, the ESV increased slightly for both arid land and paddy field, despite an insignificant decrease in their proportion. On the one hand, it demonstrates that the protection of cultivated land attracted close attention during urban development, as a result of which the expansion of construction land did not occupy a large amount of them. On the other hand, it also revealed the limited role of cultivated land in improving total ESV in the study area. There was a slight decrease in the ESV and the proportion of ESV of forest land, indicating the lack of effort in preserving and restoring forest land and the grain for the green project in the recent ten years. Consequently, the area of forest land was reduced. Due to the large area of grassland, its ESV was proportionately high. Nevertheless, its ESV declined continuously during the study period. On the one hand, the rapid urbanization process drove the expansion of construction land, which eroded the grassland. On the other hand, grassland was not preserved effectively, which led to serious degradation. Consequently, its ESV showed a downward trend [69]. Wetland displayed a massive potential to deliver high ESV. Due to its relatively minor area, however, it was not comparable to the ESV provided by other landscape types in the study area. However, in the past ten years, the ESV of wetland showed an increasing trend, from RMB 0.528 billion to RMB 0.997 billion. It suggests that Shuizuishan City stuck to the red line of wetland protection throughout development, which improved the system of wetland preservation. As a result, the area of wetland was expanded continuously. During the study period, the ESV of water increased by RMB 0.783 billion, reaching the highest level in 2020. It is because the construction of ecological civilization was carried out effectively in the study area. This is conducive to preserving important water bodies such as Xinghai Lake, Sha Lake, and the Yellow River Basin. Moreover, the conversion of farmland to lake can be promoted. Therefore, the ecological environment of water was improved (Figure 3a).

As a crucial region for water replenishment in the upper-middle reach of the Yellow River, the study area played a significant regulatory role. Therefore, among the four types of ecosystem services, the ESV of regulating services accounted for the largest proportion, exceeding 70% in all three periods. The ESV of provisioning services was considerably

lower than that of regulating services, accounting for about 10%. Moreover, it diminished over time, which is attributable to the reduction in grassland and forest land [70]. Providing a stable operating environment for the ecosystem, these two types of the landscape should be prioritized for protection in the follow-up ecological environment management. The ESV of both supporting services and cultural services accounted for less than 10%, with cultivated land as the main landscape type to provide supporting services. Although its area accounted for more than 40% of the total, the output of its service value was insignificant, which led to a tiny proportion of supporting services value across the study area. Meanwhile, the utilization of cultural tourism resources in the study area was relatively limited. As a result, the proportion of cultural services value was extremely low (Figure 3b).

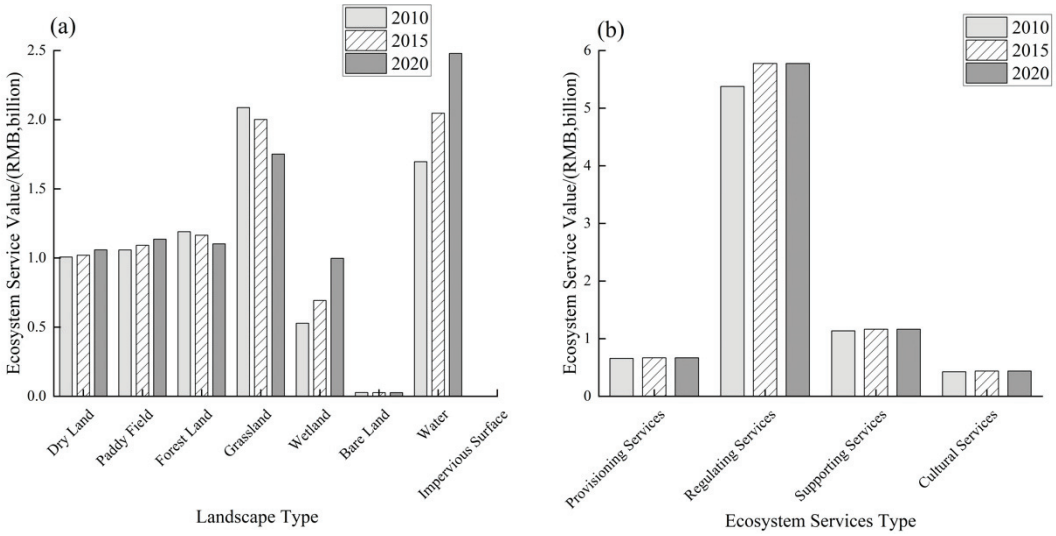


**Figure 3.** Ecosystem service value of different landscape types and services types in Shizuishan City, 2010–2020.

### *3.2. Spatiotemporal Analysis of ERI*

To reveal the spatial and temporal characteristics of ERI in the study area, the Ordinary Kriging Method was used to map the distribution of ecological risk during the three phases of the study area. This is based on the level of ERI for each evaluation unit (Figure 4). According to the interpolation results, the ecological risk values were divided into five levels using the same method: low risk (0.20 < ERI), medium-low risk (0.20 $\leq$ ERI < 0.26), medium risk (0.26 $\leq$ ERI < 0.34), medium-high risk (0.34 $\leq$ ERI < 0.52), and high risk (ERI > 0.52). Then, the area and proportion of different risk levels were calculated (Table 5).

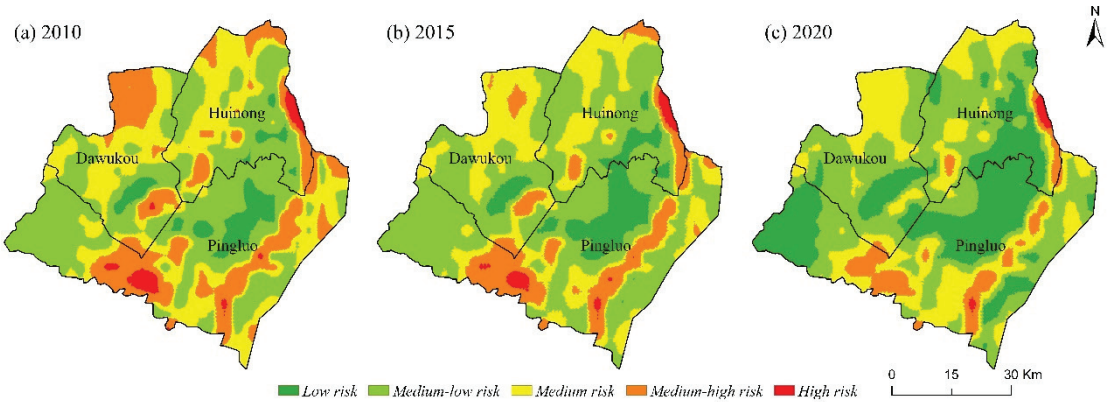


**Figure 4.** Distribution of ecological risk in Shizuishan City from 2000 to 2020.

**Table 5.** Area (%) of ecological risk classes in Shizuishan City, 2010–2020.

| Risk Level | 2010 | | 2015 | | 2020 | |
|---|---|---|---|---|---|---|
| | Area ($km^2$) | Proportion (%) | Area ($km^2$) | Proportion (%) | Area ($km^2$) | Proportion (%) |
| Low Risk | 223.69 | 5.48 | 368.97 | 9.04 | 1110.03 | 27.19 |
| Medium-Low Risk | 1744.86 | 42.74 | 2074.07 | 50.83 | 1631.94 | 39.98 |
| Medium Risk | 1213.99 | 29.74 | 1059.22 | 25.96 | 1046.34 | 25.63 |
| Medium-High Risk | 836.15 | 20.48 | 529.23 | 12.97 | 273.41 | 6.70 |
| High Risk | 63.68 | 1.56 | 48.80 | 1.20 | 20.61 | 0.50 |

In general, the ecological risk in the study area was high in the periphery but low in the middle, with the ecological risk showing a downward trend from 2010 to 2020. Among them, the medium-low-risk areas and medium-risk areas accounted for a relatively high proportion. Accounting for a relatively low proportion, both the medium-high-risk area and the high-risk area were in decline gradually. The environmental risk was mitigated by the government incorporating the construction of ecological civilization into the Five-Sphere Integrated Plan in 2012 (The Five-sphere Integrated Plan—the development of socialism with Chinese characteristics encompassing economic, political, cultural, social, and ecological development-was proposed on November 8, 2012 at the 18th National Congress of the CPC). Due to various policies implemented, a remarkable achievement was made in environmental protection.

In 2010, the low-risk areas accounted for a proportion of 5.48%, concentrating in the south of Dawukou District, the southeast of Huinong District, and the northeast of Pingluo County. Mainly distributed around the low-risk areas, the medium-low-risk areas were commonly found in the Helan Mountain area and along the Yellow River. These areas were dominated by paddy fields, arid land, forest land, and grassland, showing stable land-use trends. Additionally, the local landscape types were less affected by the exterior environment, thus maintaining a medium-low risk level. The medium-risk areas accounted for 29.74% of the study area. Moreover, except for the center of Dawukou District and the west and north of Huinong District were continuous, the rest were scattered. Most of these areas were located in the transitional belt between bare land and forest land, showing high fragmentation degrees and high disturbance degrees. Consequently, the risk level increased [71]. The medium-high-risk areas accounted for 20.48%, with apparent region heterogeneity. The distribution states in the south and north of Dawukou District were clustered, with the southern part located in Xinghai Lake, and the Northern part was distributed across a large area of bare land. The distributed state in the west of Pingluo County was also clustered, with bare land and cultivated land in dominance. The distribution state in the east of Pingluo County was banded, covering the upper reaches of the Shizuishan section of the Yellow River. Accounting for a proportion of 1.56%, high-risk areas were distributed in the east and west of Pingluo County and east of Huinong District. They were located in upstream of the Shizuishan section of the Yellow River, Sha Lake, and downstream of the Shizuishan section of the Yellow River, respectively. The landscape types of this area were water and wetland, and the ecosystem was highly brittle. Meanwhile, this area was experiencing environmental deterioration, due to urbanization construction, population growth, and growing demand for cultivated land.

Compared with 2010, the changes in the distribution of ecological risk in 2015 were less significant. Among them, the low-risk areas and the medium-low-risk areas emerged in the expansion trend, with the proportion improving from 5.48% to 9.04% and from 42.74% to 50.83%, respectively. The medium-risk areas decreased slightly, with only a few of them transformed into low-risk areas. The transformed areas were located in the middle of Dawukou District and Huiinong District and in the east of Pingluo County. Due to the increased efforts on land reclamation in these areas, some bare land was transformed into forest land, which improved the fragile environment [72]. The medium-high-risk areas were significantly reduced by 7.51%, concentrating in the north of Dawukou District.

Furthermore, the south of Dawukou District, the southwest of Huinong District, and the east of Pingluo County were all reduced but to varying degrees. The changes in Dawukou District and Huinong District resulted from land reclamation and the discontinuation of mine treatment. Thus, the bare land with high risk and the abandoned land that collapsed due to mining were reclaimed into grassland and forest land. The changes in Pingluo County resulted from the protection and restoration of the Yellow River, showing a decline in the fragmentation degree of the water landscape. This improved the resilience of the ecosystem [73]. The high-risk areas exhibited a slight decrease, concentrating in the south of Dawukou District and the east and west of Pingluo County.

Compared with 2015, the distribution of ecological risk changed significantly in 2020. To be specific, the proportion of low-risk areas increased by 18.15%. The increased areas were concentrated in the west, east, and north of Pingluo County, the south of Dawukou District, and the south of Huinong District. A vast majority of the increased areas were converted from medium-low-risk areas. The proportion of medium-low-risk areas was reduced by 10.58%, while that of the medium-risk areas remained unchanged, despite a significant change in the distribution of these areas. The medium-risk areas showed a reduction in Dawukou District and Huinong District, but an expansion in Pingluo County. The expansion areas were located in Sha Lake and the Yellow River. The proportion of the medium-high-risk areas and the high-risk areas declined by 3.27% and 0.7%, respectively, but the medium-high-risk areas remained in Sha Lake and the Yellow River Basin. A series of protection and restoration policies were enforced in Shizuishan City to reduce the ecosystem risk facing the environment of the water landscape. However, the restoration of the ecosystem was a lengthy process [74]. Thus, a high-risk level persisted in these areas. The high-risk areas were located the upstream of Shizuishan section of the Yellow River and the wetland in the east of Huinong District. The wetland in this area confronted a high-risk level for years. On the one hand, the landscape of the wetland was highly vulnerable. On the other hand, the disturbance of human activities was severe in this area. Therefore, it is indispensable to designate this wetland as a priority region of ecological management in the future. Meanwhile, supervision should be strengthened in this area to hinder further ecological degradation [75].

### *3.3. Construction of Ecological Zone Based on Value-Risk*

The ESV and the ERI of all evaluation units were standardized to obtain the quadrant distribution of the ecological zone in Shizuishan City from 2010 to 2020, where the *X*-axis indicates the ESV and the *Y*-axis represents the ERI (Figure 5). On this basis, the study area could be divided into four different ecological zones (Figure 6). Zone I and Zone III represent the high-ESV and low-ERI areas and the low-ESV and high-ERI areas, respectively, with these two areas being opposed to each other. Zone II and Zone IV represent the low-ESV and low-ERI areas and high-ESV and high-ERI areas, respectively, with these two regions corresponding to each other.

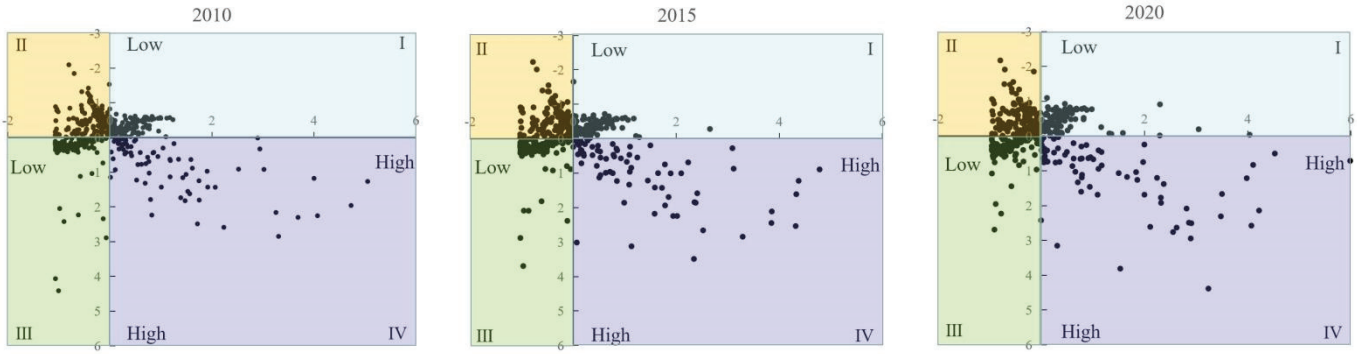


**Figure 5.** Quadrant distribution of ecological zones in Shizuishan.

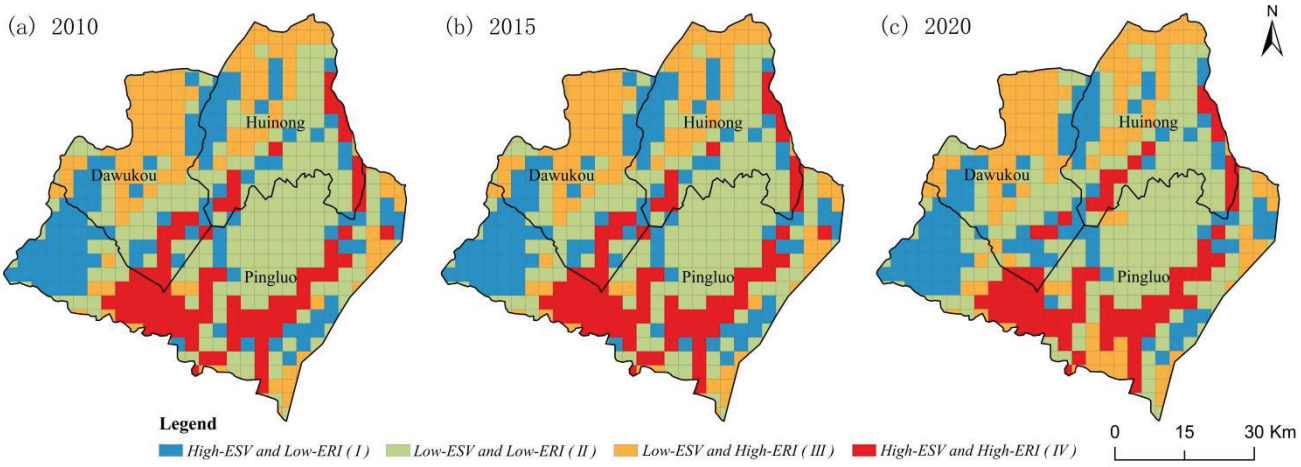


**Figure 6.** Spatial distribution of ecological zones in Shizuishan City.

Accounting for a relatively small proportion, the high-ESV and low-ERI areas (I) were mainly distributed in the west of Pingluo County, the northeast of Dawukou District, and the west of Huinong District. These areas were all located in the Helan Mountain and were dominated by forest land and grassland. Moreover, they feature high vegetation coverage and plentiful ecological resources. Therefore, these areas appeared a high level of ESV. Meanwhile, these areas were distant from the city center, which exposed them to solely limited disturbance from human activities. As a result, the ecosystem here could maintain a low level of ecosystem risk. The high-ESV and low-ERI areas (I) were also widely distributed along the Yellow River Basin in the east of Pingluo County, where hydrological resources were abundant to promote the vigorous growth of vegetation along the coast. Moreover, the long distance from the city center resulted in the low intensity and scale of human activities. Therefore, there was a high level of ESV but a low level of ERI in these areas.

Accounting for the largest proportion, the low-ESV and low-ERI areas (II) were mainly distributed in the north of Pingluo County, the south of Dawukou District, and Huinong District. The landscape type in these areas was dominated by paddy fields and arid land. Due to the strict regulation on preserving cultivated land in the study area, the intensity of urban development was relatively low, and the reduction in cultivated land did not reach a significant level. However, the dilemma is that the area of ecological lands were excessively small. Given the low level of ecosystem risk, it is difficult to achieve high ESV in these areas due to the lack of ecological lands such as grassland, forest land, and water. Therefore, boosting the Grain for Green Project would be a major task for ecological construction in these areas [76].

The low-ESV and high-ERI areas (III) were concentrated in the north of Dawukou District and the north of Huinong District. Although these areas were located in the Helan Mountain, the area of forest land was overwhelmingly limited. Virtually, the area of bare land here accounted for a larger proportion. In this case, despite these areas covering an amount of vegetation to achieve a small ESV, the intrusion of bare land caused the ecological environment to be very fragile. At the same time, these areas used to be the key region for mineral resources exploitation, which resulted in a significant reduction in ecological lands. Accordingly, the ERI of these areas was extremely high. The low-ESV and high-ERI areas (III) were also extensively distributed in the east of Pingluo County, with bare land as the dominant landscape type.

Accounting for the lowest proportion, the high-ESV and high-ERI areas (IV) were concentrated in the southwest and the southeast of Pingluo County, where Sha Lake and the Yellow River Basin were located. Due to the abundant hydrological resources in Sha Lake, the ESV was relatively high in these areas. However, there were also some impervious surfaces and cultivated land discovered here. Therefore, the water was severely disturbed

by human activities, and the distribution of impervious surfaces was extensive. As a result, there were high ESV and high ERI in this region. With a tremendous amount of cultivated land distributed along the Yellow River Basin, the ecological environment was prone to the damage caused by human activities, such as "reclaiming land from lakes". Meanwhile, studies revealed that the reclamation of cultivated and the construction of water conservancy projects contributed to the drying of lakes. In this case, they were transformed into secondary salinization land. Therefore, the ERI was relatively high in this region. Moreover, distributed in the south of Dawukou District and the east of Huinong District, the high-ESV and high-ERI areas (IV) were dominated by water and wetland. Both of them were located in densely populated regions with a large area of impervious surfaces.

## 4. Discussion

### *4.1. Policy and Planning Implications*

Environmental problems are common problems of urban development and need targeted management measures to solve. At present, the environmental problems of Shizuishan City have constrained the regional development, and the current eco-management pattern conducted by this city is insufficient. It is urgent to reinforce the integration of identification, resolution, and management of environmental issues. In this context, the zonation of ecological space provides a path to identify the barriers and clarify the directions of ecological conservation to realize sustainable development. Management measures and policy recommendations of different zones are provided according to the specific characteristics (Table 6).

**Table 6.** Management measures of different ecological zones in Shizuishan City.

| Areas | Criteria | Barriers | Countermeasures |
|---|---|---|---|
| Prioritized Development Areas | High-ESV and Low-ERI | None | (1) In these areas, the theory of sustainable development must be adhered to. It is better to strengthen the protection of ecological lands such as water and soil conservation forests and sand-fixing forests, ensuring the delivery of ESV to the surrounding areas.<br>(2) It is requisite to promote the coordinated development of economic growth and ecological conservation by giving full play to the advantages of natural conditions in these areas.<br>(3) Through sensible land use planning, eco-tourism projects should be undertaken on the basis of preserving the ecological environment, thus manifesting the value of ecosystem service and implementing the ecological civilization construction conviction of "Lucid waters and lush mountains are invaluable assets". |
| Improvement Areas | Low-ESV and Low-ERI | Lack of Ecological Lands | (1) The foremost task in these areas is to improve ESV. Therefore, it will be a good choice to carry out ecological reconstruction of bare land here to expand the ecological lands on the premise of preventing the decline in the total area of permanent basic farmland and the erosion of cultivated land.<br>(2) Apart from improving the quality of the ecological environment and optimizing the layout of the ecological structure [77], it is also essential to prevent the rise of ERI. So, it is better to strengthen the supervision of the ecological environment in these areas to prevent environmental vandalism such as deforestation, mining, and river pollution. |
| Exploitation-Prohibited Areas | Low-ESV and High-ERI | Fragile Environment | (1) The primary objective is to reduce the level of ERI, which can be achieved by giving priority to strengthening the management and restoration of bare land, reclaiming the bare land caused by coal mining, the bare land concentrated in a large area, and the bare land mixed in grassland into arbor land, shrub land, and grassland through engineering and biological measures. Meanwhile, gradually discontinuing mining activities and liquidating the existing mining enterprises are also good choices.<br>(2) The secondary aim is to improve the level of ESV, by implementing the protection and restoration of grassland on the premise of "natural restoration is the mainstay and artificial restoration is the supplementary" [78]. For the salted grassland, it is essential to prevent the irreversible damage caused by excessive grazing by taking such measures as grassland sealing and breeding and seasonal grazing [79]. |

**Table 6.** *Cont.*

| Areas | Criteria | Barriers | Countermeasures |
|---|---|---|---|
| Research-focused Areas | High-ESV and High-ERI | Strong Human Disturbance | (1) First of all, it is necessary to establish the ecological protection areas for important water bodies and wetlands such as Xinghai Lake, Sha Lake, and the Yellow River Basin, with the responsibilities for ecological protection allocated to each town and subdistrict offices in line with the principle of proximity, thus putting an end to the phenomenon of "reclaiming farmlands from lakes".<br>(2) Secondly, it is essential to reduce soil erosion and the impact of the disturbance caused by humans by strengthening the maintenance of forest land and grassland projects along the river.<br>(3) Finally, to deal with the strong human interference, the number of tourists on every scenic spot must be limited. Meanwhile, through cooperation with colleges or scientific research institutions in setting up scientific investigation stations or scenery sketching bases and prohibiting irrelevant personnel from entering, the flow of people can be controlled, while the scientific and aesthetic value of the ecosystem can be fully demonstrated. |

### *4.2. Contributions and Limitations*

This study depicts the spatial-temporal variation of Shizuishan City based on ESV and ERI, which have been widely used, and proved to be reasonable and applicable, and the evaluation results can provide a reference for the spatial zonation of the regional ecological space and formulating the corresponding countermeasures. We found that the areas with high ESV were mainly distributed in the places with high vegetation coverage and benign hydrothermal conditions, and covered by the typical ecological land uses incorporating water, wetland, forest land, and grassland, which is consistent with previous studies. The areas with high ERI were distributed in places with strong human disturbance, dominated by water, wetland, and bare land.

However, the study is unable to provide scientific support for planning and reorganizing ecological space through the approach that merely depends on ESV or ERI. An integrated methodology is required to prioritize the urban ecological space and serves as the policy design and the overall arrangements of urban ecological protection. Therefore, we established a zoning approach that integrated ESV and ERI to identify four different types of ecological zones, and comprehensively evaluated the ecological conditions of the study area. This approach can not only take into account a variety of living objects in the ecosystem but also consider regional development in terms of human well-being, and potential risks, which enhances the practicability and utility. In addition, this approach emphasizes the integrity and uniqueness of the ecosystem, which can reflect the ecological environment security status from positive and negative sides, enabling managers to measure the economic, ecological, and social factors more accurately. Thereafter targeted ecological environment management plan and future development plan will be put forward, to further promote a virtuous circle of the regional ecosystem. Finally, this approach provides an innovative research view for ecological security construction, that is, to evaluate the regional ecological environment from multiple perspectives and aspects.

This research attaches importance to establishing a zoning approach to construct ecological zones and reflect the status of the ecological environment. However, ecological zones should be considered as the result of the interaction between the ESV and ERI, but in this study, the mechanism between these two was not discussed clearly, and also the dominant driving forces affecting the construction of ecological zones are still unknown. Moreover, the evaluation models of ESV and ERI still need to be improved, only from the landscape pattern to consider the ecological risk or only from the equivalents to evaluate the ecosystem service value limiting the precision of our study. In the future, research should further explore the precise quantification of ESV and ERI, comprehensively consider the interaction between the ESV and ERI to establish a more thorough zoning approach,

and improve the accuracy and scientificity of the assessment of ecological environment status and the ecological management measures.

## 5. Conclusions

In this study, a spatial zoning approach that integrates ESV and ERI is developed to assess the state of the urban ecological environment from 2010 to 2020, with the targeted management measures put forward. The main conclusions are outlined as follows:

Firstly, the spatial distribution of ESV presents a trend of high in the south but low in the north. The total ESV exhibited an upward trend from 2010 to 2020. Among diverse landscape types, the ESV of water was the highest, mainly due to the lush vegetation along its shores and favorable hydrothermal conditions. The ESV of bare land was close to zero. In this case, it will show a state of low-ESV once invaded by several bare land. Moreover, some low-ESV areas resulted from population aggregation and impervious surfaces expansion. Among the entire ecosystems, the proportion of ESV of services types was unbalanced, with regulating services accounting for over 70%, and provisioning services and cultural services accounting for merely about 5%.

Secondly, the distribution characteristic of ERI is that it was high in the urban fringe but low in the center. The total ERI exhibited a downward trend from 2010 to 2020 due to the reclamation, protection, and restoration work. More specifically, the low-ERI areas expanded constantly, while the high-ERI areas kept shrinking. Among them, the landscape types in low-ERI areas include paddy fields, dry land, forest land, grassland, and bare land, which were concentrated, showing a strong anti-interference capability. Dominated by water and wetland, the high-ERI areas had a fragile ecological environment and were vulnerable to destruction.

Finally, among the four types of ecological zones, the high-ESV and low-ERI areas (I) accounted for a relatively low proportion. Dominated by forest land and grassland, these areas had abundant natural resources and were set as "Priority Development Areas". The low-ESV and low-ERI areas (II) accounted for the largest proportion, with paddy fields and dry land as the dominant landscape. Therefore, the ecological lands here were confined, and these areas were set as "Ecological Improvement Areas". Previously, the low-ESV and high-ERI areas (III) presented an important region of mineral resources exploitation, showing a staggered distribution of grassland and bare land. Consequently, the local ecological environment was exceedingly fragile, and they were set as "Exploitation-Prohibited Areas". Accounting for the lowest proportion, the high ESV and high-ERI areas (IV) were mainly distributed near Sha Lake, Xinghai Lake, and the Yellow River. Given the strong disturbance from human activities, they were set as "Research-focused Areas".

The study provided a deeper insight into comprehensively evaluating the ecological conditions and putting forward targeted management measures. However, the limitation of this study is that the evaluation models of ESV and ERI still need to be improved in terms of the indicator selection. Meanwhile, it will be a better choice to further explore the ecological effects behind the zoning approach. For future work, we plan to establish a more thorough zoning approach in order to improve the accuracy of the assessment of the ecological conditions.

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# Ecological Protection Alone Is Not Enough to Conserve Ecosystem Carbon Storage: Evidence from Guangdong, China

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**Abstract:** The increase in atmospheric $CO_2$ caused by land use and land cover change (LUCC) is one of the drivers of the global climate. As one of the most typical high-urbanization areas, the ecological conflicts occurring in Guangdong Province warrant urgent attention. A growing body of evidence suggests LUCC could guide the future ecosystem carbon storage, but most LUCC simulations are simply based on model results without full consistency with the actual situation. Fully combined with the territorial spatial planning project and based on the land use pattern in 2010 and 2020, we have used the Markov and Patch-generating Land Use Simulation (PLUS) model to simulate the future four land use scenarios: the Business as Usual (BU), Ecological Protection (EP), Farmland Protection (FP), and Economic Development (ED) scenario, and the ecosystem carbon storage was assessed by the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model. The results show that the built-up area experience further expansion in all scenarios, the largest scale happened in ED and the smallest in FP. Besides, the forest area in the EP scenario is the largest, while the land use pattern developed based on the previous circumstances in the BU scenario. Furthermore, the carbon storage plunged from 1619.21 Tg C in 2010 to 1606.60 Tg C in 2020, with a total decrease of 12.61 Tg C. Urban expansion caused 79.83% of total carbon losses, of which 31.56% came from farmland. In 2030, the carbon storage dropped in all scenarios, and their storage amount has a relationship of FP > BU > EP > ED. To better resolve the ecological problems and conserve ecosystem carbon storage, not only ecological protection but also the protection of the land near the city such as farmland protection strategies must be considered.

**Keywords:** carbon storage; LUCC; Markov model; PLUS model; InVEST model; Guangdong province

## 1. Introduction

During the Industrial Revolution from 1850 to 2019, the total increase in global surface temperature caused by human beings range from 0.8–1.3 °C [1], which posed a series of widespread threats to humans [2]. The main global warming was caused due to the sudden rise of atmospheric $CO_2$ concentration [3], which is attributed to the burning of fossil fuels and land use and land cover change (LUCC) caused by deforestation, urbanization, and other anthropogenic activities [4]. LUCC, as one of the most important factors in the augmentation of atmospheric $CO_2$, exerts a profound impact on regional and global climate [5]. On the one hand, from the aspect of the process of LUCC, the carbon in ecosystems has been released by factors such as forest steppe fires and soil erosion. The cumulative carbon emissions caused by those LUCC processes were unexpected in the past few centuries [6,7]. On the other hand, the impact after LUCC alters the biophysical properties of the land surface. For example, when forests are replaced by grasslands and croplands, it leads to a decrease in evaporation and surface roughness as well as an increase

in albedo [8–11]. These biophysical changes have caused severe perturbations to carbon in ecosystems and seriously compromised the capacity of the ecosystem to store carbon [12]. Although the carbon emission caused by LUCC is uncertain [13,14], it has been agreed that the concentration of $CO_2$ in the atmosphere has increased by about 25% in history [15]. Ecosystem's carbon storage service is a cost-effective nature-based solution for reducing atmospheric $CO_2$ concentrations [16–19]. Therefore, to meet global carbon challenges it is vital to take full advantage of the ecosystem services, especially in a LUCC way.

Earlier studies of ecosystem carbon storage have shown the importance of LUCC. The carbon storage characteristics differ from the land use type and the conversion between different land use types could cause severe storage change, which has been proved in many places such as Asia, Oceanic, Europe, and America [20–23]. With the development of the geographic information system (GIS), the large-scale geographic analysis technology is gradually improved, making it more closely integrated with the spatial analysis model, in which the carbon storage and sequestration module in the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model is the most popular evaluation model. Especially in Asia, each ecosystem's carbon storage change might be derived from LUCC, no matter an increase or decrease. For example, in the eastern coastal areas of Bangladesh from 1988 to 2018, the total carbon stocks rose with the increase in the trees and vegetation around rural settlements [24]. Xishuangbanna area in China witnessed a sharp decline during the 22-year period from 1988 to 2010, which was dominated by the decrease in natural coverage [25]. Moreover, as for China, the national carbon balance (carbon emission and storage) has been investigated, and the results showed that land use changes led to a large amount of carbon loss, mainly because the ecological land was occupied by construction areas [26,27]. With the development of information technology, more accurate land use simulation methods emerge in endlessly. The system dynamics (SD) model and Markov model are applied to future land use demand forecasting, and deep learning based on Cellular Automata (CA) is used in the spatial change strategy analysis, such as the Conversion of Land Use and its Effects (CLUE-S), Future Land Use Simulation Model Software (FLUS), Patch-generating Land Use Simulation (PLUS) model, etc. Combining future LUCC with ecosystem carbon storage is becoming a common trend in this field. Several scholars have undertaken the simulation experiment in plenty of areas, from the southern, central, and northern parts of China, where the model's applicability and accuracy were verified [28–31]. However, from previous studies, when predicting future ecosystem carbon storage, the land demand often relies simply on model results, with less or little consideration of integration with relevant planning projections, so the simulation results tend to deviate from the actual situation. Therefore, this study will improve the shortcomings of previous research and set the simulation scenarios in a way that not only fully grasps the development direction but also strictly follows the land use quantity according to relevant planning projections.

Guangdong Province is located at the southern end of the Chinese mainland, with a tropical and subtropical climate. As a strong economic province in China, ecological and environmental problems caused by land use changes such as urban sprawl and farmland expansion recently have become common, resulting in a large number of ecosystem carbon loss. Although the department concerned managed to resolve those ecological issues, the environmental problem continued to have a profound effect on their production and life. Therefore, it is urgent to give full support to the advantages of ecosystem services, to tackle the conflict between LUCC and carbon storage.

In order to learn about the future ecosystem carbon storage spatial pattern in Guangdong, we conducted our research via the following steps. Firstly, after fully considering the territorial spatial planning project, the Markov model was used to predict the future land use demand in 2030 under four scenarios. Then, the PLUS model was utilized to simulate the spatial land use patterns. Finally, the ecosystem carbon storage was assessed by InVEST model in separate scenarios.

## 2. Materials and Methods

### *2.1. Study Area*

Guangdong Province is located in the southernmost part of mainland China, adjacent to the South China Sea, and across the sea from Hainan Province. There are 21 cities with a total area of 179,725.07 km$^2$. The whole territory lies between 20°09′ N–25°31′ N and 109°45′ E–117°20′ E. The overall topography here is high in the north and low in the south, with complex and diverse landform types (Figure 1). There are mostly mountains and high hills in the north, plains and platforms in the south, and with dense distribution of rivers and lakes. Guangdong has a subtropical monsoon climate, with an annual average precipitation of more than 1500 mm and an average temperature of around 22 °C [32].

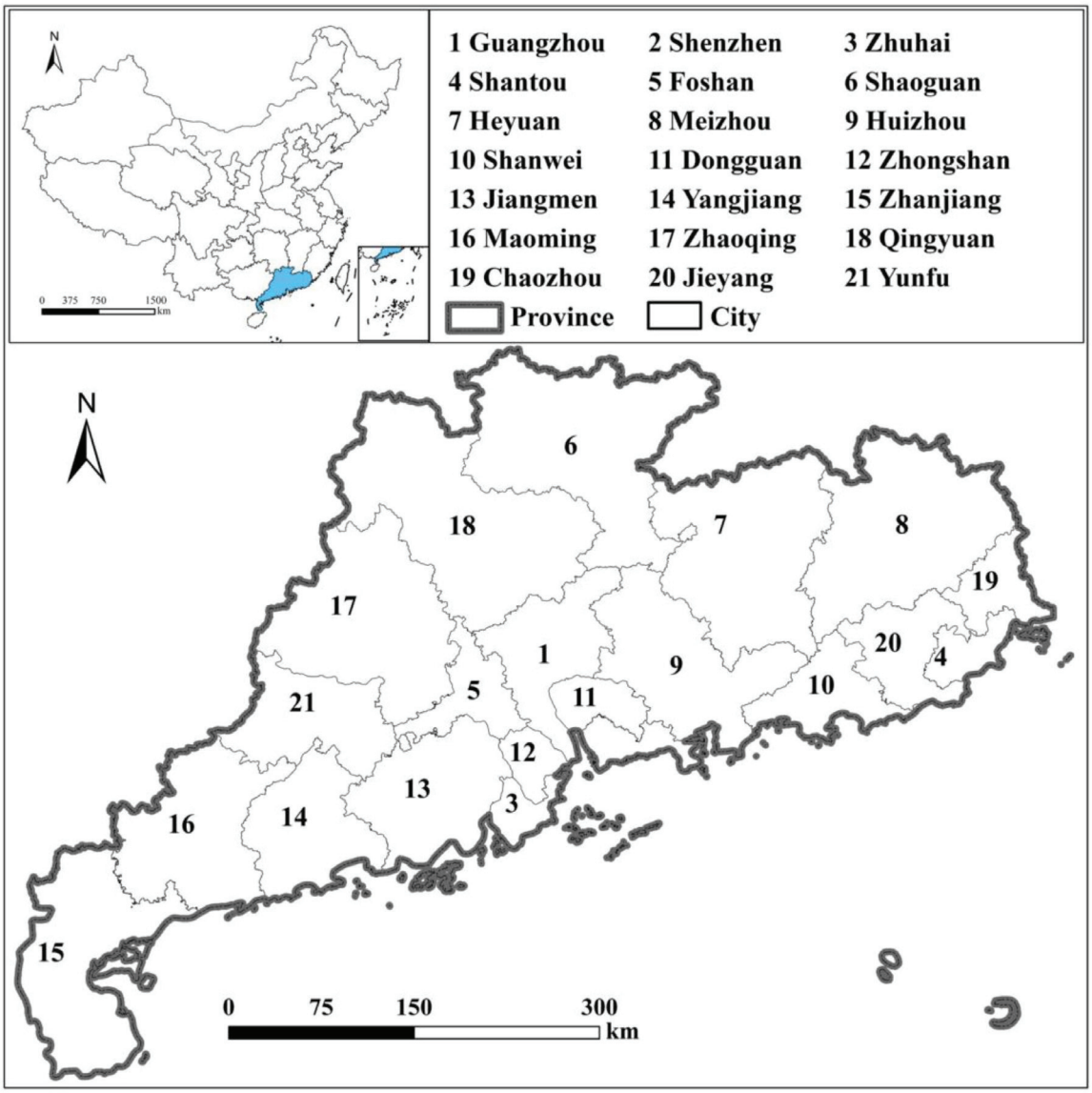


**Figure 1.** Administrative divisions in Guangdong Province, China. The blue area represents the Guangdong province in China.

In addition, Guangdong is the most economically developed province in China, with a GDP of 12.44 trillion RMB in 2021. The population also ranks first in China, with a total population of 126.24 million in the seventh national census in 2020. Energy consumption also lies at the forefront of China, with electricity consumption reaching 692.6 billion kW·h in 2019, accounting for about 1/10 of the total.

### *2.2. Data Sources*

The spatial data was used to simulate the spatial pattern of land use and ecosystem carbon storage. The LUCC data with a resolution of 100 m, and both GDP (https://doi.org/10.12078/2017121102, accessed on 9 August 2022) and soil type spatial distribution raster data with a resolution of 1 km were obtained from the Resource and Environment Science and Data Center (https://www.resdc.cn/, accessed on 9 August 2022). SRTM-DEM 90 m resolution original elevation data were from the Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences (http://www.gscloud.cn, accessed on 9 August 2022), while the slope data were obtained by using DEM data through the spatial analysis tool in ArcGIS 10.8 software. The precipitation and temperature data with a 1 km spatial resolution were accessed from the National Earth System Science Data Center, National Science and Technology Infrastructure of China (http://www.geodata.cn, accessed on 22 April 2022). Besides, 100 m resolution gridded population count data were downloaded from WorldPop (https://www.worldpop.org/, accessed on 8 December 2021). Furthermore, some basic shapefile geographic information data were from the National Geomatics Center of China (http://www.ngcc.cn/ngcc/, accessed on 7 August 2022), such as the administrative center at the county level, the spatial location of highways railways, and rivers. Via the Euclidean Distance tool in ArcGIS 10.8, the distance to those closest sources was calculated in each cell. Finally, the coordinate system of all data is unified, and the spatial resolution is resampled to 100 m.

In order to verify the accuracy of the model, the statistical data of the population in Guangdong Province were used, which were obtained from the Guangdong Bureau of Statistics (http://stats.gd.gov.cn/, accessed on 29 October 2022).

### *2.3. LUCC Simulation under Multiple Scenarios*

In this study, the Markov-PLUS coupling model is used to dynamically simulate the land use/cover types in Guangdong Province, so that we can not only use the Markov model to predict the land use demand in different situations, but also give full play to the ability of the PLUS model to deal with the spatial changes of complex systems with CA, and then simulate the spatiotemporal dynamic characteristics of land use in both quantitative and spatial aspects.

#### 2.3.1. Markov Model

Markov processes are the simplest type of stochastic processes, where it is assumed that the present states (rather than past states) affect the transition to future states (i.e., the so-called Markov characteristics), so the development of the future state can be predicted by capturing the impact of the current state [33–35]. Given that the dynamic evolution of LUCC possesses Markov properties, we used this method to simulate the land use demand in Guangdong Province. The principle is shown in Formula (1):

$$S_{(n)} = S_{(n-1)} \times P_{ij}, \tag{1}$$

where $S_{(n)}$ means the land use type at moment $n$, $S_{(n-1)}$ means the land use type at moment $n-1$; $P_{ij}$ represents the land use type transition probability matrix, as is shown in Formula (2):

$$P_{ij} = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \ddots & \vdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix}, \; 0 \le P_{ij} \le 1, \; \sum_{j=1}^{n} P_{ij} = 1, \tag{2}$$

where $P_{ij}$ means the transition probability from land use type $i$ to $j$, and $n$ represents the amount of land use type.

2.3.2. PLUS Model

PLUS model, namely Patch-generating Land Use Simulation model, is a kind of geographic Cellular Automata (CA) modeling to show complex land use/cover systems, so as to achieve the purpose of assisting land policy formulation [36]. However, among the existing CA models, on the one hand, they focused on the improvement of modeling procedures, and few studies on promoting the understanding of the underlying nonlinear relationship of LUCC [37,38]. On the other hand, the research on the causes of land use change is limited [39,40], that is to say, there are certain deficiencies in both the transformation rule mining strategy and the landscape dynamic change simulation strategy. Therefore, a rule mining framework based on Land Expansion Analysis Strategy (LEAS) and a CA model based on multiple random seed (CARS) is proposed, which can mine the driving factors of land expansion and landscape change, resulting in higher simulation accuracy and compatibility with more similar landscapes [41].

In the PLUS model, we first need to use the land expansion analysis strategy (LEAS) to extract the part of all kinds of land use expansion in the two periods, so we can obtain the samples from the increased part. Then, the random forest algorithm was used to explore all kinds of land use expansion and driving forces one by one. This process makes us obtain the development probability of all land use types and also learn the contribution of driving factors to land use expansion in this period. This strategy can well analyze the mechanism of land use change over a period of time and has strong explanatory power. Secondly, based on CARS, this module simulates local microscopic by combining random seed generation and decreasing threshold mechanism for neighborhood scope, neighborhood weight factor, random patch seed probability, and conversion cost settings, and the combined effect of adaptability coefficient, neighborhood effect, and development probability land use competition. Finally, the land use is allocated to each grid by using the CA mechanism, so that the initial land use types are transformed into those with high development probability, which makes the model more reasonable and the simulation accuracy higher [41].

There are 11 historical spatial raster data input in the PLUS model as the LUCC driving factors in our study (Table 1). They are five socio-economic factors (gross domestic product, population, and the distance to the administrative center, highway, and railway,) and six climate-environmental factors (elevation, slope, precipitation, temperature, soil type, and the distance to river). Combined with the earlier research and the availability of data, these factors basically meet the model simulation demand to reflect the impact of LUCC and conform to the actual situation in Guangdong Province [42–44].

**Table 1.** LUCC driving factors.

| Category | Factor Definition | Data Source |
|---|---|---|
| Socio-economic | Gross Domestic Product (GDP) | https://www.resdc.cn/ accessed on 9 August 2022 |
| | Population | https://hub.worldpop.org/ accessed on 8 December 2021 |
| | Distance to administrative center<br>Distance to highway<br>Distance to railway | http://www.ngcc.cn/ngcc accessed on 7 August 2022 |
| Climate-environment | Elevation<br>Slope | http://www.gscloud.cn accessed on 9 August 2022 |
| | Precipitation<br>Temperature | http://www.geodata.cn/ accessed on 8 December 2021 |
| | Soil type | https://www.resdc.cn/ accessed on 9 August 2022 |
| | Distance to river | http://www.ngcc.cn/ngcc/ accessed on 7 August 2022 |

2.3.3. Scenario Setting

LUCC is a complex process, and the spatial development of Guangdong Province is guided by various policies. In China, territorial spatial planning is a series guide for regional space development and the basis for development, protection, and construction activities, so bringing planning indicators into land use scenario simulation has important practical significance and can better guide practice. Therefore, according to the policy projects such as Guangdong Territorial Planning (2016–2035) and Guangdong Territorial Spatial Planning (2020–2035), four scenarios of business as usual (BU), ecological protection (EP), farmland protection (FP), and economic development (ED) were set up to explore LUCC in different periods and scenarios.

Business as usual (BU) scenario: only based on the expansion law and change characteristics of historical land use in Guangdong Province from 2010 to 2020, regardless of the impact of policy regulation and control. With the Markov model, the scale of land demand in 2030 is predicted.

Ecological protection (EP) scenario: this will be one of the key strategies for future development in Guangdong Province. The importance of forest ecosystems is highlighted while other natural ecosystems are also preserved. The forest land holdings in the Guangdong Territorial Planning (2016–2035) were included in the scenario setting. It is stipulated to reduce the probability of conversion of other land use types to built-up land by 50% for forest land and grassland, and by 30% for watershed and farmland [45].

Farmland protection (FP) scenario: strict implementation of farmland protection is also one of the important tasks in Guangdong Province. In this scenario, the development of farmland will be restricted, that is, farmland will not be transformed into any other land use type. In addition, the probability of conversion of unused to farmland will increase by 50% [46].

Economic development (ED) scenario: based on the rapid economic development and urbanization of Guangdong Province, further priority is given to economic benefits. However, according to China's actual policy, urban development requires a clear urban development boundary, so the upper threshold of land use development intensity specified in the Guangdong Territorial Planning (2016–2035) is considered when setting this scenario.

### *2.4. Ecosystem Carbon Storage*

The Carbon Storage and Sequestration module from the InVEST model was applied to estimate the carbon storage in the ecosystem of Guangdong Province. The InVEST model uses LUCC maps and carbon storage from four carbon pools (aboveground biomass, belowground biomass, soil, and dead matter) to estimate carbon storage in the current landscape or carbon sequestration over a period. The equation for the total carbon stock is shown in Formulas (3) and (4):

$$C_i = C_{above} + C_{below} + C_{soil} + C_{dead}, \quad (3)$$

$$C_{total} = \sum_{i=1}^{n} C_i \times A_i, \ (i = 1, 2, \ldots, n) \quad (4)$$

where $C_i$ represents the carbon density on land use type $i$ (t/ha), $C_{above}$ means carbon density of aboveground biomass (t/ha); $C_{below}$ means carbon density of belowground biomass (t/ha); $C_{soil}$ means carbon density of soil (t/ha); $C_{dead}$ means carbon density of dead matter (t/ha); $A_i$ means the area of land use type $i$; $C_{total}$ represents total ecosystem carbon storage (t).

## 3. Results

### *3.1. LUCC Features in the Historic Period and Future Scenarios*

3.1.1. LUCC Features in the Historic Period

According to historical land use data (Table 2), from 2010 to 2020, the land use type with the largest area change was farmland, with a decrease of more than $2 \times 10^5$ ha

(nearly 5%); the most obvious increase in proportion was built-up land (more than 16%), with a cumulative expansion of nearly $2 \times 10^5$ ha; In addition, the area of grassland also increased, but the magnitude was not significant, with an increase of less than $3 \times 10^4$ ha (approximately 3% only); the rest of the land use types did not change remarkably. The considerable expansion of built-up area is one of the most noteworthy features of land use change in Guangdong Province.

**Table 2.** Land use area in 2010, 2020, and 2030 under multi-scenario (Business as Usual, Economic Development, Ecological Protection, and Farmland Protection, unit: $10^4$ ha).

| Year/Scenario | | Farmland | Forest | Grassland | Water | Built-Up | Unused |
|---|---|---|---|---|---|---|---|
| Previous period | 2010 | 429.92 | 1078.56 | 73.62 | 77.73 | 115.38 | 1.28 |
| | 2020 | 409.83 | 1079.12 | 76.43 | 77.88 | 133.98 | 1.05 |
| Future scenario in 2030 | Business as Usual | 405.03 | 1078.46 | 76.84 | 77.88 | 139.08 | 1.01 |
| | Ecological Protection | 396.97 | 1084.50 | 75.93 | 79.57 | 140.40 | 0.94 |
| | Farmland Protection | 410.64 | 1079.49 | 75.59 | 77.62 | 134.00 | 0.96 |
| | Economic Development | 370.01 | 1064.81 | 76.37 | 71.09 | 195.23 | 0.80 |

Spatially, built-up land has spread to different degrees in all parts of the land around the towns during the decade, with the conversion of farmland around cities being the most significant source of expansion (Figure 2). The most obvious expansion occurred in the Pearl River Delta urban agglomeration area, where the scale of built-up land is larger than it was 10 years ago, making it more concentrated and contiguous. In addition, since Guangdong is mostly mountainous and hilly, the eastern part is a plain area with comfortable temperatures and abundant precipitation, which creates natural conditions for orderly development in the east. The built-up areas in the eastern part of Guangdong Province have also undergone significant urban expansion, and according to the relevant plans, this area will be developed into the "Shantou-Chaozhou-Jieyang Metropolitan Area" with the spatial form of a compact combination city.

The increase in the area of forest and grassland is another important feature. Recent years, as one of the fastest-growing urbanized regions, ecological and environmental problems have become increasingly prominent as the economic level continues to rise. For this reason, Guangdong Province has focused on the health and stability of natural ecosystems and has vigorously promoted plantation and ecological restoration, which has resulted in an increase in the area of forest and grassland ecosystems [47].

#### 3.1.2. LUCC Features in Future Scenarios

Based on the characteristics of historical land use changes in Guangdong Province, and combined with planning projects such as Guangdong Territorial Planning (2016–2035) and Guangdong Territorial Spatial Planning (2020–2035), the land use pattern under four future scenarios was simulated. The common feature of the four scenarios is that they have carried out different degrees of urban expansion, which is in line with the actual development strategy of Guangdong (Table 2).

In the BU scenario, the farmland around the city will be further occupied, but to a minor extent, and the area of the remaining land use types is essentially the same as in 2020. In the EP scenario, as required in the planning policy to ensure the forest land holdings in 2030, a portion of other natural ecosystems (farmland, grassland, unused land) will be converted to forest land, and those will also convert to built-up land due to the need for urban construction.

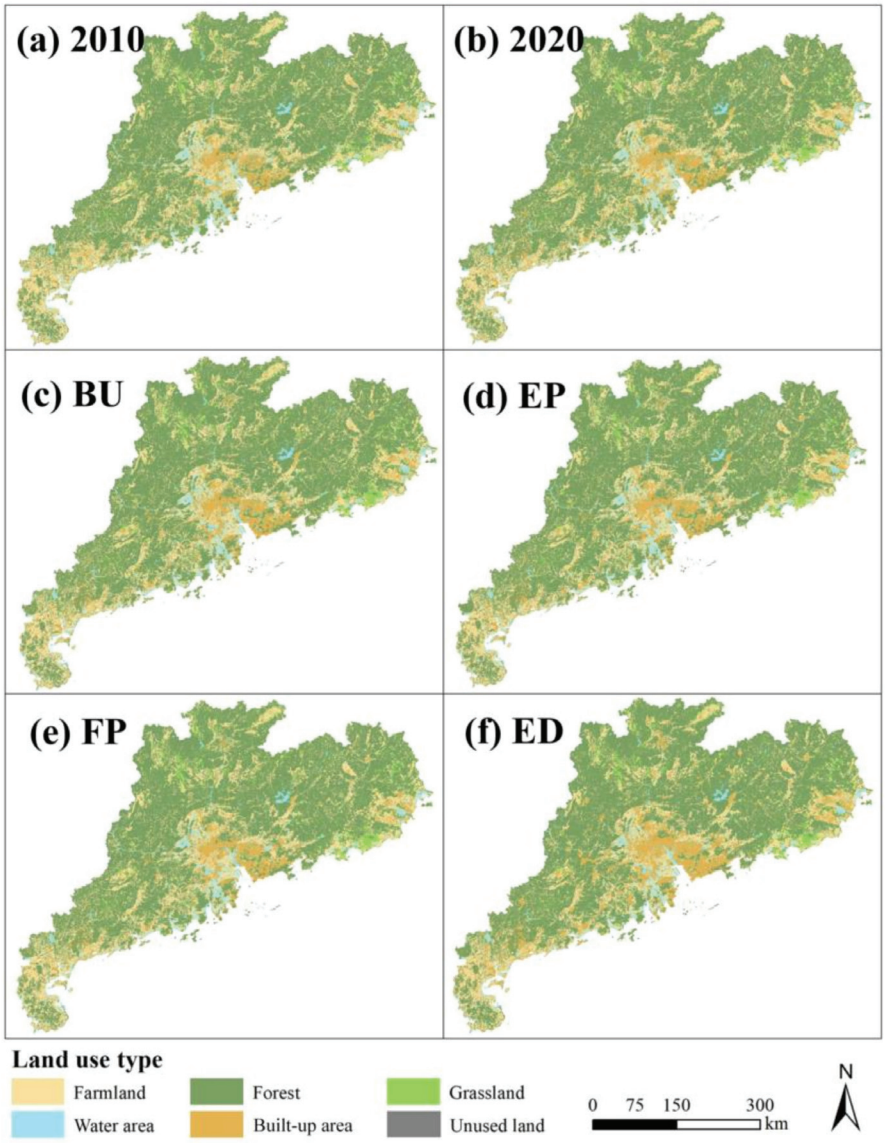


**Figure 2.** Spatial distribution of various land use types in (**a**) 2010, (**b**) 2020, and 2030 under (**c**) business as usual (BU), (**d**) ecological protection (EP), (**e**) farmland protection (FP), and (**f**) economic development (ED) scenario.

In the FP scenario, it is assumed that farmland will not be converted to any other land use types, indicating that they will not be transformed into built-up land. However, the urban expansion will happen still. The forest is generally far away from the city, so important sources of built-up land expansion turn out to be the unused land and grassland around the city, whose land use area is much smaller than farmland, so the city expansion will be on a not big scale.

In the ED scenario, the expansion of towns and cities is greatly increased for the pursuit of economic interests. Under the premise of meeting the upper limit of development intensity in the planning projects concerned, the built-up land will no longer be restricted by spatial conditions, and the farmland, forest, grassland, and unused land around them will be utilized. In this scenario, the built-up land in the entire Pearl River Delta will be more concentrated and larger in scale than ever before. The spatial mapping of land use under each scenario is shown in Figure 2.

### *3.2. Ecosystem Carbon Storage*

From the perspective of Table 3, the carbon reserves decreased significantly from 2010 to 2020, which decreased 12.61 Tg C. During this decade, drastic urban expansion has taken place in Guangdong Province, and the area of built-up land increased from $115.38 \times 10^4$ ha in 2010 to $133.98 \times 10^4$ ha in 2020, resulting in the transformation of a large area of natural ecosystem to built-up land. There are 79.83% of carbon loss areas are caused by the conversion of other land use types to built-up areas, among which the conversion of farmland to built-up land is the largest (31.56%).

**Table 3.** Carbon storage amount in 2010, 2020 and 2030 in future scenarios (Business as Usual, Economic Development, Ecological Protection, and Farmland Protection).

| Year/Scenario | | Carbon Storage/Tg |
|---|---|---|
| Previous period | 2010 | 1619.21 |
| | 2020 | 1606.60 |
| Future scenario in 2030 | Business as Usual | 1602.41 |
| | Ecological Protection | 1601.92 |
| | Farmland Protection | 1606.51 |
| | Economic Development | 1558.98 |

In each scenario, carbon storage will further reduce. In the BU scenario, there will be a loss of 4.19 Tg C. Only the carbon storage in the FP scenario is higher than that in the BU, with merely a small loss (0.09 Tg C). The carbon storage of the other scenarios has decreased significantly. The remaining scenarios showed a significant decline in carbon storage, with the ED scenario reaching the upper limit of development in terms of urban expansion and incurring the most carbon loss of any scenario, with a loss of 47.62 Tg C, which is 3.7 times the amount lost in 2010–2020. The EP scenario is second only to the ED scenario in terms of carbon loss (4.68 Tg C).

In 2030, urban expansion under each scenario will continue, and various natural ecosystems will be transformed into built-up land at different scales, so carbon storage will decline in each scenario. In the ED scenario, the urban development intensity will reach saturation, while the cities, such as the Pearl River Delta, will occupy large areas of farmland, grassland, forest, so the carbon storage will decline significantly. The carbon storage in the FP scenario will be higher than that in the EP scenario, indicating that the interaction between spatially adjacent elements cannot be ignored when the planned land use amount meets the need.

Considering the actual situation in Guangdong Province (Figure 3), since farmland is key to providing food and other consumer goods for the residents in the town, most of the farmland is also distributed around the city. In the FP scenario, farmland is strictly restricted, so while protecting farmland, it also greatly constrains the sprawl of towns and cities and reduces the damage to natural ecosystems and carbon loss. In the EP scenario, the protection of forest land and grassland is often emphasized, they are far away from the city, so the phenomenon of urban expansion in this scenario is still obvious enough. In order to increase ecosystem carbon storage, it is also important to consider the significance of farmland along with ecological protection.

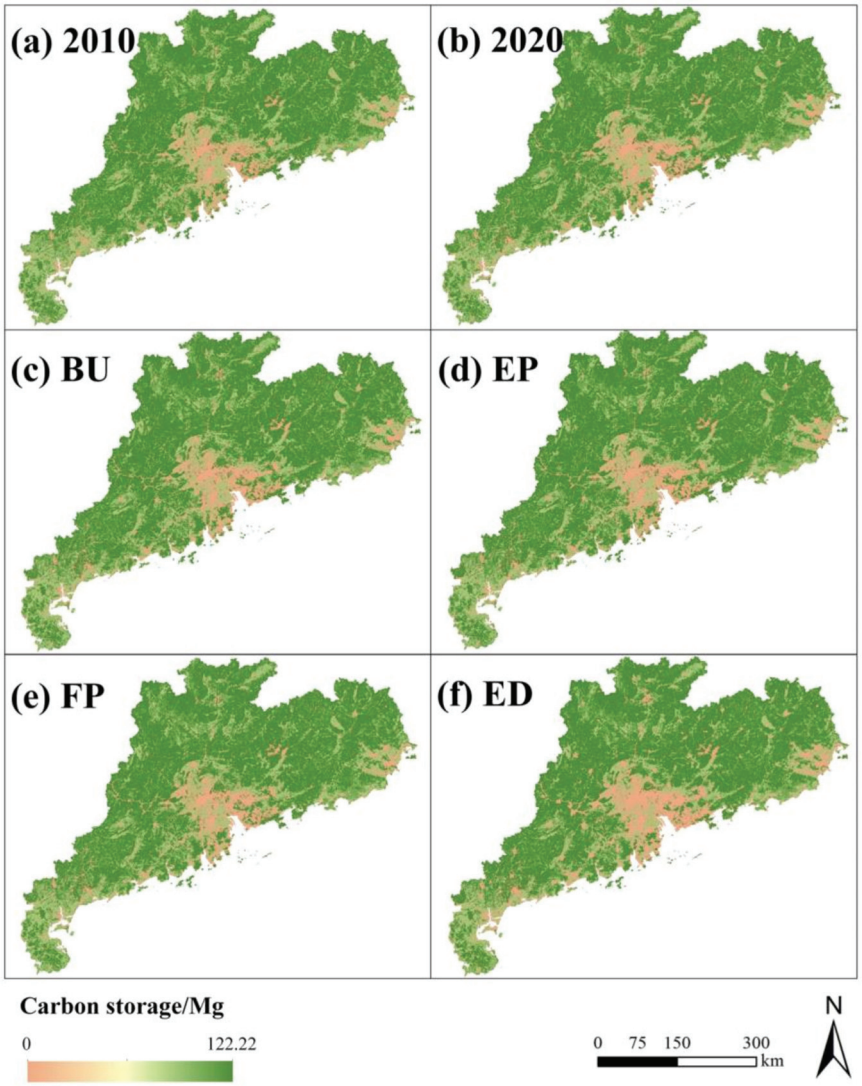


**Figure 3.** Spatial distribution of carbon storage in (**a**) 2010, (**b**) 2020, and 2030 under (**c**) BU, (**d**) EP, (**e**) FP, and (**f**) ED scenario.

## 4. Discussion

### *4.1. Verification of PLUS Model*

Studies have shown that in the context of global change, population size and built-up area tend to be positively correlated [48,49]. This study explores future urban scale changes through the trend of the future population, thereby verifying the demand for land use. As machine learning is increasingly considered an effective tool for future population prediction, three methods, Holt-Winters, Damped Holt-Winters method, and ARIMA Model, have proven to be effective tools [50,51]. In this study, by using the forecast and tseries packages in R language, the predictions of the future population of Guangdong Province are made by the above three models.

Each model passes the goodness-of-fit test and is statistically significant. The population number prediction results can be seen in Table 4. Although there are differences in the prediction results of each model, it is affirmative that the population of Guangdong Province will further increase by 2030, so it is presumed that the scale of built-up land will also increase accordingly. The area of built-up land will increase from each scenario, so the land use demand can be proved to be correct.

**Table 4.** Predicted population by different machine learning methods.

| Year | Holt's Method | Damped Holt's Method | ARIMA Model |
|---|---|---|---|
| 2020 | | 9783.091 | |
| 2030 | 10,721.533 * | 10,089.474 ** | 10,643.284 * |

Note: * $p < 0.05$; ** $p < 0.01$.

Taking 2010 as the base period, the PLUS model simulated the LUCC in Guangdong Province in 2020 by combining a variety of LUCC drivers. Compared with the actual situation, it can be concluded (Figure 4) that there is an extremely high spatial distribution similarity between those two. From the quantitative relationship, the Kappa coefficient is 0.8571, which shows the applicability of the model and the accuracy of the driving force selection.

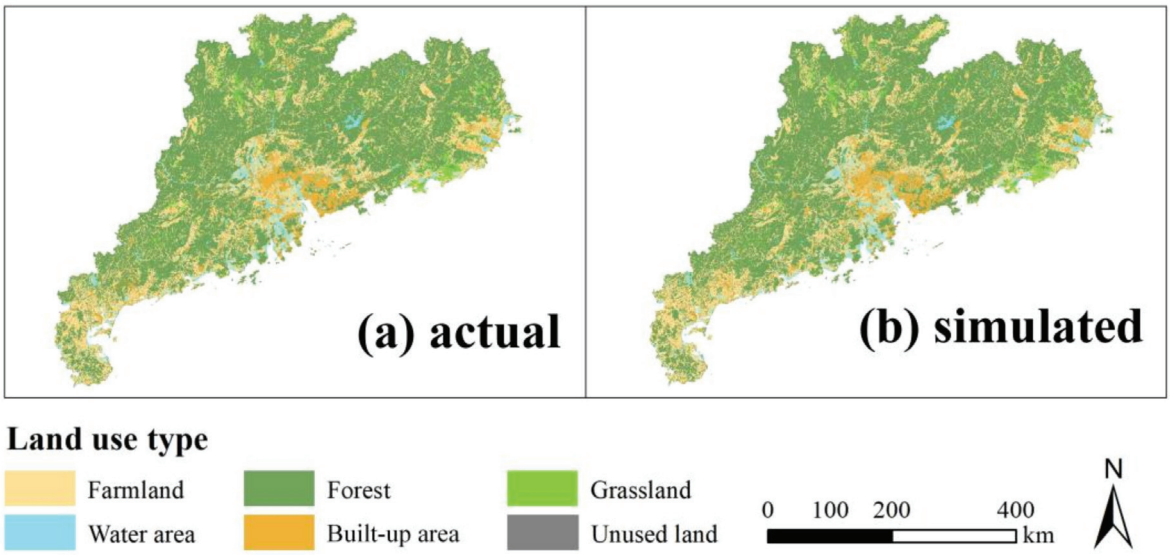


**Figure 4.** The comparison between (**a**) actual and (**b**) stimulated LUCC in 2020.

*4.2. Comparison of Carbon Storage Result*

In this study, ecosystem carbon storage was calculated by the InVEST model. In order to make the research results more objective and accurate, a set of carbon density by land use type under different carbon pools was derived by comparing it with other scholars' studies. The specific data and reference sources are shown in Table 5.

**Table 5.** Carbon density in different carbon pool on diverse LUCC and their references.

| LUCC | $C_{above}$ (Mg/ha) | $C_{below}$ (Mg/ha) | $C_{soil}$ (Mg/ha) | $C_{dead}$ (Mg/ha) | Reference |
|---|---|---|---|---|---|
| Farmland | 27.89 | 2 | 47.52 | 1 | [52,53] |
| Forest | 48.18 | 8.3 | 49.24 | 6.5 | [52–54] |
| Grass | 38.24 | 5.2 | 50.45 | 1.9 | [52,53,55] |
| Water | 0 | 0 | 0 | 0 | - |
| Built-up land | 0 | 0 | 0 | 0 | - |
| Unused land | 30.23 | 20 | 40.75 | 5 | [52,55] |

In addition, the ecosystem carbon storage in other regions of China with similar natural background characteristics was compared. Due to the large differences in the study area between different study results and the lack of comparability of the respective total carbon storage, the amount of contained carbon per unit area, i.e., carbon density, was used for comparing with each other [56].

The result of this study and others (Table 6) are in the same order of magnitude, which can demonstrate the accuracy of the results. On the other hand, the carbon density of

ecosystems in Guangdong Province is not as high as in other regions with similar natural background characteristics. Although Guangdong Province has low latitude, adjacent to the ocean, and has year-round high temperatures, humid climate, and evergreen seasons, which are suitable for vegetation growth, the urbanization rate of Guangdong Province is among the highest in China. Large areas of natural ecosystems have been developed into built-up land, which is the main reason for the low carbon storage level.

**Table 6.** Carbon storage in previous studies.

| Author(s) | Study Region | Year | Carbon Density (Mg/ha) |
|---|---|---|---|
| This study | Guangdong Province | 2010 | 90.09 |
| | | 2020 | 89.39 |
| Kaiqi, Z. et al. [57] | Guilin City | 2010 | 199.13 |
| | | 2020 | 197.92 |
| Qi, F. et al. [58] | Su-Xi-Chang Region | 2010 | 48.44 |
| Qing, L. et al. [59] | Hainan Province | 2010 | 127.37 |
| Rubo, Z. et al. [60] | Pearl River Delta | 2000 | 115.00 |
| | | 2015 | 115.48 |
| Zhiqiang, Z. et al. [61] | Guangzhou City | 2010 | 50.54 |

### *4.3. Suggestions for the Conservation of Carbon*

According to the Climate Action from the United Nations, it is imperative to take credible actions to achieve the Net-zero goal. Net zero means the remaining emissions are reabsorbed from the atmosphere by the natural ecosystem. Therefore, the ability to store carbon is of vital importance to avoid the catastrophic impacts of climate change and preserve a livable planet. Many countries pledged to achieve the net-zero target, including some big emission objects, like China.

Although China plays the biggest emission role all around the world, the government aims to cut its $CO_2$ emissions to zero by 2060. China takes up-to-down measurements to make this commitment come true, indicating that the provincial governments were required to achieve their Net-zero goal. Taking Guangdong Province as an example, several planning documents were released in 2021 to guide the departments concerned to achieve the net-zero target, the 14th Five-Year Plan of Ecological Environment Protection and the 14th Five-Year Plan for Ecological Civilization Construction for instance. These two documents are updated every five years, and the Net-zero goal became one of the most essential objectives for the first time. However, to take advantage of the absorption ability of the ecosystem, both two planning documents proposed the explicit protection target indicators to the proportion of forest coverage, wetland protection, and green infrastructure area, but the contribution of farmland was ignored. There are multiple documents aiming to achieve the Net-zero goal that only concentrates on ecological protection approaches, and lacks the consideration of farmland protection methods.

To sum up, it is highly advisable that the importance of both ecological and farmland protection indicators should be taken seriously in future planning documents concerned in not only China but also in other countries or areas.

### *4.4. Limitations and Prospects*

As society evolves and population numbers further rise, more necessities such as food, energy, and water will be obtained from natural ecosystems, resulting in a further complex relationship between humans and natural ecosystems [62]. However, in this study, only the characteristics of historical changes and the constraints of planning projects on future LUCC were considered in the simulation of LUCC, but the coupling of human-land systems was less considered. Few major LUCC events were taken into consideration, such as logging, river damming, and forest fires.

Moreover, the climbing population is bound to cause higher-intensity human activities, and anthropogenic processes have already produced significant changes to the climate [63].

However, this study took less account of the effects of climate change when predicting future land use patterns. It is hoped that more indicators that can reflect these two points will be incorporated into the influencing factors of LUCC simulations in further studies.

Besides, the model can properly be implemented in a local area such as Guangdong Province, but whether this model is appropriate for a larger scale is not explored, in our future studies we will be able to consider answering such important questions.

## 5. Conclusions

We integrated the Markov-PLUS-InVEST model to simulate the land use pattern of Guangdong Province in 2030 based on the land use pattern in 2010 and 2020 and assessed the ecosystem carbon storage under each historical and future land use scenario. The main conclusions are as follows.

During 2010–2020, the area of built-up land in Guangdong Province increases significantly, the area of farmland decreases by nearly 5%, the area of grassland increased by about 3%, and the area of the remaining land use types does not change much. The scale of built-up land increases in all four future scenarios, but the scale of expansion varies due to the constraints of spatial patterns and policies. Due to the location limitation, construction land expansion is minimal in the FP scenario, and the area of natural ecosystems such as farmland and forest land grows significantly; the land use change in the BU scenario is a continuation of 2010 and 2020. Forests are well protected in the EP scenario, but due to the lack of constraints on urban sprawl, the expansion is still obvious. In the ED scenario, with economic development as the guide, the urban sprawl encroaches on many natural ecosystems.

The ecosystem carbon storage declined significantly during the last decade 2010–2020, this could be due to urban expansion. In the four scenarios in 2030, the further development of urban size will decrease carbon storage, and there will be a relationship of FP > BU > EP > ED for ecosystem carbon storage. Therefore, it is suggested that not only the quantitative coordination of land use should be considered in planning but also the spatial locational factors need to be taken into account, so as to enhance the protection of land use types close to cities such as farmland. This could simultaneously increase ecosystem carbon storage in terms of both limiting urban sprawl and increasing ecosystem carbon potential, which makes it an efficient nature-based solution to reserve carbon.

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# County-Level City Shrinkage in China: Representation, Cause, and Response

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**Abstract:** Shrinkage in China's cities has gradually received increasing attention. Specifically, county-level shrinking cities are numerous and widely distributed. City shrinkage even appears throughout Zhejiang Province, which is highly developed and has stable economic growth. County-level shrinking cities resulting from regional competition can still maintain long-term and stable economic growth, but their economic growth lags behind the whole competitive region. We identified five county-level shrinking cities in Zhejiang Province, and characterized the shrinkage phenomenon in Changshan County using census, nighttime lighting (NTL), and Tencent Location Big Data. City shrinkage resulted from the comprehensive effects of declining traditional industries, backward per capita income, highly skilled labor force shortages, and population age structure changes. Given the shrinkage status of Changshan, we proposed countermeasures and suggestions including aspects of industrial development, urban planning, social governance, and care for the elderly.

**Keywords:** city shrinkage; representation; cause; response; nighttime lighting data; China; Changshan

## 1. Introduction

City shrinkage has become an international phenomenon [1] and a new challenge for global population development [2]. Shrinkage started in the 1950s, with stagnating population growth in some European cities and regions [3]. Up to the 1980s, numerous cities in developed European and American countries underwent shrinkage, accompanied by sustained population losses, declining economic vitality, decaying buildings, and increasing social contradictions [4,5]. Recently, the shrinkage phenomenon has been observed in cities of some developing countries, especially in emerging economies [6]. China, a developing country and the world's second-largest economy [7], is faced with an increasingly aggravated challenge of city shrinkage. Over 260 cities sustained population shrinkage from 2010 to 2020 as Beijing, Shanghai, Shenzhen, Chongqing, Guangzhou, Chengdu, and Tianjin grew into megacities with urban populations exceeding 10 million [8]. Presently, several cities face various problems such as economic recession, industrial shortage, imperfect infrastructures, deteriorated living environment, and housing vacancy [9–11].

Such shrinkage phenomena have attracted close attention from the Chinese government. At the Central Urban Work Conference in 2015, General Secretary Xi Jinping pointed out the requirements for enhancing shrinking city sustainable development. Seventh census data show that the population urbanization rate in Mainland China grew rapidly from 49.7% (2010) to 63.9% (2020). Now China remains in the rapid urbanization phase, in which large-scale and high-speed population aggregation from rural areas towards cities will not slow, not to mention be reversed [12]. To meet the challenge, China is implementing a new type of people-oriented urbanization strategy and has vowed to devise a new development path for county seats suffering from population outflows [13]. In recent years, continuously deepening research has been conducted on city shrinkage in China. The connotations of

city shrinkage have been discussed, international experience has been generalized and summarized [14–16], and the uniqueness and complexity of city shrinkage in China has been recognized [10,17]. More data are required to profoundly explore the impacts, development mechanisms, and response measures of county-level city shrinkage in more dimensions [17] in combination with more actual local context [18]. Moreover, Chinese shrinking cities have been empirically analyzed [19–21]. Most of these studies were conducted before 2015, although the city shrinkage phenomenon in China has been reflected, to some extent, by existing research results [22]. In most previous studies, the causes of shrinkage were analyzed mainly at the macro-level or with a focus on declining and resource-exhausted cities in relatively economically backward regions; however, county-level city shrinkage in developed regions has been largely ignored [23].

To address this research gap, our study aims to identify county-level shrinking cities in Zhejiang Province from population and industrial structure changes and investigate the shrinkage characteristics of a county-level city (Changshan County, Zhejiang Province) from population age structure and short-term population changes based on census, nighttime lighting (NTL), and Tencent Location Big Data perspectives. Furthermore, shrinkage causes were explored from industrial structure, income gap, highly skilled labor force, and population age structure angles. This study contributes a practical observation and a case study of county-level city shrinkage in a relatively economically advanced region in China to broaden the understanding of city shrinkage.

## 2. Literature Review

In the 1970s, the term "shrinking city" was initially used by German scholars to describe some urban areas subjected to reduction in employment opportunities and population size. Later, this term became popular because of a famous paper published by German scholars Häussermann and Siebel in 1988 [24,25]. City shrinkage also appeared in America [26,27], the UK, France [28], and Portugal [18], arousing increasing attention. In a Western city shrinkage context, the shrinkage connotative definition, representation characteristics, driving factors, and development tracks have been extensively explored by scholars [3,5,28,29], and a "smart decline" strategy to cope with challenges has been proposed [30,31]. Oswalt and Rieniets [32] proposed that population losses in shrinking cities accounted for 10% of the total population, or the annual average population loss rate was >1%. Schilling and Logan [27] believed that shrinking cities are a subset of industrial cities, in which population loss rate has been 25% or more over the past 40 years and is accompanied by a continuous increase in urban vacant land and abandoned properties. Shrinking cities are defined by the Shrinking Cities International Research Network as densely populated (population size >10,000) urban areas facing population losses for over two years and experiencing structural economic crises [29,31]. It is quite difficult to give a globally universal and accurate city shrinkage definition considering enormous urban context differences. Presently, city shrinkage has been defined from a singular population perspective [33] or by other factors such as economy [31], land, and public services [21,22].

As generally believed by scholars, shrinkage is a complex and pluralistic process with no universally applicable evolution model [29]. Many causes for city shrinkage have been summarized by scholars through unremitting efforts in relevant studies. Such causes are divided into economic (e.g., globalization, deindustrialization, regional economic recession, industrial transformation failure, and resource exhaustion) [17,34–36], population (e.g., population aging, declining birth rate, ethno-racial transition, and out-migration) [5,37–39], social (e.g., urban decay, congestion diseconomies, excessive suburbanization, infrastructure aging, aggravated regional unfairness, and deteriorated climatic conditions) [18,31,39–41], and political (e.g., socialist transformation, administrative division adjustment, and reform and development) [5,18,42,43].

Western society has responded to city shrinkage challenges in various ways. Smart growth, a representative planning concept in North America in 1990, proposed to implement measures such as urban growth boundary delineation and advocated for mixed land

use and recovery of vitality of old communities. The smart growth concept helps, to some extent, relieve problems of suburban sprawl and declining population density, yet fails to cast off traditional growth-oriented constraints. Wiechmann and Pallagst [31] pointed out that more inclusive attitudes and a broader field of view are required to cope with the city shrinkage problem. In 2002, the smart decline concept was proposed in America, which was defined as "planning for less—fewer people, fewer buildings, fewer land uses". The smart decline concept worked very well, as evidenced in the Youngstown 2010 Citywide Plan, in which the vision of "accepting Youngstown will be a smaller city" was proposed, with residential lands and commercial lands reduced by 30% and 16%, respectively. In Germany, which pioneered the changing values of shrinkage, good results have been achieved through revitalization of shrinking cities [44]. When formulating a new plan in 2001, the Dresden government abandoned growth orientation, reduced land consumption, and highlighted the creation of an attractive city center and a stably populated "compact" city. In Plagwitz, Leipzig, the regional population has once again grown through projects such as dismantling vacant properties and transforming vacant land plots into open space [45]. Such changes conforming to the concept of "Less Is More" have injected new vitality into powerless and helpless shrinking cities.

Less attention has been paid to population losses in Chinese cities compared with Western shrinking cities [46]. Long, Wu, and Wang [17] pointed out that many Chinese cities have shrinking populations according to the fifth (2000) and sixth (2010) census data in China. The Northeast China region has the most serious net population outflows and the most significant city shrinkage throughout the country [11]. Here, over half of the resource-based cities have been caught in severe recession and showed a shortage of alternative industries and industrial structural imbalance due to resource exhaustion, making it difficult to resuscitate their populations and economies [20]. Other shrinking cities occur in relatively economically underdeveloped western and central regions of China, although they are in a smaller proportion and have a lower shrinkage degree than those in the northeast [47]. Due to the weak economic base and slow development rate, the shrinking cities in western and central regions are prone to low per capita income, imperfect urban infrastructures, and deteriorated living environments, along with an ever-declining attraction to the population [47]. In the eastern region, which enjoys the highest economic development level in China, city populations continue to decline in Yancheng and Huai'an in Jiangsu Province and Shanwei and Chaozhou in Guangdong Province [48]. Zhang et al. [49] thought that Chinese city shrinkage generally was due to a mismatch between market-driven resource flow and allocation with the vigorous promotion of the government's growth supremacism. Xu [15] pointed out that inter-regional utility differences are strengthened by factors such as government control, and small- and medium-sized city populations are relocated to maximize utilities such as incomes and urban public services. Li [50] believed that household registration constitutes the greatest institutional barrier obstructing the migration of rural workers, and internal migration in China does not follow the normal law of push and pull. Chen et al. [51] summarized system restrictions, economic and environmental transition, and development model defects as the causes of small town shrinkage in China, and thought that their large-scale shrinkage will be unavoidably triggered by the sustained promotion of China's urbanization, strong megacity momentum, and decline in the function and position of small towns. Gao, Wang, and Gu [21] believed that an external factor, anti-globalization, generates enormous impacts on the population and economy of Chinese cities, thus leading to regional city shrinkage.

City shrinkage characteristics are inseparable from local contexts [29], which vary substantially between Chinese and Western cities [49]. As reported by Long, Wu, and Wang [17], the degree of population shrinkage in Chinese shrinking cities is lower than those in the West, with the coexistence of population shrinkage and economic growth. Liu and Yang [10] pointed out that the shrinkage degree of foreign shrinking cities is generally 2–5% with a duration of several decades, while that of Chinese cities is <2% with a duration

of <10 years. Additionally, suburbanization, deindustrialization, industrial recession, and population structure changes are embodied in a minority of Chinese cities, without representativeness or universality [19]. Different from the American Rust Belt Region, the Greater London Region in the UK has witnessed a so-called "doughnut effect" spatial shrinkage pattern due to deindustrialization and suburbanization. The Chinese shrinkage pattern is the opposite (i.e., "central fullness and marginal hollowness"), where shrinkage mainly prevails in villages, towns, and counties at the periphery of megacities [10,21]. Most Chinese shrinking cities are county-level cities [17], where the population shrinkage phenomenon is quite prominent [22]. The county-level city is a hybrid institutional system between city and county, which combines urban management with rural management, not only emphasizing city construction and management but also taking villages into account at the same time [52]. Due to the Chinese administrative division system, there are generalized and narrow senses of cities. The generalized cities refer to the region corresponding to the jurisdiction of cities, and narrowly defined cities refer to the physical regions of cities [53]. Based on this, scholars have proposed the generalized and narrow sense of urban shrinkage in China, referring to the continuous decline in the population within the counties or cities and urban district, respectively [53,54]. Sun [55] believes that the narrow urban shrinkage can fully reflect the strength of urban population agglomeration and is more in line with international practice. Liu and Zhou [54] argue that the generalized city is more suitable as a spatial scale to explore Chinese shrinking cities, because administrative division is the basic unit for urban management and urban planning. Guan et al. [56] and Zhang et al. [57] believe that the government administrative ability has significant impacts on the urbanization and it is inseparable from the policy system to explain urban shrinkage in China. Liu, Qi, Qi, and Liu [22] discovered that nearly 70% of county-level cities in Northeast China have shrinking populations, and the proportion of severely shrinking cities is growing. Wu, Long, and Yang [19] found that the period 2000–2010 witnessed gradually aggravated local shrinkage in 1/2 and nearly 1/5 of county-level cities, respectively, in two extremely dynamic urban agglomerations—the Yangtze River Delta and Beijing–Tianjin–Hebei Region. For the current shrinkage status of Chinese county-level cities, more typical cities should be included to deeply explore the context and causes of local city shrinkage and to provide countermeasures [17,58].

## 3. Data Methodology and Case Study

### *3.1. Data*

The following data were included in our research:

(1) Version 4 DMSP/OLS Nighttime Lights Time Series dataset (non-radiometrically calibrated) (a total of 34 images shot by six satellites F10, F12, F14, F15, F16, and F18 during 1992–2013) released by the National Oceanic and Atmospheric Administration (NOAA) of America, global radiometrically calibrated NTL products (6 images in total), and VIIRS/DNA synthesized monthly average light radiation dataset (96 images in total during 2013–2020).
(2) Vector data of the administrative division (1:1,000,000) released by the National Geomatics Center of China.
(3) Global location data released by the Tencent Location Big Data platform on 30 August, 13 September, and 27 September 2019.
(4) Data of the fourth (1990), fifth (2000), sixth (2010), and seventh (2020) Zhejiang Province censuses.
(5) Data of the fifth (2000) and sixth (2010) Changshan County censuses.

### *3.2. Methodology*

The city shrinkage explored in this research refers to shrinkage in a generalized sense, and the whole region within the boundary of the urban administrative district served as the research object, covering built-up and non-built-up areas. Moreover, the population included urban and nonurban populations. As aforementioned, the generalized cities

research scope likely better reflects the actual situation in China and helps explore greater county-level city shrinkage details [54,56]. Given that population losses and structural economic crises are common in shrinking cities [31,59], the city shrinkage phenomenon was depicted in this research in two aspects: population and economy.

Firstly, the long-term variation trends of the city population and economy were represented by the population change within a time period and the change in NTL intensity. Based on Oswalt and Rieniets [32] and Liu, Qi, Qi, and Liu [22], the annual average population change rate was adopted for analysis:

$$P = \sqrt[30]{\frac{P_{2020}}{P_{1990}}} - 1 \quad (1)$$

where $P$ indicates the annual average population change rate during 1990–2020. $P_{2020}$ and $P_{1990}$ refer to the total population in 2020 and 1990, respectively. According to the population shrinkage concept, a city is subjected to population shrinkage when $P < 0$, and a greater absolute value of $P$ indicates a higher shrinkage degree, or otherwise, a city is free from population shrinkage. We divided cities into types I, II, III, IV, and V based on the annual average population change rate of [1%, +∞), [0.3%, 1%), [−0.3%, 0.3%), [−1%, −0.3%), and (−∞, −1%), respectively.

According to Kuznets [60], a certain industrial structure is formed in an economy through professionalization and social division of labor, which, in some sense, decides the economic growth mode. Specifically, a reasonable industrial structure contributes to highly stable economic growth [61]. A reasonable or optimal industrial structure is determined by the composition of different factor endowments (including land, labor, human capital, physical capital, etc.) or endowment structure [62]. Moreover, when the endowment structure evolves over time, the optimal composition of industries also changes accordingly and optimal growth is achieved only when the industrial development follows the comparative of the endowment structures of the economy [62]. Chen and Deng [63] discovered that China's structural change presents a quantitative relationship with the economic growth rate. As pointed out by Liu and Li [64], the economic scale growth in China is positively influenced by primary and secondary industries but negatively affected by tertiary industry. Based on the above studies and economic growth rate comparisons between cities, the ratio of urban to economic growth rate of the whole province was used to represent urban industrial structure change. Given shortcomings such as inconsistent statistical standards, inaccurate price indices, and political pressure to maintain strong local economic growth [65], economic changes were investigated using NTL data in our research. NTL data, which can reflect population and urban changes, is applicable to socioeconomic research with the advantages of higher accuracy and comprehensiveness over traditional data [66]. The regional NTL intensity is significantly linearly correlated with the regional gross domestic product (GDP), as evidenced in some present studies [67,68]. In our research, NTL data were processed using the method proposed by Cao et al. [69] and Liang et al. [70] to overcome low NTL data comparability due to time and sensor differences.

$$NTLR = \frac{CNTL_{2020}/CNTL_{1992}}{PNTL_{2020}/PNTL_{1992}} \quad (2)$$

where $NTLR$ denotes the ratio of the growth amplitude of urban NTL intensity to that of the whole province during 1992–2020. $CNTL_{2020}$ and $CNTL_{1992}$ stand for the urban NTL intensity in 2020 and 1992, respectively. $PNTL_{2020}$ and $PNTL_{1992}$ represent the provincial NTL intensity in 2020 and 1992, respectively. If $NTLR < 1$, then the NTL intensity in this city grew more slowly than that in the whole province, or otherwise, the growth rate of urban NTL intensity was higher than that of the provincial NTL intensity. We divided cities into types A, B, C, D, and E according to the urban NTL values of [1.1, +∞), [1.03, 1.1), [0.97, 1.03), [0.9, 0.97), and (−∞, 0.9), respectively.

In our research, cities with a *P* value belonging to types IV or V and *NTLR* value belonging to types D or E were classified as shrinking cities, i.e., cities of types IVD, IVE, VD, and VE. The other cities were excluded from the scope of shrinking cities. Notably, NTL data during 1990–1991 were not accessible, so we only used NTL data during 1992–2020, thus leading to certain differences in the time horizon between population changes and NTL intensity changes. Nonetheless, the influences caused by such differences were acceptable.

Additionally, more details of city shrinkage were presented from population age structure, as well as population changes during holidays and festivals on the basis of age-specific population data and Tencent Location Big Data. Urban population age structure has enormous influences on cities, especially shrinking cities [3], and measures coping with shrinkage can be formulated by acquiring these data. Hence, we depicted the age composition characteristics of populations as well as those of outflowing populations using the age-specific Changshan County population data. Long and Wu [71] believed that shrinking cities would be better understood, analyzed, and responded to by strengthening monitoring and evaluation of the intensity of human activities. In the past, due to the restriction of the low spatial–temporal resolution of traditional data, short-term population changes could hardly be displayed. However, short-term population change could also be used to describe the characteristics of shrinking counties (e.g., residents' behavior, mobility communication, etc.) [72]. The rapid development of information technology has taken us into the "Big Data Era", causing transformation of the methods in urban temporal and spatial research [73]. Big data have been applied to urban temporal and spatial behavior research from the perspectives of residents' behavior, urban space, and development [74–77]. Compared with traditional statistical data, Tencent Location Big Data have higher temporal and spatial resolution [78], thus meeting display requirements. During holidays and festivals, people choose to enjoy leisure by leaving their regular workplace or even leaving their workplace city. In China, most people who work and study away from home traditionally return during the Spring Festival or Mid-Autumn Festival, and cities experience short-term population change. During the period before the festivals, the main population flow goes from central or developed cities to non-central or undeveloped cities, and opposite occurs after the festivals [79]. Therefore, we revealed the population change characteristics in Changshan County using Tencent Location Big Data on the Mid-Autumn Festival (an important Chinese festival) two weeks before and after the 2019 festivals. The standardized data provided by Tencent have spatial resolution of 5 km and temporal resolution of 30 min. Through comparison, it is found that the user activity between 14:30–15:00 is relatively high, largely because most people use Tencent applications for communication, entertainment, purchasing, etc., during this time period. Therefore, we chose the data between 14:30 to 15:00 over these three days and used the ordinary kriging method to map the user activity in Changshan County by ArcGIS 10.5.

### *3.3. Research Area*

Changshan is a county under the jurisdiction of the prefecture-level city of Quzhou in the west of Zhejiang Province, People's Republic of China, which covers 1099 $km^2$ and has a permanent population of 260,000, of which 127,700 (49.12%) is urban (Table 1 and Figure 1). As a relatively economically underdeveloped county-level city in Zhejiang Province, Changshan County's GDP ranks 78th among county-level units in Zhejiang Province, and its per capita GDP is only about 60% of that of Zhejiang Province. In 1949, namely the initial post-liberation period, Changshan County remained an agriculture-dominated city, with a population of about 140,000. The proportion of industrial output value was <15%, and there were only several lime kilns, brick and tile kilns, and manual workshops. After liberation, modern industry gradually developed, and industries such as bearings, construction materials, and calcium developed and grew stronger by virtue of locally abundant non-mineral resources. In the 1980s, the industrial output value in Changshan exceeded the agricultural output value, with the total population rapidly growing to 286,000 because of the high birth rate. Since the reform and until now, regional

GDP in Changshan County grew at a high annual average rate of over 10%, stabilizing at 6.5% in the most recent decade. Despite sustained overall growth, the population has not kept up with the growth trend. According to census data, the population started declining after peaking in 1990, and in 2010 was only about 80% of that in 1990, indicating significant population shrinkage. In 2020, the population rose again slightly, but did not recover to the 2000 level.

**Table 1.** Permanent Changshan County population.

| Year | 1953 | 1964 | 1982 | 1990 | 2000 | 2010 | 2020 |
|---|---|---|---|---|---|---|---|
| Population size (ten thousand people) | 13.92 | 18.87 | 28.60 | 30.00 | 26.55 | 24.14 | 26.00 |

Source: Changshan County censuses.

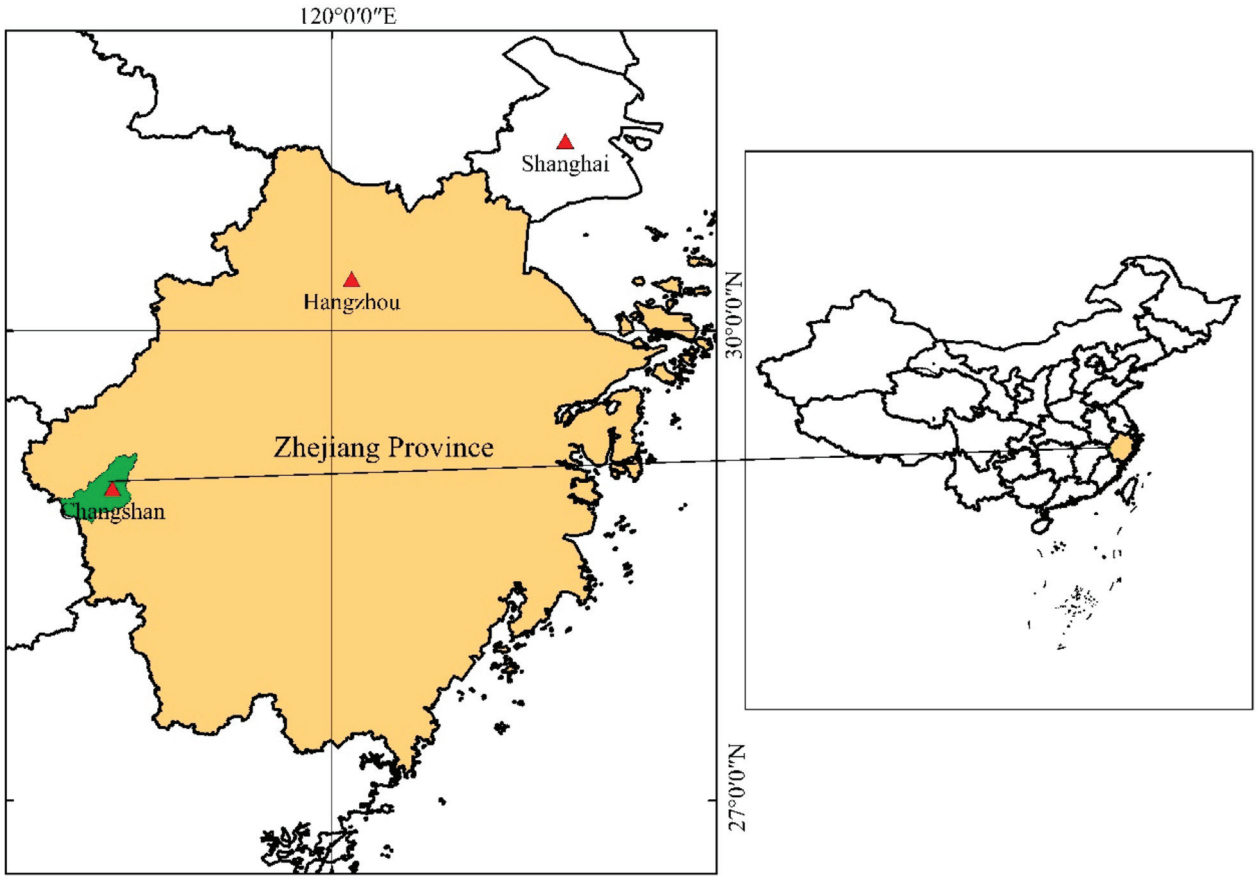


**Figure 1.** Location map of Changshan County.

We selected Changshan County for our research for the following main reasons: Firstly, previous shrinking city research has focused on northeastern, central, and western cities, but shrinking cities such as Changshan County located in the economically developed eastern region have been scarcely studied. Secondly, city shrinkage in the eastern region does not completely equal the "absolute shrinkage" brought to resource-based cities when they are stuck in an economic downturn and even a negative economic growth cycle, but instead, it is equivalent to "relative shrinkage", resulting from regional competition in competitive regions such as Zhejiang Province. Finally, both population size and economic development in Changshan County are low among Zhejiang Province county-level cities, so it is representative.

## 4. County-Level City Shrinkage Representation

Changshan County city shrinkage was represented by population size, NTL intensity, population age structure, and population size change during holidays and festivals.

### *4.1. Population Size and NTL Intensity*

From the *P* value perspective, a total of 64 county-level units in Zhejiang Province belonged to types I and II (annual average population growth exceeded 0.3%), which were collectively distributed in the northern and eastern coastal areas and some central areas (Figure 2). Such areas possessed a relatively favorable economic base with a high economic growth rate, thus attracting a large population from other areas in the province and other provinces. Additionally, a total of 10 county-level units belonged to types IV and V (Table 2), which were mainly concentrated in relatively economically underdeveloped western and southern areas, with the annual population rate exceeding 0.3%. For *NTLR* value, the NTL intensity growth rate in 45 county-level units was higher than the average overall province level, and they were collectively distributed in the southern and central areas. Moreover, the NTL intensity of 40 county-level units grew at a lower rate than the average overall province level, and they were mainly distributed in the northern and western areas.

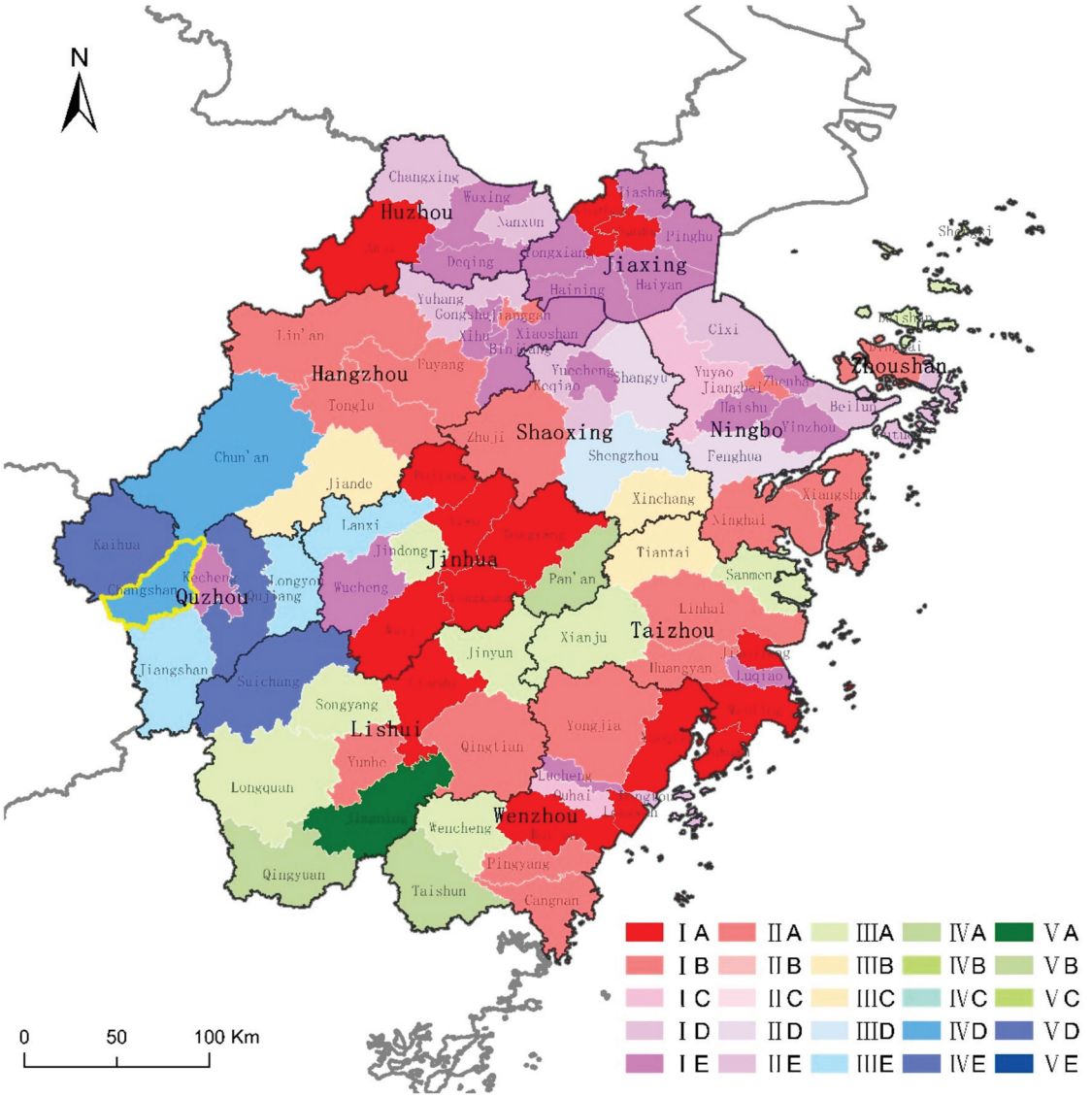


**Figure 2.** Changes in population and NTL intensity in Zhejiang Province county-level cities during 1990–2020.

**Table 2.** Quantity of Zhejiang Province county-level cities belonging to each change type of population and NTL intensity.

| | I | II | III | IV | V |
|---|---|---|---|---|---|
| A | 14 | 12 | 8 | 4 | 1 |
| B | 5 | 0 | 1 | 0 | 0 |
| C | 2 | 0 | 2 | 0 | 0 |
| D | 3 | 2 | 1 | 2 | 0 |
| E | 20 | 6 | 3 | 3 | 0 |

For the *P* and *NTLR* values combined, population and NTL intensity grew fast in the peripheral parts of central urban areas in Hangzhou, Ningbo, Wenzhou, Taizhou, and Jinhua, as well as the Lishui urban central area (IA, IB, IIA, and IIB). This is mainly because urbanization and economic development levels were low in the peripheral parts of Hangzhou, Ningbo, Wenzhou, Taizhou, and Jinhua in the early stage, which, however, enjoyed rapid economic growth owing to radiation from the city centers, along with fast NTL intensity growth. In peripheral areas, an increasing population flowed from rural areas to towns, and rapid secondary industry development contributed a lot to NTL growth intensity, which reflects these changes. In central urban areas, however, the industrial structure was gradually transited into a model centering on the tertiary industry, which boosted NTL intensity growth at a relatively low level, and the past high-energy-consumption and high-pollution industrial sectors were phased out. Hence, the population continued to grow in the central urban areas of Hangzhou, Ningbo, and Wenzhou, although their NTL intensity was not as high as that in surrounding areas and even lower than the average overall province level. In Lishui and Quzhou, the NTL intensity growth rate developed slowly with a poor overall economic base, although their central urban areas did not obviously fall behind peripheral areas due to the lack of powerful outward radiation capacity.

A total of five shrinking county-level cities (types IVD, IVE, IVD, and IVE) were subjected to declining populations and NTL intensity slow growth in Zhejiang Province (Changshan, Qujiang, and Kaihua Counties in Quzhou City as well as Chun'an and Suichang Counties in adjacent Hangzhou and Lishui, respectively) (Table 3). Changshan County NTL intensity grew more slowly than in the whole province, which reflected its primitive industrial structure and low economic growth rate as well as its competitive disadvantages in the whole province. Wuyi County (type IA) near Jinhua serves as a very good area for comparison with Changshan County (type IVD). In 1990, the GDP and population sizes were RMB 377,000,000 and RMB 440,000,000, and 300,000 and 318,000 in Changshan County and Wuyi County, respectively, indicating the approximate economic development and population size of the two cities. Up to 2020, however, the GDP in Changshan County was RMB 16,015,000,000 with the population declining to 260,000, while the GDP in Wuyi County was RMB 27,133,000,000 (1.69 times that in Changshan County) with the population growing to 462,500 (1.78 times that in Changshan County). Moreover, the NTL intensity growth rate in Wuyi County was 1.67 times that in Changshan County. All of the above data highlight significant economic and population differences between the two cities. In industrial structure, tertiary industry accounted for the highest proportion (52.53%) in Changshan County, while secondary industry accounted for the highest proportion (48.04%) in Wuyi County. The industrial structure in Changshan County seemed to be better than in Wuyi, which contradicts their relationship in GDP growth rate. In fact, secondary industry developed slowly in Changshan County with a lag in industrial upgrading and transformation, which slowed increase in the output value of secondary industry and resulted in failure to improve local employment, thus causing backward local economic growth. In short, Changshan County industrial structure was inadequate, as the proportion of secondary industry was not high enough. Comparing Changshan and Jiangshan Counties, both of which are county-level cities in Quzhou City, further highlights the comparative disadvantages in their industrial structures. The Changshan

County (type D) NTL intensity growth rate was higher than in Jiangshan County (type E), but the annual average population loss rate (−0.8%) in the former was four times that (−0.17%) in the latter.

**Table 3.** Zhejiang Province and the shrinking county-level cities.

| | Population Change (% P.A.) | NTL Intensity Growth Ratio |
|---|---|---|
| Chun'an (IVD) | −0.93 | 8.80 |
| Qujiang (IVE) | −0.95 | 8.06 |
| Changshan (IVD) | −0.48 | 8.82 |
| Kaihua (IVE) | −0.80 | 7.66 |
| Suichang (IVE) | −0.47 | 8.11 |
| Zhejiang | 1.48 | 9.57 |

### *4.2. Population Age Structure*

When the Changshan County population was further subdivided, it transpired that the population age structure had already shrunk in 2000, and the population at age 10–49 created a "sandglass" shape (Figure 3). In 2010, the total permanent population declined from 265,000 to 241,400, indicating a more prominent shrinkage-type population age structure. A large young population, especially from age 20 to 39 flowed out, which led to a rapid decline in this age group and its proportion, accompanied by the thinner "grip" part of the "sandglass". Moreover, the average population age rose from 34.69 to 39.92 years, and the median age increased from 30 to 40 years. Compared to in 2000, in 2010, the population of 0–14 years old declined by 13,600 in this county (3.49%), while the 15–59 cohort dropped by 20312 (1.90%), and those 60 years and above increased by 9800 (18.70%). Notably, the proportion of the population aged 65 or above reached 12.58%, which was closer to the standard (14%) for a deeply aging society given by the United Nations (UN).

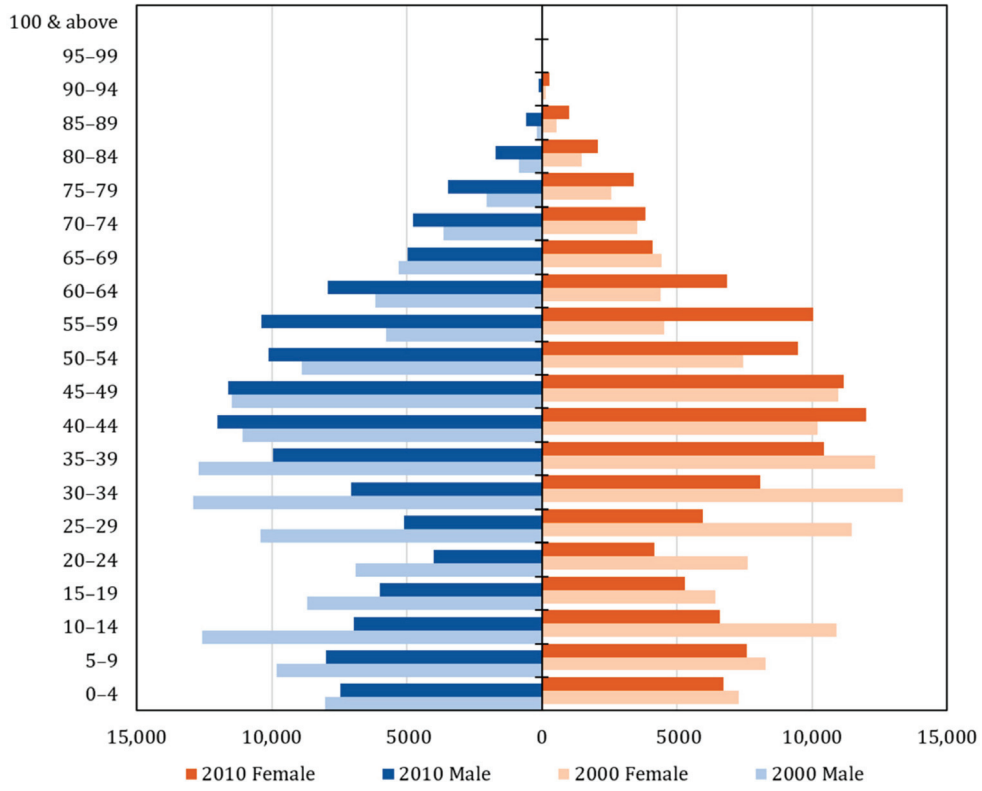


**Figure 3.** Variation diagram of population age structure in Changshan County during 2000–2010.

According to the latest seventh census, the total population in Changshan County was 260,000 in 2020, a slight increase compared to 2010. The latest changes in the population age structure in Changshan County could only be interpreted through some already released data considering the confidentiality of detailed data. By comparing the situation in 2020 and 2010, we found that the 0–14 age group declined by 1800, the 15–59 age cohort declined by 3800, and the 60+ age group grew by 24,200. The proportion of the population 65 years and above reached 19.27%, which approximates the standard (20%) for a super-aging society proposed by the UN and is much higher than the average level (13.27%) in Zhejiang Province. Generally, Changshan County total population experienced a 20-year shrinkage since 1990. The population has risen again in the most recent decade yet has not recovered to the 2000 level. Moreover, the population age structure has been transformed from an early-stage rapid growth type into a shrinkage type, and the sustained reduction in the young population and the population aging trend will continue. Even worse, a society already on the verge of super-aging is estimated to experience accelerated aging in the next 10 years, which will impose considerable elderly care pressure on the whole society.

### *4.3. Population Changes during Holidays and Festivals*

On 13 September 2019 (Mid-Autumn Festival in the Chinese lunar calendar) when people were enjoying short-term leisure leaving their workplace, the world was not yet severely impacted by COVID-19, and population flow and economic development were still normal. According to traditional customs, families come together to admire the full moon and eat moon cakes at night. Most people who work and study away from home will return on this festival and soak themselves in the sweet and warm atmosphere with their family members.

In our research, the intensity of population activities in Changshan County on 30 August, 13 September, and 27 September 2019 was largely determined using Tencent Location Big Data (Figure 4). Overall, the intensity of population activities was the highest in the central urban area of Changshan County owing to the large number of residential and business districts, containing over half of the total county population. Within the county territory, population activity intensity continuously declined with increasing distance from the central urban area. Population activity intensity in the central urban area on the day of the festival was higher than on the other two days, but in the peripheral areas was basically similar over the three days. This suggests that a large outflowing population returned to Changshan County and gathered in the central urban area with developed business and entertainment industries, while there was almost no population change in peripheral villages and small towns without large shopping malls. Two weeks after the festival, however, the intensity of population activities recovered to the level two weeks before the festival. Population fluctuations triggered by the short-term festival were evidence of large population losses in Changshan County. Meanwhile, the evidence also revealed that a secure emotional bond was kept between the outflowing population and their families in their hometown.

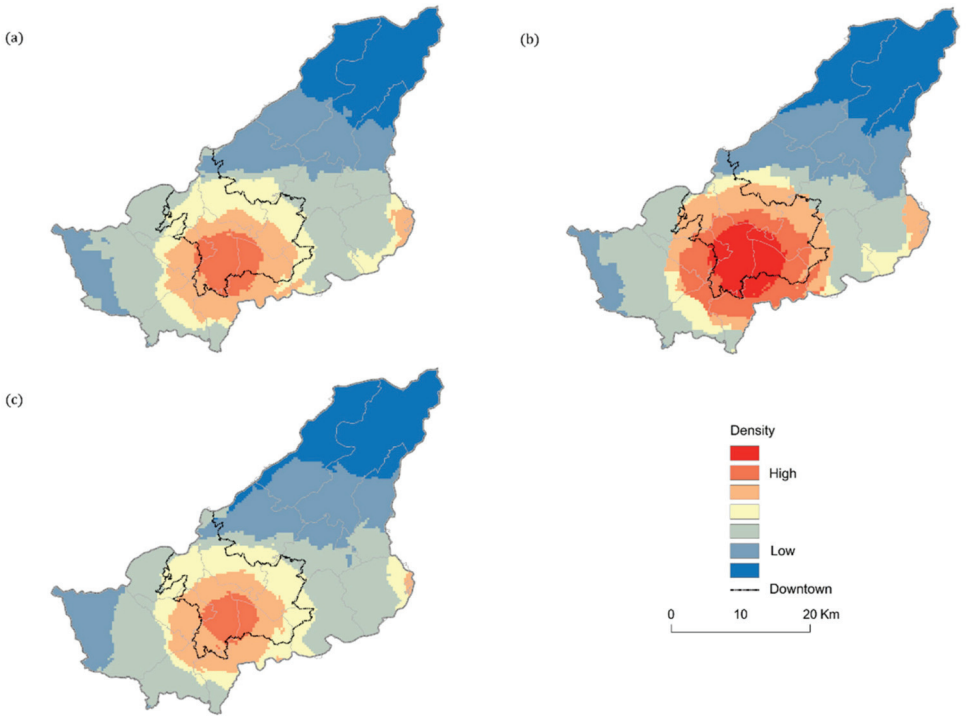


**Figure 4.** User density map of Tencent Location Big Data in Changshan County: (**a**) 30 August, (**b**) 13 September, (**c**) 27 September (the density value, which was standardized, does not represent the actual number of people).

## 5. Analysis on the Causes of County-Level City Shrinking

### *5.1. Decay of Traditional Industry*

Changshan County has suffered shrinkage mainly due to the decline in traditional industrial sectors. Traditional enterprise productivity is restricted due to an outdated management system. After the reform and opening-up policy in 1978, the Changshan County economic base was poor, but industry then began vigorous development. Based on rich nonmetallic mineral resources and the local first-mover advantages of the bearing industry, a batch of state-owned industries such as cement, bearings, and chemical engineering developed and rapidly grew strong, boosting local economic development. As China's economy shifted to a socialist market economy system, the drawbacks of state-owned enterprises under the background of a traditional planned economy were gradually exposed, and enterprise enthusiasm, proactivity, and creativity (and their employees) were repressed [80]. In 1997, many state-owned industrial enterprises in Changshan County were affected by competition from other enterprises, product sales declined, a large number of products piled up in warehouses, and enterprises suffered severe financial arrears [81]. Employee incomes fluctuated due to such problems. Without a basic living guarantee, some employees were not paid, and they lost confidence in enterprise prospects. The industrial employment population decreased by 14,000 during 1996–2003.

Traditional enterprises were subjected to a continuous decline in product competitiveness owing to the gradual loss of their competitive edges. Previously, Changshan traditional enterprises had won the market by virtue of advanced technologies and locally abundant non-mineral resource advantages. Most enterprises were small and had low product technology content, accompanied by very limited economic profits due to fierce competition for similar products with low added values. Additionally, there was little innovation in product input and output from enterprises in Changshan County due to the comprehensive influence of small capital scale, high financing difficulties, and the general lack of entrepreneurship among enterprise operators. Moreover, the competitive edges of traditional enterprises in Changshan County disappeared with the continuous emergence

of high-quality new products developed by enterprises in other regions and the declining transportation cost of raw materials. In 2014, traditional leading industries declined across the board, including the output values of 50% of bearing manufacturers, 80% of organic chemical manufacturing enterprises, and 100% of cement enterprises decreased. Over 70% of enterprises above the designated size in the county subject to output value declines were old enterprises. Among such enterprises, 80% never conducted technological innovation, and 65% still focused on old products [82]. Unprofitable industrial enterprises above the designated size in Changshan County increased from 18% in 2003 to 41% in 2015.

### *5.2. Widening Gaps in Per Capita Income*

Census data show that over 70% of the outflowing population in Changshan County emigrates because of economic factors. In Zhejiang Province, one of the most economically vigorous provinces throughout China, most outflowing Changshan County residents stay in the province and mainly flow towards Hangzhou (the most economically developed city in Zhejiang) and Kecheng (central urban area of Quzhou). Urban and rural per capita disposable incomes in Changshan County have been steadily growing, although they have been lower than the overall level in Quzhou City, and the income gap with Hangzhou has widened every year (Figure 5). In 2011, the urban and rural per capita disposable incomes in Changshan County were RMB 18,600 and RMB 9300, respectively, declining by RMB 15,500 and RMB 5900, respectively, in comparison with those in Hangzhou. In 2020, the two figures reached RMB 42,000 and RMB 24,000, respectively, but the gaps with Hangzhou expanded to RMB 26,800 and 14,700, respectively. Urban per capita disposable income in Changshan County was basically equivalent to the rural per capita disposable income in Hangzhou (Figure 5). In per capita disposable income, income from wages, which accounted for the highest proportion, better reflected the income status of most bottom-layer labor forces. In 2020, urban and rural per capita incomes from wages in Changshan County were RMB 25,800 and RMB 12,500, respectively, equaling 87% and 80% of the overall level in Quzhou, respectively, and 65% and 53% of the overall level in Hangzhou. Such enormous and ever-broadening income gaps directly led to the long-term outflow of labor forces in Changshan County.

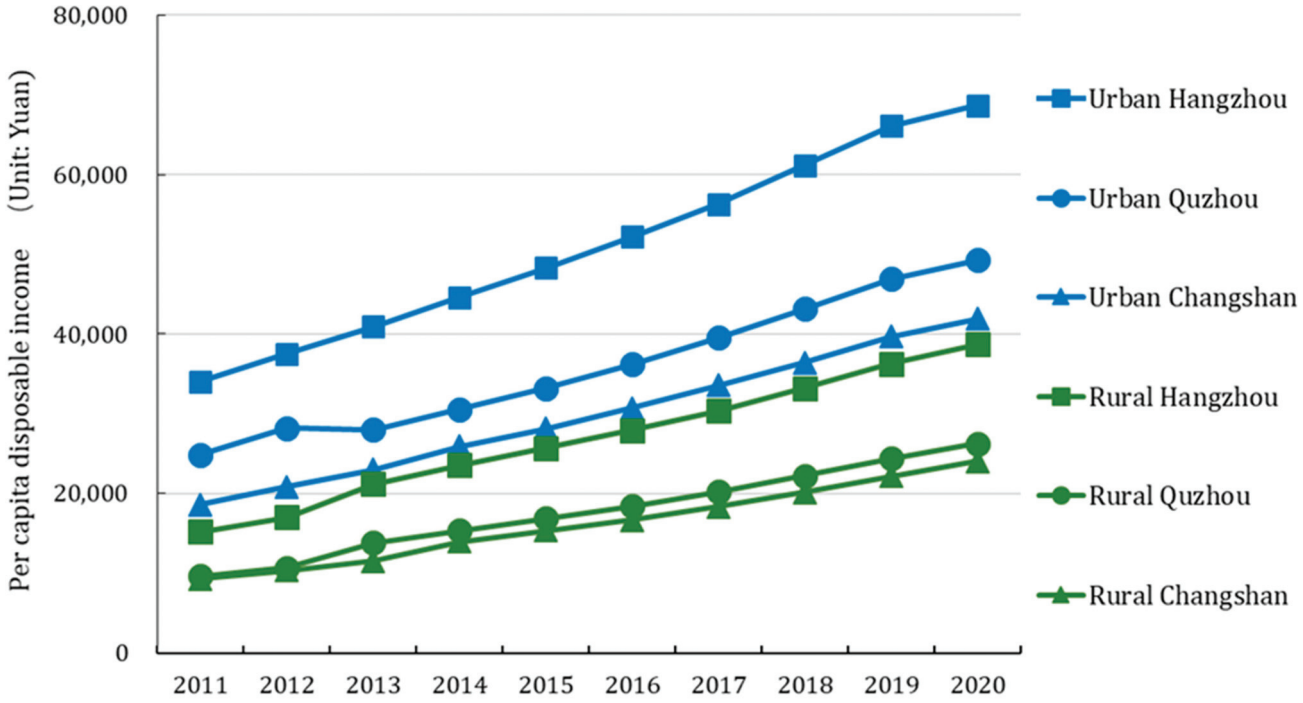


**Figure 5.** Urban and rural per capita disposable incomes in Hangzhou, Quzhou, and Changshan during 2011–2020.

Notably, the Changshan government has exerted some effects on outflow of the labor force population. Firstly, the government has carried out labor skill training, established solid cooperative relationships in labor services with enterprises in other places, and facilitated the employment of originally less-skilled labor forces. Secondly, the government has established a tracking management and visit system for output labor populations, helping them to solve practical difficulties. All of the above measures have effectively reduced employment difficulties faced by local labor forces. Meanwhile, the originally spontaneous and disorderly labor output became increasingly well-organized. From January to September 2003, a total of 6728 labor forces in the whole county were well-organized through government organizations, labor intermediaries, and vocational schools, accounting for 68.2% of the newly added labor output in that year.

### *5.3. Shortage of Highly Skilled Labor Forces*

In the 1980s, traditional industrial enterprises remained in the rough processing stage of resources such as minerals, with simple product craftsmanship and low requirements for labor skills and quality. A lot of surplus labor forces outflowing from rural areas were competent for jobs in most plants just through short-term training. However, traditional industrial enterprises not only consume a large quantity of energy resources with declining operating benefits but can also cause serious environmental harm. For instance, Fangcun Town in Changshan County has become a fire-coal-pollution-type local fluorosis area. With greater importance attached by the local government to the ecological environment, the development of traditional high-energy-consumption and high-pollution industries has been strictly restricted [83]. The government has tried to cultivate an environment-friendly and high-value-added industrial economy through advanced manufacturing and modern service industries, although these develop slowly due to difficulty in recruiting labor forces that meet their skill requirements.

Recently, the shortage of highly skilled labor forces has severely restricted Changshan County development. The demand–supply relation in the whole-county labor market is strained despite the transfer of numerous surplus rural labor forces to cities and towns. Nevertheless, most county labor forces are relatively old, poorly educated, and unskilled. In 2010, those with a college degree and >age 5 population in Changshan County was only 4.89%, which was much lower than the overall level (9.53%) in Zhejiang Province and the level in Kecheng, Quzhou (15.06%). This is because Changshan has a relative shortage of education and training resources, which considerably limits the number of locally cultured highly skilled labor forces. Moreover, highly skilled labor forces in the county usually prefer to work in economically developed regions such as Hangzhou, Ningbo, Wenzhou, and Kecheng of Quzhou after graduation, while few of them are willing to develop in Changshan County. A vicious circle of backward economic growth, highly skilled labor force shortages, and insufficient regional development vigor has developed in Changzhou.

### *5.4. Population Age Structure Changes*

In the last 30 years, the population age structure in Changshan County has changed dramatically and become a primary cause of city shrinkage. The number of births has declined rapidly due to a substantial drop in the proportion of 20–34-year-olds in the population. In 2010, the female population at the age of 20–34 was only 56% of that in 2000, and the male population accounted for an even lower proportion (53%). This age group was the main cohort breeding the next generation, and 80% of mothers of newborns in the county fell into this group. In 2000, the number of births was 5670, while in 2010 it was 3773, a decline of 33.46%. In this period, the population loss rate was not low (9.08%), but less than 1/3 of the decrement in the number of births. The Changshan County population rose again slightly from 2010 to 2020, but the 0–9 years cohort decreased by 2300.

Aging is another characteristic of the population age structure in Changshan County which has importantly influenced regional development. In 2020, 19.27% of the Changshan County population was >65 years old, quite close to the standard for super-aging. The aging

population has brought ever-increasing financial endowment pressure to the government. In 2022, local expenditure (RMB 5,831,000,000) in the general public budget outlay in Changshan County declined by 5.27% compared with the amount allocated in the previous year (RMB 6,155,000,000). The total expenditure on endowment-related aspects grew from RMB 463,000,000 to RMB 535,000,000, a growth rate of 15.58%. Additionally, the growing number and proportion of old people mean that they need increased care and more pension services. However, most pension services need to be provided by families due to "aging before getting rich" of the population and the incomplete development of the county pension service market, which, to some extent, results in a decline in labor force size and quality. Notably, the increased number of old people does not necessarily slow economic development, as the region is already at a high development level and economic development is driven by conducting scientific and technological innovation and enhancing productivity. Nevertheless, Changshan County has not yet achieved such a high development level, and so sustained aging has imposed an ever-increasing burden on regional development.

## 6. Policy Response to County-Level City Shrinking

The impacts generated by county-level city shrinkage in China have been gradually aggravated, so local governments should guide transformation and development of counties subjected to population losses [13]. Shrinkage can bring about multi-aspect influences, including population, economic, and social aspects; accordingly, the policy response to city shrinkage should cover multiple fields [84,85]. Based on our analysis of shrinkage characteristics in Changshan County, we suggest that the local government could relieve the shrinkage-induced negative impacts by boosting the upgrading and transformation of industrial structure, shaping compact and green urban space, perfecting social governance, and caring for the elderly.

### *6.1. Boost the Upgrading and Transformation of Industrial Structure*

The first measure suggested is to promote the scale expansion and deep processing of the health food industry. The health food industry is the "sunrise industry" developed in the context of the globalization of social consumption [86]. With the improvement of living standards, Chinese people are paying increasing attention to their health, and the pursuit of health food has reached unprecedent heights [87]. Depending on locally abundant agricultural product resources, the health food industry centered on "two grapefruit and one tea" (grapefruit, sesame oil, and tea-oil camellia) is one of the leading industries in Changshan. However, local health food enterprises are mostly small or medium enterprises with deficient financial strength and very limited R&D capabilities [87,88]. The local government should offer tax incentives for R&D or the introduction of innovation and more guaranteed loans to strengthen its financial support for healthy food deep processing enterprises, actively forging a base featured with the integrated development of the primary, secondary, and tertiary industries to extend and strengthen the industrial chain. Moreover, the local government should enhance publicity through various channels to create geographically symbolic and highly popular agricultural product brands.

The second is to boost the digital transformation of traditional manufacturing enterprises. Advances in enterprise technology can streamline processes and deepen insights, giving companies the support to weather an unpredictable marketplace and capitalize on opportunities for growth. Digital transformation has been an irresistible trend for high-quality economic development, because it can effectively simplify enterprise production processes, thereby improving production economic efficiency [89]. Hengjia, for example, a local bearing company, has increased productivity by more than 20% and reduced production costs by more than 10% through digital transformation [90]. In addition, another local company, Zhejiang Advanced Precision Machinery, has improved product quality and increased sales by more than 100% through digital transformation. However, skill shortages and lack of funds are holding most local manufacturing enterprises back from

pursing their transformation goals. Therefore, it is suggested that the local government should reduce enterprise digital transformation costs by building digital infrastructures and introducing incentive measures, and create multiple data sharing platforms and perfect data governance systems to facilitate the steady operation of industry standards.

### *6.2. Shaping Compact and Green Urban Space*

Reasonably enhancing the compactness of built-up urban space is suggested. Presently, the planned population for built-up areas in Changshan County is much higher than the actual population, and existing population density is only 50% of expected density, along with low utilization efficiency of infrastructures. Excessive urban construction is mainly attributed to the growth-oriented development strategies [91], which will probably strengthen the negative impacts of city shrinkage [5]. Some cities provide good references for taking measures, such as planning for a smaller city (Youngstown, USA) [31], transit-oriented development and mixed land use (Fuji, Japan) [92], and industrial area rehabilitation (Magdeburg, Germany) [93]. During urban planning, the past development strategy should be transformed to create more compact and simplified urban space. The government should strictly control urban land use expansion, improve urban development quality within the existing built-up scale boundary, attract new transportation-oriented concepts to promote the layout of infrastructures with diversified functions, and intensify the reasonable mixing of land use and land functions to prevent the degradation of land utilization efficiency due to overly pure urban functional zoning.

Another suggested measure is to increase the proportion of urban green space to create a more beautiful living environment. In shrinking cities, greening transformation of vacant and inefficient land plots can increase the values of surrounding areas, boost benign community development, and reshape social capitals [27]. A green and livable environment is, to a great extent, the yearning for and pursuit of high-quality urban development. The local government needs to support more funds to transform abandoned inefficient brownfields into green space, construct park systems of distributive equilibrium, and provide residents with more comprehensive functions such as leisure and recreation, physical fitness, and emergency and disaster prevention.

### *6.3. Improve Social Governance*

It is necessary to improve social security and welfare to achieve common prosperity. A perfect social security system is conducive to securing people's lives and social development in a harmonious way. However, the present social security still features low insurance quality of social health care, in which pensions are inadequate for maintaining basic life, and imprecise welfare policies that lead to detached supply–demand. For example, less than 1/4 of jobless workers can benefit from unemployment insurance, and the average benefit is less than 1/10 of the average salary of urban workers [94]. What is more, there is a huge disparity between the benefits received by urban and rural unemployed individuals [95]. Especially impacted by COVID-19, residents' living standards cannot be guaranteed in the face of such a great challenge. The local government should enlarge public investments to enhance social security, implement more precise social security policies to improve treatment for groups with greater social security needs, and fill legal gaps in important fields such as social assistance, medical security, and pension services as soon as possible.

Strengthening social security administration and enhancing residential life security are also essential. The rising crime rate is a possible serious negative impact of city shrinkage [42]. Social security services in small county-level cities are not as complete as those in large cities. Rural communities especially are prone to crimes due to population unemployment, poverty, and weak public security. The local government needs to be vigilant about such risks, strengthen the social security prevention and control system, reduce illegal criminal activities, perfect education and propaganda, and enhance resident legal and self-protection awareness.

*6.4. Care for the Elderly*

Accelerating the development of a health pension industry and meeting the ever-increasing pension service needs are suggested. As the county is on the verge of super-aging, it will continue to grow rapidly in the future, so there is an urgent need for more high-quality services such as life care, medical rehabilitation, cultural learning, physical fitness and leisure, and entertainment. The local government should enhance related policy support through financial support and tax reduction and exemption, encourage pension industry development, loosen social capital access conditions, attract more enterprise and social capital by purchasing services and providing fiscal subsidies, and establish supporting institutional systems such as supervision, evaluation, and guarantees to boost sustainable and healthy development of the pension industry.

The next step is to attach importance to the needs of the elderly and provide them with more company. The needs of old people for spiritual consolation, which are as important as their needs for economic support and daily care, should also be satisfied [96]. Because the large young population has outflowed and will only return to their hometown during holidays and festivals, old people are short of company and spiritual consolation, accompanied by the substantial degradation of their living quality. Faced with such a situation, the local government needs to formulate and perfect related legal policies, provide active policy support and reliable legal protection policies for socialized spiritual endowment, allocate special funds to help communities build more harmonious and intimate neighborhoods and provide more care for the elderly, and promote the formation of the socio-cultural atmosphere of "respecting the elderly and valuing their spiritual needs".

## 7. Conclusions

The city shrinkage phenomenon in China has been reflected by existing research results [22], while county-level city shrinkage in developed regions has been largely ignored [23]. Based on dimensions of population and economy, our study identified five county-level shrinking cities (Chun'an, Qujiang, Changshan, Kaihua, Suichang) in Zhejiang, and characterized the population age structure change between 2000-2020 and population changes during short-term holidays in Changshan County by using census, NTL, and Tencent Location Big Data. In Zhejiang Province, an economically powerful province in China, the five shrinking cities at the periphery of the metropolitan area concentrate in the western area and have undergone long-term population losses due to regional competitive disadvantages. County-level shrinking cities resulting from regional competition can still maintain long-term and stable economic growth, but their economic growth lags behind the whole competitive region. City shrinkage can result from comprehensive effects [36], and we found the causes of shrinkage in Changshan including declining traditional industries, backward per capita income, highly skilled labor force shortages, and population age structure changes. Negative impacts brought by city shrinkage involve various fields such as population, economy, and society; accordingly, the policy response to shrinkage should cover multiple fields combined with the actual local context [18]. Therefore, we proposed countermeasures and suggestions for the local government, such as boosting the upgrading and transformation of industrial structure, shaping compact and green urban space, improving social governance, and caring for the elderly.

Our study makes three key contributions. First, we expand the research paradigm of city shrinkage from the Western context and economically declining regions [5,18,20] to a relatively economically advanced region in China. Second, our study employs a novel methodology to identify and characterize shrinking cities by utilizing census, NTL, and Tencent Location Big Data, and provides more reliable identification and characteristics of shrinking cities than those that use population as the only indicator of city shrinkage [2,27]. Third, based on actual local context, our study proposed constructive suggestions which can be useful to the government of Changshan and other shrinking cities with similar conditions.

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# Multi-Scenario Simulation of Land Use Carbon Emissions from Energy Consumption in Shenzhen, China

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**Abstract:** Investigating the future land use patterns and carbon emissions are of great significance for carbon reduction. This study established the relationship between land use types and carbon emissions from energy consumption and adopted three future scenarios that combine shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs), the system dynamics (SD) model, and the patch-generating land use simulation (PLUS) model to simulate land use patterns in 2030 and 2035. Then the spatial distribution of future carbon density and its change in Shenzhen were obtained. Under scenario SSP245, a large amount of industrial and mining land is converted into living land from 2020 to 2035, and new living land is mainly located in Bao'an District and Guangming District. Under scenario SSP370, a large amount of living land replaces other land due to a plentiful population from 2020 to 2035, which is rare under other scenarios. The expansions of areas with high carbon density during 2020–2030 are mainly distributed in Nanshan District and Longhua District under all three scenarios. During 2030–2035, carbon emissions will decrease under scenarios SSP126 and SSP245. The results confirmed various trends in carbon emissions under different scenarios and emphasized the association between land use types and carbon emissions.

**Keywords:** land use patterns; carbon density; PLUS model; shared socioeconomic pathways

## 1. Introduction

Land use patterns on Earth are closely related to anthropogenic exploitation and natural processes. The carrier of human activities and terrestrial ecosystem cycles is land, and frequent changes in land use have an impact on carbon emissions [1,2]. Carbon emissions from fossil energy combustion are mainly accounted for anthropogenic activities and these activities are always based on built-up land [3], including urban residential land, traffic land, and industrial land. Thus, carbon emissions vary considerably depending on the type of land use [4], and the expansion of land associated with a high carbon emission density might lead to increases in total carbon emissions. A rational land use pattern is conducive to low-carbon development and the achievement of China's pledged goal of carbon peak and carbon neutrality at the General Debate of the 75th Session of the United Nations General Assembly [5]. In addition, the 2035 Vision targets propose that China will complete basic socialist modernization in 2035, with a steady decline in carbon emissions after reaching a peak [6]. To achieve these goals, accurate projections of the trends in land use carbon emissions in 2030 and 2035 are necessary to support the formation of future land-use regulation policy.

Scholars have made some attempts to account for land use carbon emissions. Zhao and Huang [7] matched the land use types with carbon emission items to explore the carbon emissions from energy consumption of different land use types in Jiangsu Province. Zhao et al. [8] discussed the carbon emission intensity of different industrial spaces in China

and found that living and industrial-commercial space, as well as transportation industrial space, were industrial spaces with high carbon emissions. Wu et al. [9] established the relationship between different types of land and carbon emissions in Zhejiang Province and concluded that carbon emissions were driven by the inelastic demands of energy-intensive land. Due to technological innovation, some cities, such as Shenzhen, have achieved widespread adoption of electric vehicles [10,11], which has a certain impact on the carbon emissions of road transportation [12]. As a result, the previous conclusions about land use carbon emissions should be challenged and updated. Previous research [7–9] adopted the term "carbon intensity" to represent carbon emissions per unit of land area, while "carbon intensity" is more frequently used to refer to "carbon emissions per unit of gross domestic product (GDP)" [13–17]. To avoid any ambiguities, energy-related $CO_2$ emissions per unit of land area in this study is represented by "carbon density" instead of "carbon intensity".

Simulation and prediction of future situations require setting various scenario assumptions and analyzing potential changes under different paths. Existing studies generally designed a baseline scenario and several comparison scenarios by controlling for change rates of parameters [18–20]. However, these specific indicators and scenario designs depend on the researchers' subjective judgments about the future. In addition, climate change has an impact on land use that cannot be ignored [21,22], which was less often considered in land use scenario design. O'Neill et al. [23] proposed five shared economic pathways (SSPs) from two dimensions of socioeconomic challenges faced by humans in mitigating and adapting to climate change, respectively. Domestic scholars have applied SSPs to predict precipitation [24,25], temperature [25,26], population [27], urban land expansion [28], land use dynamics [29], and land use demand [30]. Shared socioeconomic pathways (SSPs) were combined with representative concentration pathways (RCPs) in Phase 6 of the Coupled Model Intercomparison Project (CMIP6) to define more reasonable future scenarios under the background of global climate change [31–33]. SSP-RCP scenarios have been adopted by an increasing number of scholars to simulate land use changes in the future. Dong et al. [34] designed eight scenarios with various combinations of SSPs and RCPs to predict future land use demand and discovered that the future land patterns varied greatly depending on the scenario. Wang et al. [35] simulated future land use/cover change (LUCC) in Bortala using projected socioeconomic and climate data from existing studies under three SSP-RCP scenarios. They analyzed the distribution of different land use types, including cultivated land, pasture areas, grassland, and construction land, without discussing the situation of various construction land. SSP-RCP scenarios are adopted in this study to incorporate climate change into land use patterns simulations in Shenzhen, and construction land is split into various categories, further filling the gap in existing studies.

In the field of simulating the spatial distribution of different types of land, studies have been conducted to develop simulation models with increasing accuracy. The cellular automata (CA) model is a dynamic model that focuses on spatiotemporal interactions and underlying rules, which is well suited to simulating intricate geographic evolution processes [36]. Many simulation models based on CA models have been widely used in land use studies, including Logistic-CA [37,38], CA-Markov [39,40], ANN-CA [41], and FLUS model [28,34,42]. These models, which can produce valuable results, are either based on the transition analysis strategy (TAS) or based on the pattern analysis strategy (PAS). However, they can neither adequately disclose the driving factors of land use types transitions and their contributions to land change [43], nor can they simulate multiple land use types at the patch level with spatiotemporal dynamics [35]. An improved patch-generating land use simulation (PLUS) model combines the advantages of TAS and PAS but overcomes their weaknesses through a random forest classification (RFC) algorithm [36,44], while satisfying the requirement for patch-level simulation of multiple land use types based on random seed growth mechanisms [20], which increases accuracy. Although some scholars have adopted the PLUS model in their studies and obtained high simulation accuracy [20,30,36,44,45], the PLUS model has not yet been applied as a new method to

simulate multiple types of land use changes in Shenzhen, a developed city with complex land use patterns [46].

Land use changes in Shenzhen, Guangdong Province, have intensified [47] and become more diverse due to location and regional industrial development [48]. This study took Shenzhen City as the study area and firstly constructed the relationship between land use types and carbon density, i.e., energy-related $CO_2$ emissions per unit of land area, and predicted land use demand under three SSP-RCP scenarios based on a system dynamic (SD) model. The land use patterns in 2030 and 2035 were simulated using the PLUS model. The distribution of future land use carbon density in Shenzhen was obtained, and its spatial variations were analyzed to put forward some valuable policy recommendations. The purposes of this study were to (1) predict land use demand precisely using the SD model and SSP-RCP scenarios, taking into account future climate change; (2) obtain more accurate future land use patterns using the PLUS model; and (3) associate land use types with carbon emissions and analyze carbon density change in the future. The greatest novelty of this study is the fact that climate change is included in the land use patterns simulations, with construction land split into different types such as industrial and mining land, traffic land, etc., and their possible future distributions are discussed separately, providing a new perspective to simulate future land use patterns.

## 2. Materials and Methods

In this study, the relationship between land use types and carbon emissions was constructed. Meanwhile, land use demand under future scenarios was predicted using SSP-RCP scenarios and the SD model. Then, land use data in 2015 and 2020 and various driving factors were adopted to validate the PLUS model, followed by the simulation of land use patterns in 2030 and 2035 with the constraint of predicted future land use demand. Finally, spatiotemporal variations of land use carbon density in Shenzhen were discussed incorporating the relationship between land use types and carbon emissions and simulated results of future land use patterns. In summary, the technical flowchart of this study is shown in Figure 1.

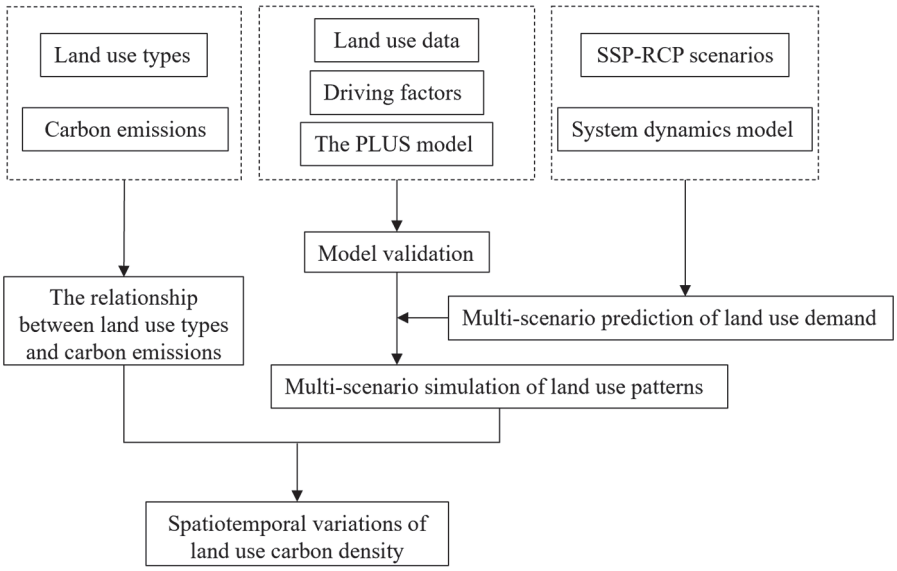


**Figure 1.** Technical flowchart.

### *2.1. Study Area and Data Sources*

Shenzhen is located on the eastern bank of Pearl River Estuary in the southern coastal area of Guangdong Province. As shown in Figure 2, Shenzhen ranges geographically between 113°43′ E–114°38′ E and 22°24′ N–22°52′ N, occupying an area of 1986 $km^2$ in 2020. It is a megacity with a total population of 17.63 million in 2020 and a population density of 8879 person/$km^2$, which explains its scarcity of land resources. It is composed of

9 administrative districts, including Bao'an District, Guangming District, Nanshan District, Futian District, Luohu District, Longhua District, Yantian District, Pingshan District, and Longgang District.

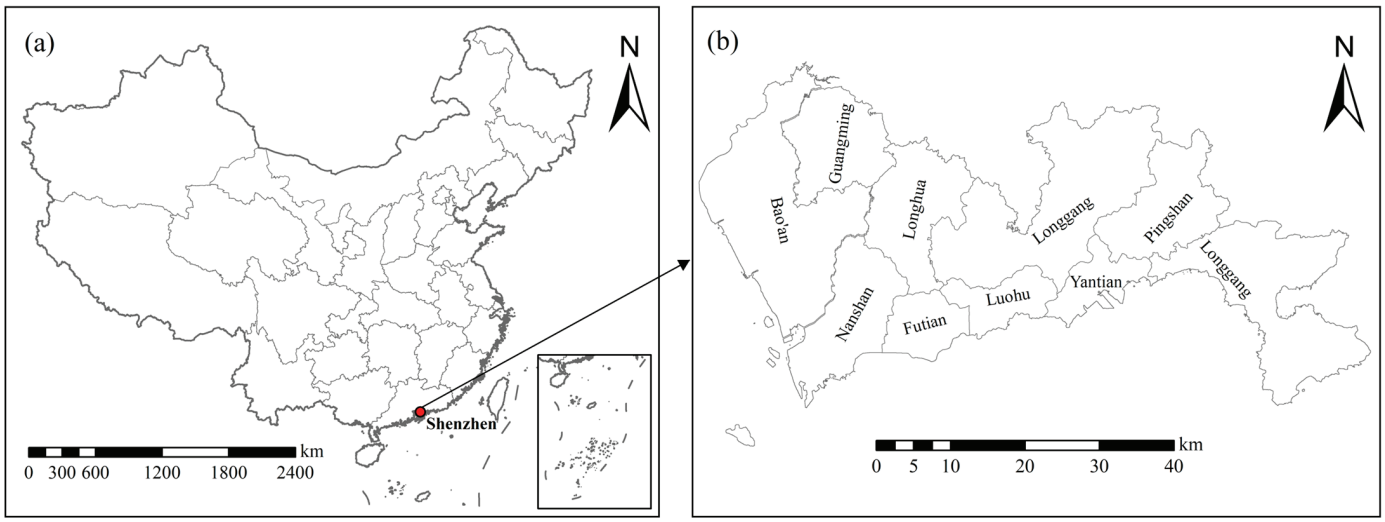


**Figure 2.** (**a**) Location of Shenzhen in China; (**b**) the administrative districts in Shenzhen.

Energy consumption data and its composition were referred to Shenzhen Statistical Yearbook (2015–2020) and Shenzhen 13th Five-Year Plan for Energy Development (2015–2020). The SD model required figures of GDP, population, annual average temperature, annual average precipitation, investment in fixed assets, and growth rate of investment in fixed assets of each national economic industry. These figures were obtained from Shenzhen Statistical Yearbook (2015–2020). Data required in the PLUS model should be in raster form, different from data adopted in the SD model. Population data were extracted from Population Count datasets of WorldPop (https://hub.worldpop.org, accessed on 17 March 2022). Land use data of Shenzhen from 2015 to 2020 was obtained from the Land Use Change Survey data of the Shenzhen Municipal Bureau of Planning and Natural Resources. The five land categories of industrial and mining land, traffic land, living land, agricultural land and water area, and other land were obtained through land category consolidation and then rasterized to 30 m resolution. GDP, temperature, and precipitation were obtained from the Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences [49,50]. Nighttime light data were extracted from the VIIRS_DNB_VNL V2 datasets of the Earth Observation Group (EOG) [51]. Digital elevation model (DEM) data were obtained from NASADEM_HGT V001 datasets [52], from which slope and degree of relief were calculated. Vector data such as cities, towns, waters, rivers, railways, motorways, and other roads from OpenStreetMap (https://www.openstreetmap.org, accessed on 18 February 2022) were adopted and processed into raster data by Euclidean distance analysis. Data for all driving factors used are from 2015.

### *2.2. Energy-Related Land Use Carbon Density*

As a carrier of various natural processes and human activities, different uses inevitably affect the carbon density on the land [4]. This study adopted the method of Zhao and Huang [7] and divided different land use types into five categories (Table 1): industrial and mining land, traffic land, living land, agricultural land and water area, and other land. To assign carbon emissions to each type of land, energy consumption of several sectors was merged. Carbon emissions on industrial land and mining land stem from the energy consumption of industry. Energy consumptions of transportation, storage, postal and telecommunication services contribute to traffic land use carbon emissions. Living land in this study carries human activities such as eating, trading, entertaining, receiving

medical treatment, and schooling. Therefore, living land use carbon emissions derive from energy consumption of residential lifestyles, wholesale and retail trade and catering, construction, and services others. Carbon emissions on agricultural land and water area derive from energy consumption of farming, forestry, animal husbandry, and fishery. Other land includes special designated land and unused land. Some scholars assigned energy consumption of "other industries" to other land [8,53] or neglected directly [3]. However, there is only an energy consumption item called "services others" which represents other service industries in the tertiary sector in Shenzhen Statistical Yearbook, and its figures are not negligible. Therefore, this study allocated the energy consumption of services others to living land, similar to the approach taken by Wu et al. [9]. As a matter of course, it was assumed that human activities that generate carbon emissions do not take place on other land. Energy-related carbon emissions were calculated based on the IPCC method [54]:

$$CE_k = \sum SC \times E_i \times \alpha_i \times 44/12 \quad (1)$$

where $CE_k$ ($10^4$ tons) refers to the energy-related $CO_2$ emissions of each land use type, $k$ = 1, 2, 3, 4, 5; $SC$ represents the consumption of standard coal; $E_i$ depicts the proportion of energy consumption of $i$th fossil fuel energy; and $\alpha_i$ means the emission factor of the $i$th fossil fuel energy. The fossil fuel energy in this study is consists of coal, oil and natural gas. The emission factors are taken from the research results of the Energy Research Institute of the National Development and Reform Commission, where the carbon emission factors for coal, oil, and natural gas are 0.7476 t/tce, 0.5825 t/tce, and 0.4435 t/tce, respectively.

**Table 1.** Relationship between land use types and energy-related carbon emission items.

| Land Use Types | Specific Types | Energy Consumption/Carbon Emission Items |
|---|---|---|
| Industrial and mining land | Industrial land<br>Mining sites | Industry |
| Traffic land | Transportation land<br>Warehousing land | Transportation, storage, postal, and telecommunication services |
| Living land | Urban residential land<br>Rural residential land<br>Commercial land<br>Public administration and public service sites | Residential consumption<br>Construction<br>Wholesale and retail trade and catering<br>Services others |
| Agricultural land and water area | Cropland<br>Garden area<br>Woodland<br>Grassland<br>Water and Water Facilities Land | Farming, forestry, animal husbandry, and fishery |
| Other land | Special designated land<br>Unused land | None |

Energy-related land use carbon density can be represented by $CO_2$ emissions per unit of land area and obtained by the following formula:

$$CI_k = \frac{CE_k}{S_k} \quad (2)$$

where $CI_k$ (t/ha) refers to the energy-related carbon density of land use type $k$, and $S_k$ ($m^2$) represents the total area of land use type $k$. The carbon density on each type of land use in 2030 and 2035 were set using the mean value of carbon density on each land use type during 2015–2020.

### *2.3. Land Use Demand Prediction Using Future Scenarios and System Dynamics Model*

The Scenario Model Intercomparison Project (ScenarioMIP) is the major project of CMIP6, consisting of eight future pathways. These eight pathways are divided into two tiers, and tier 1 contains a wide range of uncertainties in future forcing pathways and key

scenarios, including SSP126, SSP245, SSP370, and SSP585 [55]. SSP126 incorporates SSP1 and RCP2.6, representing a sustainable socioeconomic development pathway with a low radiation forcing which peaks at 2.6 $W/m^2$ by 2100. SSP245 is the combination of SSP2 and RCP4.5, which represents a moderate socioeconomic development path that continues historical patterns with medium-low radiation forcing which peaks at 4.5 $W/m^2$ by 2100. SSP370 combines the SSP3 with RCP7.0, representing a medium-high socioeconomic development path with radiation forcing which peaks at 7.0 $W/m^2$ by 2100. SSP585 represents a highly energy-intensive scenario and the number of its emissions is high enough to bring the radiation forcing to 8.5 $W/m^2$ by 2100 [35,56,57]. Both SSP126 and SSP 585 are positive human development pathways, and the difference is that SSP126 is a sustainable practice, while SSP585 has an energy-intensive economy [55]. However, Shenzhen has achieved a strong decoupling of economic growth and carbon emissions [58,59], which means economic growth in Shenzhen no longer comes at the cost of increased carbon emissions [60]. Thus, the scenario with the most rapid economic development based on high energy consumption is not in line with the reality in Shenzhen and is not considered in this study. Future scenarios were decided by four parameters: population, GDP, annual average temperature, and precipitation. The future data for Shenzhen was extracted from existing predicted data and change rates were calculated to obtain the values of parameters after 2020. The values of socioeconomic factors were calculated using future predicted grid data of population [27] and GDP [61] under SSPs scenarios. The future climate data were obtained based on the model output of the medium-resolution Beijing Climate Center Climate System Model version 2 (BCC-CSM2-MR) [62].

The system dynamics (SD) model is an effective tool to allow the evolution of a complex system to be predicted through the feedback and interactions among various elements [63]. This study assumed that land use demand can be only determined by GDP, population and climate change (temperature and precipitation) in the SD model. GDP is linked with investment in fixed assets. Investment in each type of land is the investment in corresponding national economic sectors carried on it. Population increases can contribute to the expansion of living land and traffic land due to greater demand for houses and roads. More population can also bring increasing demand for agricultural products and livestock products, but Shenzhen is a food inflow city, so this effect is negligible. Climate change mainly affects agricultural land and water area through temperature and precipitation. Based on the socioeconomic data, climate data, and land data from 2015 to 2020, the SD model of land use demand in Figure 3 was constructed, and the quantitative relationships between variables were analyzed and finally determined through several experiments. The future land use demand under each SSP-RCP scenario was simulated according to this SD model.

### *2.4. Patch-Generating Land Use Simulation (PLUS) Model*

The PLUS model derives from the CA model and integrates the dynamics of geographical cells with the impacts of various factors over space to enhance prediction ability [36]. It involves two main modules, i.e., a rule mining module based on a land expansion analysis strategy (LEAS) and a CA module based on multi-type random seeds (CARS). The LEAS excavates the impacts of various driving factors on land expansion using the random forest classification algorithm and derives the spatial distribution of development potential for each type of land. The LEAS calls for the input of land data for two dates and then extracts cells with a change in state from the later dated land data. To procure transition rules, the training dataset is used to train the data mining algorithm [43]. The CARS includes a patch-generation mechanism and simulates local land competition to adjust the amount of land to meet future demands through development potential, self-adaptive coefficient, and neighborhood effect [35]. The development potential derives from the result of the LEAS module. The self-adaptive coefficient of cells is determined by the gap between the number of existing cells in their own types and their future demands, and the neighborhood effect

of a land use cell is influenced by the proportion of cells in its type and the priori diffusion coefficient [36].

Land use data for 2015 and 2020 was input to the LEAS module, and waters were extracted as the conversion constraint area. The neighborhood weight represents the expansion ability of each land-use type [30]. In this study, the neighborhood weight of each type of land use shown in Table A1 was determined by calculating the proportion of the expansion areas of a land-use type to the total land expansion based on the land expansion map (the map outputted in the LEAS module). A total of 14 driving factors of the land use change were selected and listed in Table A2, including population, GDP, the distance from town, the distance from highway, the distance from railway, the distance from other roads, nighttime light index, annual mean temperature, annual precipitation, DEM, slope, degree of relief, the distance from waters, and the distance from waterways. Taking land use data in 2015 as the initial land use pattern and applying the PLUS model, the simulation results of the land use pattern in 2020 were finally obtained. Comparing the simulated land use pattern and the actual land use pattern in 2020, the simulation accuracy can be evaluated by the Figure of Merit (FoM) metric, the kappa coefficient, and the overall accuracy. The FoM can reflect consistency at the unit level and similarity at the pattern level, with a value mostly falling between 0 and 0.3 [44]. The kappa coefficient proposed by Cohen [64] is commonly used to verify the consistency between two data images [45] and has values ranging from −1 to 1, with higher values representing better consistency [20]. The predicted land use demand in 2030 and 2035 under future scenarios were input into the CARS module of the validated PLUS model to simulate future land use patterns.

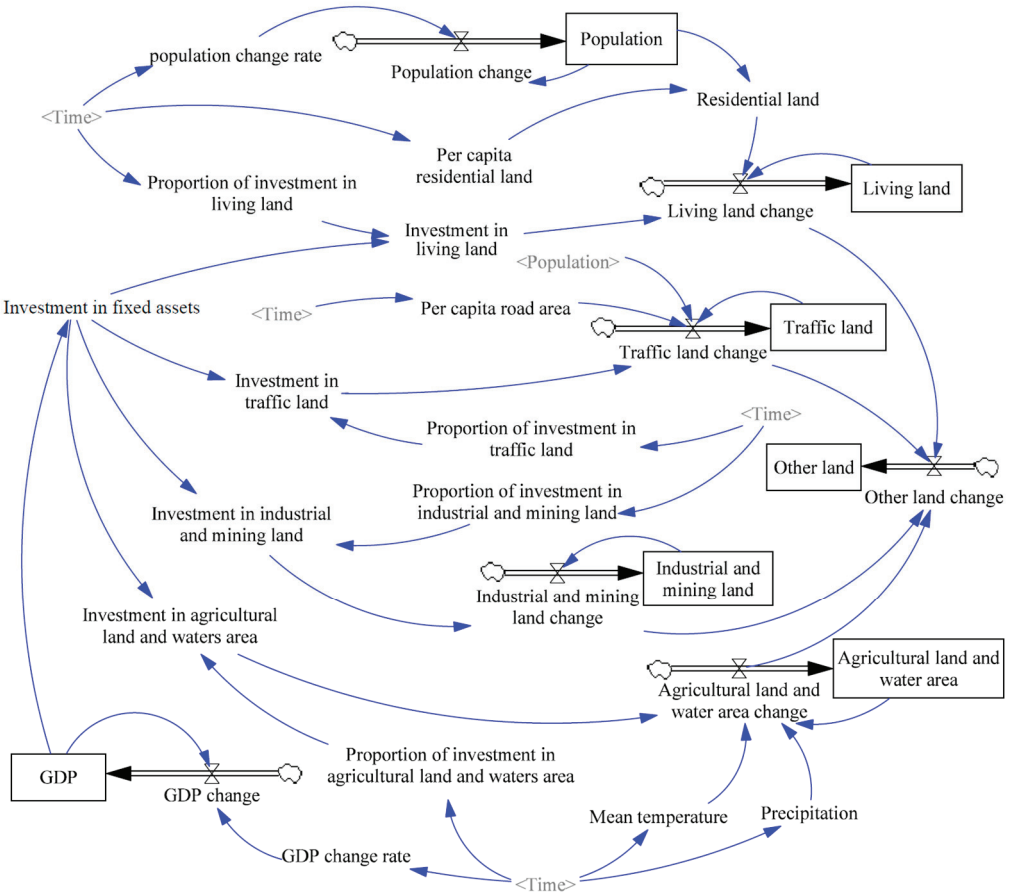


**Figure 3.** The system dynamics (SD) model of land use demand in Shenzhen.

## 3. Results and Discussion

### *3.1. Energy-Related Land Use Carbon Density*

According to the relationship between land use types and carbon emission items defined above, energy-related carbon density on each type of land in Shenzhen during 2015–2020 is displayed in Table 2. The total energy-related land use carbon emissions in Shenzhen increased from 40.63 million tons in 2015 to 46.00 million tons in 2020, while carbon density increased from 203.45 t/ha in 2015 to 231.60 t/ha in 2020. Ke et al. [65] calculated total carbon emissions in Shenzhen and found that the amount of carbon emissions in 2015 is 13.68 MtC (million metric tons of carbon), which is close to the result of 11.08 MtC (12/44 of 40.64 million tons of $CO_2$) in 2015 in this study. The mean carbon density is in the following order from highest to lowest: industrial and mining land > living land > traffic land > agricultural land and water area. Industrial and mining land use carbon density kept decreasing until 2019, while the carbon density on traffic land changed oppositely. Shenzhen actively promoted the transformation of inefficient industrial land into emerging industry in recent years [48], which improved the intensive use of industrial land but concentrated industrial activities on fewer amounts of land, resulting in a higher carbon density of industrial and mining land. The intensive industrial land use had been proved to be conducive to carbon reduction [66], and efficient utilization of energy through improved technology will be an effective way to control carbon density in the future. The carbon density on traffic land began to decrease in 2019, which can be attributed to the widespread adoption of electric buses [10–12]. If electric private cars also become common in the future, the carbon reduction situation will be more optimistic. Living land is home to a large population, which explains its high carbon density between 436.02 t/ha and 551.41 t/ha. Carbon density on agricultural land and water area fluctuated between 0.90 t/ha and 1.70 t/ha, much less than carbon density on other types of land.

**Table 2.** Carbon density (t/ha) on different types of land during 2015–2020.

| Land Use Types | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Mean Value |
|---|---|---|---|---|---|---|---|
| Industrial and mining land | 610.58 | 591.77 | 587.52 | 558.93 | 779.91 | 720.68 | 641.56 |
| Traffic land | 294.76 | 321.45 | 345.18 | 372.65 | 363.08 | 312.09 | 334.87 |
| Living land | 470.24 | 488.83 | 517.97 | 551.41 | 436.02 | 462.15 | 487.77 |
| Agricultural land and water area | 1.13 | 1.67 | 0.90 | 1.36 | 1.70 | 1.19 | 1.33 |
| All lands | 203.45 | 217.46 | 226.82 | 234.08 | 243.48 | 231.60 | 226.15 |

### *3.2. Predicted Land Use Demand under Multiple Scenarios*

The simulated values of various land use types in 2020 and their actual values were compared to test the simulation accuracy of the SD model. According to the results shown in Table 3, relative errors are all less than 5%, indicating that the SD model constructed can be considered to have a high simulation accuracy [35]. Using this SD model, future demand for each type of land use under three SSP-RCP scenarios were predicted and displayed in Figure 3. The trajectories of demand in Figure 4 indicates that different types of land have distinct changes, and these changes vary considerably under different SSP-RCP scenarios. The demand for industrial and mining land decreases under all scenarios. In contrast, the demand for living land keeps growing under all three scenarios, with a maximum growth rate of 13.3% under scenario SSP370. The demand for traffic land increases under all scenarios before 2030, then this demand increases only marginally during 2030–2035, and even turns to drop under scenario SSP126. Due to volatile climate, the demand for agricultural land and water area varies greatly at different times and, of course, under different scenarios. The scenario SSP370 has the most dramatic decline in the demand for agricultural land and water area. Under scenario SSP126, a sustainable socioeconomic development scenario, changes in the demand for agricultural land and water area are relatively stable. As the total amount of land in Shenzhen is considered to be unchanged,

the land outside the area of the four land types mentioned above is counted as other land. The area of other land (unused land and special designated land) is largest under scenario SSP126 and smallest under scenario SSP370.

**Table 3.** The accuracy test of system dynamics (SD) model simulation results.

| Land Use Types | Simulated Value in 2020 (ha) | Actual Value in 2020 (ha) | Relative Error (%) |
|---|---|---|---|
| Industrial and mining land | 22569.4 | 22508.7 | 0.27% |
| Traffic land | 27197.6 | 27352.2 | −0.57% |
| Living land | 46206.7 | 45693.0 | 1.12% |
| Agricultural land and water area | 100437.0 | 100953.9 | −0.51% |
| Other land | 2187.1 | 2090.6 | 4.61% |

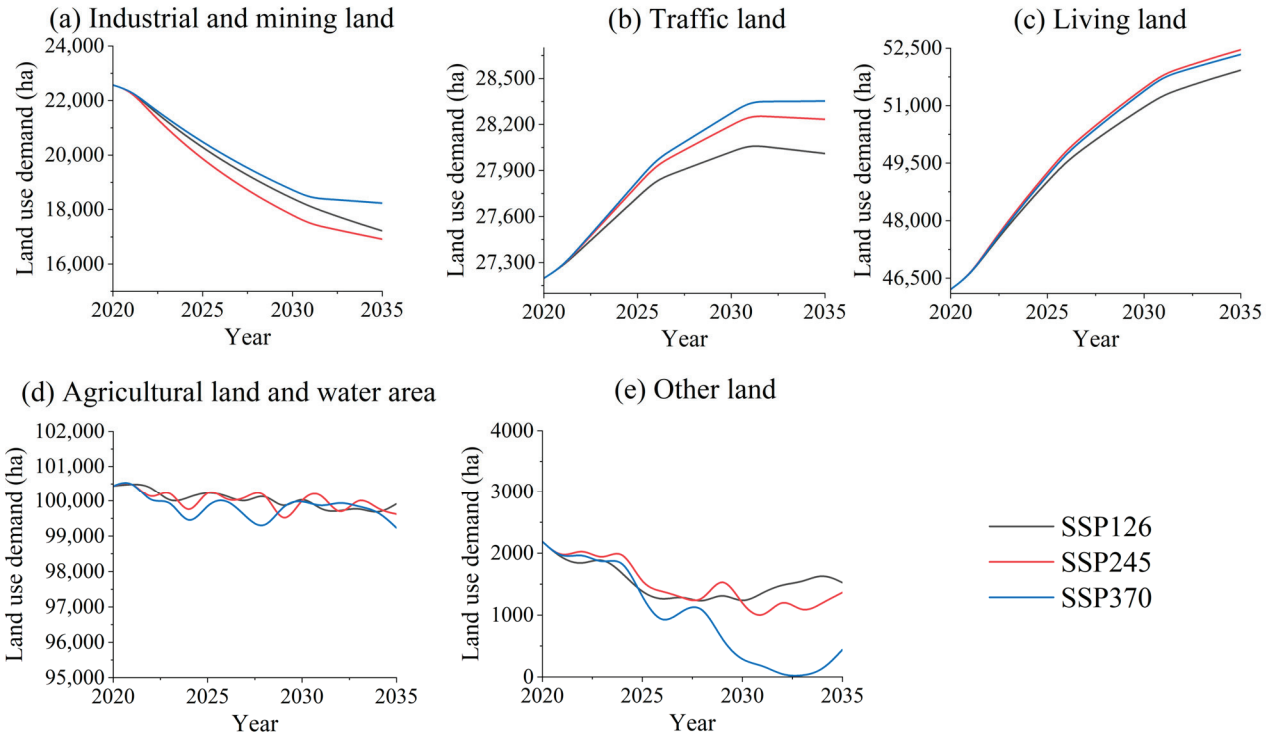


**Figure 4.** Trajectories of demand for each land use type from 2020 to 2035 under SSP-RCP scenarios: (**a**) future demand for industrial and mining land; (**b**) future demand for traffic land; (**c**) future demand for living land; (**d**) future demand for agricultural land and water area; (**e**) future demand for other land. Note: SSP is the abbreviation for shared socioeconomic pathways and RCP is the abbreviation for representative concentration pathways.

### *3.3. Simulated Land Use Patterns under Multiple Scenarios*

The results of the PLUS model validation show a kappa coefficient of 0.69, an overall accuracy of 0.79, and a FoM of 0.09, indicating that simulation results have substantial consistency with the actual land use patterns [30,44]. Therefore, the PLUS model can accurately reflect historical variations in the land use pattern and simulate future changes in Shenzhen. The future land use patterns under SSP-RCP scenarios generated by the CARS module of the PLUS model were shown in Figure 5. Compared to other scenarios, the conversion of industrial and mining land to living land during 2020–2035 is the largest under scenario SSP245, followed by the scenario SSP126. Most of the new living lands are located in Bao'an District and Guangming District. As new special economic zones with convertible land still available, the industrial-dominated high-tech industrial zones in Bao'an Districts and Guangming District have gradually evolved into comprehensive urban areas, which can attract residents to settle down and drive the emergence of new

living land in these areas [67]. A considerable amount of living land expands at the expense of other land during 2020–2035, especially under scenario 370, but this phenomenon is rare under scenarios SSP126 and SSP245. The total population is highest under scenario SSP370, which drives other land to convert into living land. Most of the emerging traffic land during 2020–2035 originates from industrial and mining land and agricultural land and water area and is distributed along the original traffic land.

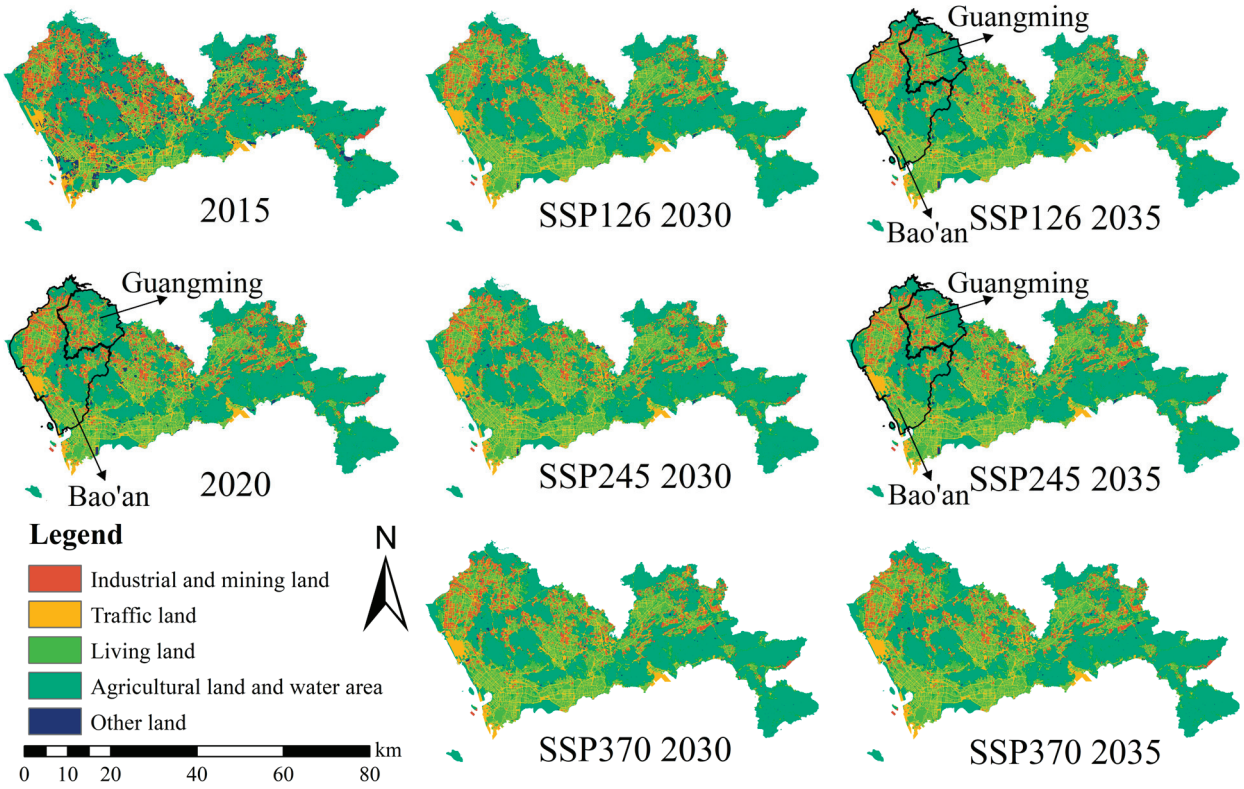


**Figure 5.** Future land use patterns under SSP-RCP scenarios in Shenzhen.

### *3.4. Spatiotemporal Variation of Land Use Carbon Density in 2015, 2020, 2030, and 2035*

Using the relationship between land use types and carbon density constructed above (Table 2) and future land use patterns (Figure 4), the total carbon emissions and spatial distribution of future land use carbon density in Shenzhen can be obtained. The results of total carbon emissions illustrated the different trends under three SSP-RCP scenarios. The total amount of carbon emissions in 2020 was 46.00 million tons, an increase of 13.2% compared to that in 2015. Under scenarios SSP126, SSP245, and SSP370, total carbon emissions continuously grow after 2020. The amount of carbon emissions in 2030 under SSP370 is the largest, reaching 46.26 million tons, and it still increases to 46.56 million tons in 2035. However, the amount of carbon emissions in 2035 under SSP126 and SSP245 shows a decline compared to 2030, and this decline is more pronounced under SSP126. The total carbon emissions in 2035 under scenarios SSP126 and SSP245 is 45.79 million tons and 45.93 million tons respectively. Compared to the emissions in 2030, Shenzhen's total land use carbon emissions in 2035 will only decrease under scenarios SSP126 and SSP245, indicating that the achievement of carbon peak is possible under these two scenarios.

Figure 6 depicts the spatial distribution of land use carbon density in 2015, 2020, 2030, and 2035 under multiple scenarios. High carbon density areas are mostly distributed in the northern regions of Shenzhen, including Bao'an District, Guangming District, Longhua District, Longgang District, and Pingshan District. Compared with 2015, there was a significant decline in the amount of high carbon density areas in Longhua District and Nanshan District in 2020. To more specifically analyze future changes in land use carbon density, the changes in carbon density in 2030 compared to carbon density in 2020 and

the changes in carbon density in 2035 compared to carbon density in 2030 are spatially distributed as shown in Figure 7. Under scenarios SSP126 and SSP245, the expansions of high carbon density areas in 2030 are mainly distributed in Longhua District, Nanshan District, Futian District, and Luohu District. However, these extended areas return to low carbon density areas in 2035, and this change is more obvious under scenario SSP126. Compared with the changes under the previous two scenarios, the emerging high carbon density areas in 2030 under scenario SSP370 are concentrated in Longhua District, Yantian District, Nanshan District, and Longgang District. The scenario SSP370 still shows a few concentrated expansions of high carbon density areas in 2035, mainly in Bao'an District and Longgang District. High carbon density areas in Nanshan District and Longhua District exhibit a significant expansion under all three scenarios SSP126, SSP245, and SSP370. Both districts are located in the western part of Shenzhen, with rapid urban development and high population density [68], which can stimulate the growth of carbon emissions [69,70].

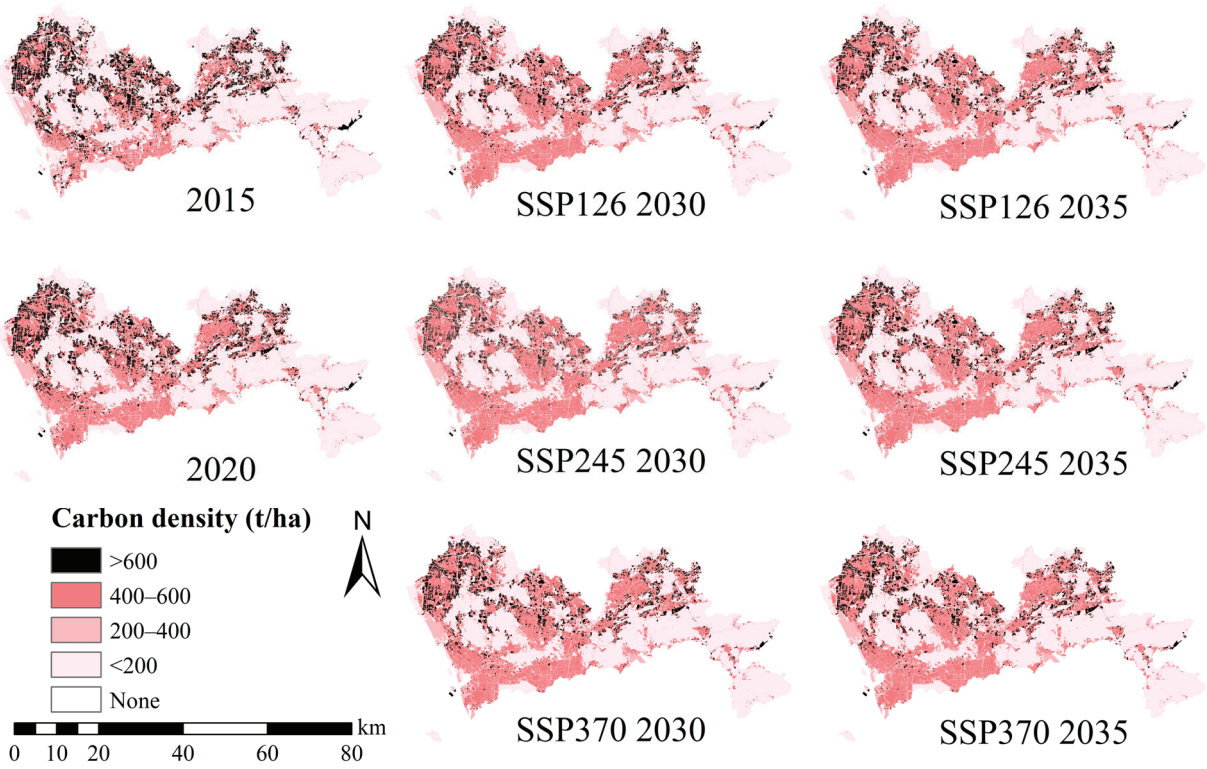


**Figure 6.** The distribution of land use carbon density under SSP-RCP scenarios in Shenzhen.

### *3.5. Uncertainties*

While predictions can provide valid information for Shenzhen, there exist some uncertainties as well. The carbon emissions on one land use type are assumed to be homogeneous due to limited statistics, which is not the case in reality. For example, both residential land and public service sites are classified as living land, but these two types of land might not have the same carbon density, let alone the difference in energy consumption between light and heavy industry. Moreover, carbon density on each land use type is assumed to be a constant after 2020, which limits the results of this study for that carbon density changed obviously during 2015–2020. In the future, the prediction of energy consumption under different scenarios can be a topic of interest. In addition, the scale of the traffic land data is too fine, which might result in a simulation inaccuracy of traffic land in the PLUS model. In practice, changes in traffic land often arise from organized transport planning and are mostly in the form of a whole road, which cannot be predicted accurately through several socioeconomic and natural influencing factors. Last but not least, the scale effect can be further investigated. When choosing data in this paper, data

at a finer resolution was preferred, and several simulations of land use patterns in 2020 were performed using data from different sources and validated by the kappa coefficient to generate a comparison, through which the best series of data sources that would lead to higher accuracy were identified. However, the future data under SSP-RCP scenarios adopted in the SD model were extracted from global scale raster datasets and might not be sufficiently accurate at the city level, which is inevitable in the absence of data. More studies on SSP-RCP scenarios for China, and even for specific provinces and cities, are expected in the future to provide the basis for various investigations of the future human living environment under the background of climate change.

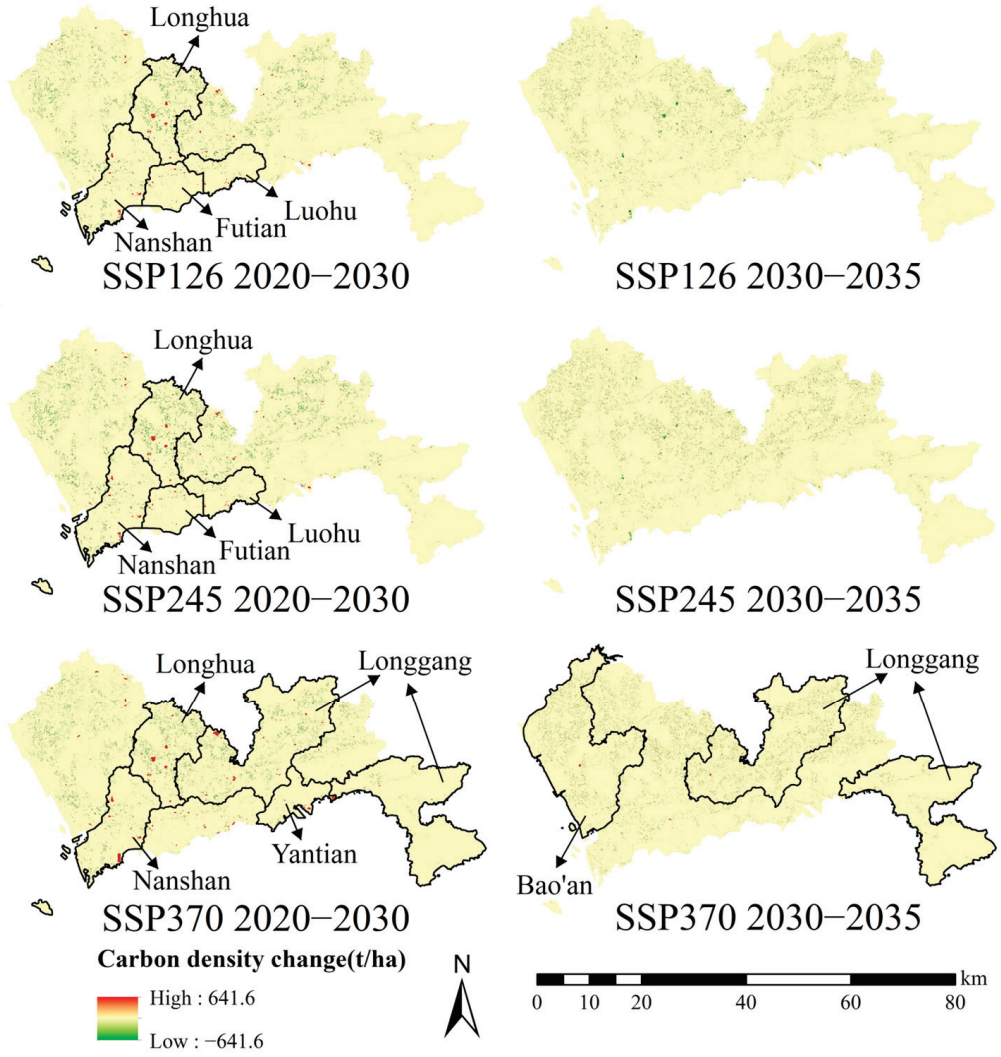


**Figure 7.** Carbon density change for 2020–2030 and 2030–2035 under SSP-RCP scenarios. Note: The left column represents the carbon intensity change from 2020 to 2030 under SSP-RCP scenarios and the right column represents the carbon intensity change from 2030 to 2035 under SSP-RCP scenarios.

## 4. Conclusions

This study constructed the relationship between land use types and carbon emissions from energy consumption, then integrated it with the SD model and the PLUS model to simulate future land use patterns, carbon emissions, and the variations of carbon density in Shenzhen under multiple SSP-RCP scenarios. Predicted land use patterns vary greatly under different SSP-RCP scenarios. More living land replaces industrial and mining land under scenarios SSP245 than under other scenarios, and these new living lands are mainly located in Bao'an District and Guangming District. Under scenario SSP370, the large amount of population drives other land to convert into living land, which is very rare

under scenarios SSP126 and SSP245. Regarding total carbon emissions from 2030 to 2035, there is a decline under scenarios SSP126 and SSP245, so carbon peaking is expected to be achieved under these two scenarios. Under three SSP-RCP scenarios, expansions of areas with high carbon density are mainly located in Nanshan District and Longhua District due to rapid urban development and high population density. The simulation model applied in this study is advanced and has been validated to be accurate, confirming various trends in land use patterns and carbon emissions under different future scenarios. The results can provide a scientific basis for future urban planning and land expansion in Shenzhen, which is closely related to its carbon emissions and will be conducive to the achievement of carbon peak and carbon neutrality. Shenzhen should pay attention to the environmental impacts when promoting urban development in Nanshan District and Longhua District. In addition, considering the demand for more living land as Shenzhen continues to increase the supply of housing, the rise in carbon density on living land should be curbed as soon as possible through technological progress and the promotion of clean energy [16,71]. In the future, planning factors will be considered in the land use simulation using the PLUS model, machine learning can be adopted in further studies to predict future land use demand more precisely, and the input-output model can be employed to analyze the relationship between land use types and consumption-based carbon emissions rather than production-based carbon emissions.

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**Data Availability Statement:** The data in the article are detailed in Section 2.1. All the data used are reflected in the article. If you need other relevant data, please contact the authors.

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**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

**Table A1.** Neighborhood weight of each type of land use.

| Land Use Types | Industrial and Mining Land | Traffic Land | Living Land | Agricultural Land and Water Area | Other Land |
|---|---|---|---|---|---|
| Neighborhood weight | 0.0712 | 0.2006 | 0.4469 | 0.2596 | 0.0217 |

**Table A2.** The spatial driving factors of the land use change.

| Category | Data | Spatial Resolution | Data Sources |
|---|---|---|---|
| Socioeconomic driving factors | Population | 100 m | WorldPop (https://hub.worldpop.org/, accessed on 17 March 2022) |
| | GDP | 1000 m | Resource and Environment Science and Data Center (RESDC) (https://www.resdc.cn/, accessed on 16 March 2022) |
| | The distance from town<br>The distance from highway<br>The distance from railway<br>The distance from other roads | 30 m | OpenStreetMap (https://www.openstreetmap.org/, accessed on 18 February 2022) |
| | Nighttime light data | 1000 m | VIIRS_DNB_VNL V2 (https://eogdata.mines.edu, accessed on 25 February 2022) |

**Table A2.** *Cont.*

| Category | Data | Spatial Resolution | Data Sources |
|---|---|---|---|
| Climatic and environmental driving factors | Annual mean temperature<br>Annual precipitation | 500 m | Resource and Environment Science and Data Center (RESDC) (https://www.resdc.cn/, accessed on 16 March 2022) |
| | DEM<br>Slope<br>Degree of relief | 30 m | NASADEM_HGT V001 (https://www.earthdata.nasa.gov/esds/competitive-programs/measures/nasadem, accessed on 18 February 2022) |
| | The distance from waters<br>The distance from waterway | 30 m | OpenStreetMap (https://www.openstreetmap.org/, accessed on 18 February 2022) |

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# Will Good Service Quality Promote Real Estate Value? Evidence from Beijing, China

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**Abstract:** In the field of land use and urban management, real estate value-added issues have attracted much attention. Previous studies mainly focused on the premium of basic public services (such as infrastructure) in real estate value. As an important part of urban management, the contribution of property service is often underestimated. Few empirical studies mentioned the potential contribution of property service quality. Based on this, this paper aims to confirm and quantitatively evaluate the premium of good service quality in real estate value utilizing 155,845 samples of housing resale transactions in Beijing from 2012 to 2019. Furthermore, we also explore the dynamics and heterogeneity of the above premium. Our results show the following: Firstly, good service quality does show premium in real estate value, and the higher the service quality, the greater the premium in housing price. Secondly, this premium keeps increasing during our study period. With urbanization and rising incomes of residents, property service is increasingly important. Thirdly, the contribution of service quality to real estate value is greater when serviced houses have a higher price or larger area, are relatively newer, or further away from the city center. The findings of this current research not only deepen our understanding of service quality's premium in real estate value, but also provide implications for urban management.

**Keywords:** land value-added; urban management; hedonic price model; housing price; property service; property management fee

## 1. Introduction

With urban development and the improvement of residents' living quality, urban management becomes increasingly important. Urban management is a rich connotation of the concept, including basic public services, public safety management, land-use management, property services and so on. Good urban management can increase real estate value. Many scholars have found that basic public services (such as transportation, parks, etc.) have a premium in real estate value. Du et al. [1] used statistical methods to analyze the price of houses near a subway station in Sunderland, England, and argued that the rail transit system has an impact on the value of land in the short term. Cervero et al. [2] pointed out that the rapid transit system (BRT) affects land use and land value, which increases the price of land. Kong et al. [3] found that neighboring parks will make the land price premium.

In addition to basic public services, good public safety management also has a premium in property or land value [4]. George et al. [5] pointed out that violent crimes will be capitalized into the local housing market, and the average impact of crime rate on housing prices is misleading. Besides, land-use management in urban management can also promote real estate value. DiPasquale [6] established three spatial models of the land

value of huge cities in Asia, and concluded that the spatial type of land value and the characteristics of the land market can affect the value of urban land, which are important reference factors in urban planning. Yang et al. [7] explored the impact of mixed land use of land parcels and living circle scales on housing prices.

However, as an important part of urban management [8], few scholars pay attention to the premium of property service in real estate value. Based on this, this paper aims to confirm and quantitatively examine the premium of service quality. We use housing prices to measure real estate value, and use two indicators to measure service quality respectively, which are the property management fee [9] and whether the service is provided by top-tier companies [10]. The hedonic price model is used to analyze nearly 160 thousand pieces of housing resale transaction data in Beijing from 2012 to 2019. As there are many options for resale houses, and residents are more cautious when buying resale houses, they have a full understanding of all aspects of housing characteristics, including the service quality in the community. Furthermore, we then explore the changes in the above premium over time, and its heterogeneity from the perspectives of housing prices, housing area, housing age, and whether in the city or suburbs.

Therefore, this paper makes an original contribution to the existing literature by deepening our understanding of service quality's premium in real estate value, and to the best of our knowledge, this is the first study to explore the dynamic changes and heterogeneity of the above premium. The rest of this paper is organized as follows: the second part is a literature review; the third part includes the conceptual framework, hypotheses, and data; the fourth part presents the empirical results; followed by a discussion and conclusion.

## 2. Literature Review

Real estate value-added mainly includes land value-added and real estate value-added. With the progress of urbanization and the limited land resources [11], the issue of land value-added has attracted much attention [12,13]. Using information from the real estate market to study land value-added has always been a main method, because there is a relationship between housing prices and land value-added [14–17]. Muth et al. [14] and Manning [15] created the derivative demand theoretical model of the land market, proposing that land is a derivative demand of housing service, and the price of land is determined by housing prices. Liu et al. [17] also hold this view. When housing demand exceeds the supply market, it will lead to rising housing prices, which in turn drives up land prices. Housing prices are in a dominant position as a whole, and their impact on land prices is greater than that of land prices on housing prices. The direction of interaction is positive, which means that rising housing prices lead to land value-added [16]. Whether in classic research or current research, scholars recognize the relationship between housing prices and land value-added.

On the issue of real estate value-added, focusing on the housing market, the hedonic price model is widely used to quantify the premium in housing price. Characteristics affecting real estate value mainly include basic public services (such as infrastructure, etc.), public safety management, land-use management, and property service.

To be specific, basic public services have a premium in real estate value. First, good educational resources can affect real estate value [18]. Wang et al. [19] found that human capital measured by average years of education has a significant positive effect on housing prices. Clapp et al. [20] reported that the test scores of students in the community have become more and more important reference factors for choosing real estate in Connecticut, USA, while the demographic composition of the community has become less important. Every increase in the quality of primary school education will increase housing prices by 5.8 percent in Hangzhou, China [21]. Gibbons [22] pointed out that for every 1 percent increase in the proportion of residents with higher education in a community, the average housing price will increase by 0.24 percent. Second, convenient transportation can affect real estate value. Zhang et al. [23] reported that subway stations have a significant impact on the increase in rental prices in the suburbs. For every additional kilometer from the subway

and bus station, housing prices fall by 15.02 percent and 5.1 percent, respectively [24]. Dai et al. found that the transfer station and non-transfer station of Beijing Rail Transit have a value-added effect on the price of surrounding houses [25]. Third, parks near the communities can affect real estate value [26]. Compared with new apartments built before 1989, the impact of parks and forests on housing prices is more significant. For every kilometer from the community center to the nearest park, housing prices in Hangzhou increase by 2.9 percent [21], and housing prices in Shenzhen increase by 1.7 percent [27]. Theme parks can bring a 3.7% premium in housing price [28]. For every 1 percent increase in the area of nearby parks, housing prices will increase by 0.013 percent [29]. In addition, for every kilometer increase in the distance from the community to the nearest city park, housing prices increase by 3.1 percent [30], based on Beijing housing data in 2019 and 2012–2019, respectively.

In addition to basic public services, good community safety management also has a premium in property or land value. The premium of community safety is mainly reflected in areas with high crime rate [31], and the average appraisal of housing price in unsafe areas is 1.27% lower [32]. Lynch and Rasmussen [31] used the sales data of more than 2800 houses in Jacksonville, Florida to estimate the impact of crime on housing prices, and they pointed out that high crime rate will seriously reduce housing prices. Besides, land-use management of urban management can also promote property or land value. DiPasquale [6] established three spatial models of the land value of huge cities in Asia and concluded that the spatial type of land value and the characteristics of the land market can affect the value of urban land, which are important reference factors in urban planning. Foster et al. [33] discussed that the annual real estate value rate is related to the characteristics of specific locations, and there are significant geographic differences. Yang et al. [27] explored the impact of mixed land use of land parcels and living circle scales on housing prices. Ge et al. [34] revealed that urban land use efficiency high-value areas have a larger market scale than the low-value areas. As an important part of urban management, property service has also attracted much attention [35], which not only can maintain the cleanliness and comfort level of the living environment of the community [36], but also improves the residents' quality of life [4] and promotes urban development. However, few studies mention the role of property service [9,10,37]. To the best of our knowledge, none of the studies explore the changes over time and its heterogeneity.

Based on the existing research, we aim to confirm and quantitatively evaluate the premium of service quality in real estate value. On the one hand, this paper will contribute to deepening the understanding of service quality's premium in real estate value. On the other hand, this paper will provide implications for making an effective use of property service to promote urban management.

## 3. Conceptual Framework, Hypotheses and Data

### *3.1. Conceptual Framework*

Since the hedonic price model is based on actual behaviors rather than expected behavior [38], it is usually called the "revealed preference method" to distinguish it from the method of stating preference as the contingent valuation method [39]. As a kind of heterogeneous commodity, the house itself is composed of a series of internal characteristics, which will produce different effects due to the number of characteristics and the different combination methods. The relationship between service quality and housing price, which is the focus of this paper, is shown in Figure 1. When residents buy goods, they are aiming for the combination of characteristics that can bring them the greatest total utility, and these combinations of housing characteristics represent the value of real estate. The key point of such residential location choice behavior mechanism is that characteristics of houses will bring effect to residents, but they do not have a market price. Therefore, they will not appear explicitly in the cost paid by households, but will be implicitly included in the cost of houses. Because of this, it is possible to identify the preference households' intensity

or willingness to pay for various characteristics by observing their actual location choice behaviors, or by observing the spatial differences and changes of housing prices or rents.

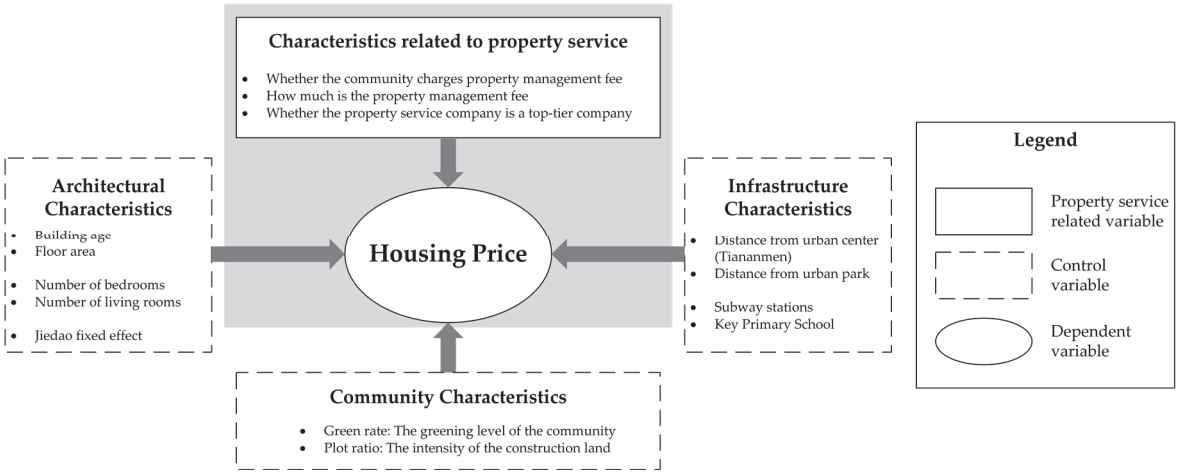


**Figure 1.** The relationship of property service and housing price.

According to previous studies, the semilogarithmic form of the hedonic price model performs better in improving the estimation accuracy and allowing variable heteroscedasticity [30]. We adopt this form of the hedonic price model, which is shown in Equation (1).

$$lnP = \alpha_0 + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (1)$$

Among them, $lnP$ is the natural logarithm of the housing price $P$; $\alpha_0$ is the sum of other constants that affect housing prices; $X_i$ is the feature vector, usually including three aspects: architectural characteristics, infrastructure characteristics, and community characteristics; $\alpha_i$ is the semi elasticity coefficient of the characteristic vector, which means the percentage of change in housing price $P$ when $X_i$ changes by one unit amount; $\varphi_t$ is the year-fixed effect; and $\varphi_s$ is the Jiedao-fixed effect. Jiedao is the sub-district and basic administrative management unit of China. The administrative system in Beijing has three levels: municipality, district, and street office (Jiedao). Jiedao is the lowest administrative level. Within the BMA, there are 123 Jiedaos with an average size of about 10 km$^2$ each. Unlike the United States, which has a highly decentralized public goods provision system, the Beijing Municipal Government provides most of the public infrastructure and services, such as transportation, education, and health care. The Jiedao is only responsible for administering basic services such as garbage collection [40]. The results after excluding the influencing factors of time and spatial changes are relatively more credible; $\varepsilon$ is the error term.

### *3.2. Hypotheses and Empirical Models*

Based on the conceptual framework, we use housing prices to measure real estate value, and use two indicators to measure service quality respectively, which are the property management fee [9], and whether the service is provided by top-tier companies [10]. Property service refers to the activities provided by property service companies to maintain and manage houses, facilities, and sites, and keep environmental sanitation and order. It is worth mentioning that the service is only provided by one property service company. Property management fee is paid by the owners for the services provided by the property service company. In the new home market, first-time buyers buy from developers. The property management fee is exogenous, which is determined by the property service company, and remains consistent throughout the ownership period. It is very difficult to adjust the fee or change the property service company after determined [41–44], due to the difficulty of negotiating with owners. For example, as shown in Table A1, property

management fee is fixed, and housing price is variable. Therefore, other things being equal, we estimate the residents' willingness to pay for property service quality which measured by property management fee.

We propose three hypotheses. Firstly, good service quality has a premium in real estate value. Specifically, compared with no service, property with service has value added; the better the service quality, the higher the real estate value-added; top-tier service quality have more premium in real estate value. Our research hypotheses have the following factual background: First, property service is provided by one property service company for each community. Therefore, when a community does not charge the property management fee, we assume that the community does not enjoy any property services; second, among communities where property management fees are charged, the higher the property management fees means that property service is more comprehensive and caring. The property service provided by a top-tier company means that community can enjoy the highest quality of service. Therefore, we assume that the service quality is better when the property fee is high or the service is provided by a top-tier company. Third, the property service company in the community rarely replaced for a long time and the property management fee is also stable due to the difficulty of negotiating with homeowners. Thus, the service quality is almost unchanged during the whole ownership period. We will not consider the potential change of service quality in this current research.

Secondly, the premium of good service quality in real estate value becomes stronger in 2012–2019. With the development of economy and growth of both income and wealth, residents' demand for a better life or better quality of life is keeping growing. As residential experience is an important part of residents' life, residents' demand and willingness to pay for high quality of property service will be stronger, which will bring more premium in housing prices. Thus, we assume the demand becomes stronger.

Lastly, the premium of good service quality in real estate value is heterogeneous, in terms of housing price, housing area, housing age, or whether the house is in the suburbs. Residents living in higher prices houses, larger houses and newer houses have relatively higher income or wealth level, and have stronger willingness to pay or demand for quality services. The public service resources in the suburbs are relatively poor, thus residents would have higher willingness to pay for the service quality in the community. Therefore, we assume that there is heterogeneity in the premium.

According to the first hypothesis, the equation of the hedonic price model after introducing the variable *D_PS* is shown in Equation (2). Among these, $\beta_1$ is the coefficient of *D_PS*. *D_PS* indicates whether communities charge a property management fee; if a property management fee is charged, the value of this variable is 1; otherwise, it is 0. Property management fees are the cost that residents have to pay for enjoying property services. The expected sign is a positive number, indicating that the existence of property management fee will lead to a premium in housing prices.

$$lnP = \alpha_0 + \beta_1 \times D_PS + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (2)$$

The variables *PS* and $PS^2$ are introduced, and the models are Equations (3) and (4). Among these, $\beta_2$, $\beta_3$, and $\beta_4$ are the coefficients. *PS* represents the specific amount of the property management fee, and the expected sign of this variable is positive; $PS^2$ represents the quadratic term of *PS*, and the expected sign is negative. This is because the premium of property management fee in housing prices is extremely high; that is, the premium of property management fee in housing prices is not unlimited.

$$lnP = \alpha_0 + \beta_2 \times PS + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (3)$$

$$lnP = \alpha_0 + \beta_3 \times PS + \beta_4 \times PS^2 + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (4)$$

The variable *D_top100* is introduced, and the specific hedonic price model is shown in Equation (5). Among these, $\beta_5$ is the coefficient of *D_top100*. *D_top100* is a dummy variable

indicating whether the property service company is a brand company. The expected sign of this variable is positive, which means that the property service company has a premium when it is a brand company.

$$lnP = \alpha_0 + \beta_5 \times D_top100 + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (5)$$

According to the second hypothesis, we introduce the variable *Year* and two interaction-terms, which are *D_PS* × *Year* and *PS* × *Year* on the basis of Equations (2) and (3). Among these, *Year* is a continuous variable to represent the time of transaction, and assigned a value of 1–8 for the year of 2012–2019. *D_PS* × *Year* is the interaction-term of the variables for whether the community is charged a property management fee and the year variable. *PS* × *Year* is the interaction-term of the variables of property management fee and the year variable. The expected signs are all positive numbers, indicating that the variables *D_PS* and *PS* have a higher premium over time. $\beta_6$–$\beta_{11}$ are the coefficients of the corresponding variables.

$$lnP = \alpha_0 + \beta_6 \times D_PS + \beta_7 \times D_PS \times Year + \beta_8 \times Year + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (6)$$

$$lnP = \alpha_0 + \beta_9 \times PS + \beta_{10} \times PS \times Year + \beta_{11} \times Year + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (7)$$

According to the third hypothesis, in order to identify the heterogeneous effects of service quality on real estate value, we divided the types of housing by housing prices (*D_highprice*, differentiated by sample housing price median, high housing price = 1, low housing price = 0), housing area (*D_large*, differentiated by sample housing area median, big house = 1, small house = 0), housing age (*D_old*, differentiated by sample housing age median, old house = 1, new house = 0), and whether the house is in the suburbs (*D_suburbs*, differentiated by the median of the ring of the road, housing outside the Fourth Ring Road = 1, housing inside the Fourth Ring Road = 0). (The ring roads are the names of ring-shaped highways surrounding Beijing, and the number of rings from the inside to the outside is increasing. Thus, the Fourth Ring Road refers to the fourth ring highway from the inside to the outside in Beijing). We regard houses outside the Fourth Ring Road as further away from the city center, while inside the Fourth Ring Road as in the city center. Then, we introduce the cross-term *D_highprice* × *PS*, *D_large* × *PS*, *D_old* × *PS* and *D_suburbs* × *PS*. The coefficient of the cross term represents the impact gap between two different types of housing. For example, the coefficient of *D_highprice* × *PS* represents the impact gap between high housing prices and low housing prices on the premium of good service quality in real estate value.

$$lnP = \alpha_0 + \beta_{12} \times D_highprice \times PS + \beta_{13} \times D_highprice + \beta_{14} \times PS + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (8)$$

$$lnP = \alpha_0 + \beta_{15} \times D_large \times PS + \beta_{16} \times D_large + \beta_{17} \times PS + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (9)$$

$$lnP = \alpha_0 + \beta_{18} \times D_old \times PS + \beta_{19} \times D_old + \beta_{20} \times PS + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (10)$$

$$lnP = \alpha_0 + \beta_{21} \times D_suburbs \times PS + \beta_{22} \times D_suburbs + \beta_{23} \times PS + \sum \alpha_i X_i + \varphi_t + \varphi_s + \varepsilon \quad (11)$$

This paper will take the various factors that affect housing prices as independent variables and pay particular attention to the premium of property service-related variables in housing prices. Through the hedonic price model, the dependent variables and service quality will be linked.

### *3.3. Data*

Beijing has determined the list of prohibited industries in accordance with three types of functional areas: six urban districts, new urban development areas, and ecological conservation development areas. The distribution of communities in the study area is shown in Figure 2. Most communities are located within the Fifth Ring Road in Beijing. The distribution of communities presents the coexistence of agglomeration and dispersion,

among which there is obvious agglomeration in the central city. This paper selected six urbanized districts as the study area, which are Dongcheng District, Xicheng District, Chaoyang District, Haidian District, Fengtai District, and Shijingshan District. From the perspective of the distribution of communities, Chaoyang District, Haidian District, and Fengtai District occupy most of the communities in the city, and the communities in Dongcheng District and Xicheng District have a much higher density than other areas. This spatial area is the most concentrated urbanized area in Beijing's built-up area, which has been widely recognized and used many times by the local statistics and research institutions [30]. In the 2015 edition of the new industrial restriction catalogue released by Beijing, the sixth district is considered as a whole, which is a combination of the capital functional core district and the urban functional expansion district. The six districts of Beijing include the capital functional core area (Dongcheng, Xicheng) and the urban functional expansion area (Chaoyang, Haidian, Fengtai, Shijingshan). The total permanent resident population of the central six districts was 12.8 million in 2014, accounting for 59.3% of the total permanent resident population in Beijing and contributing to 69.9% of the total GDP in Beijing [45].

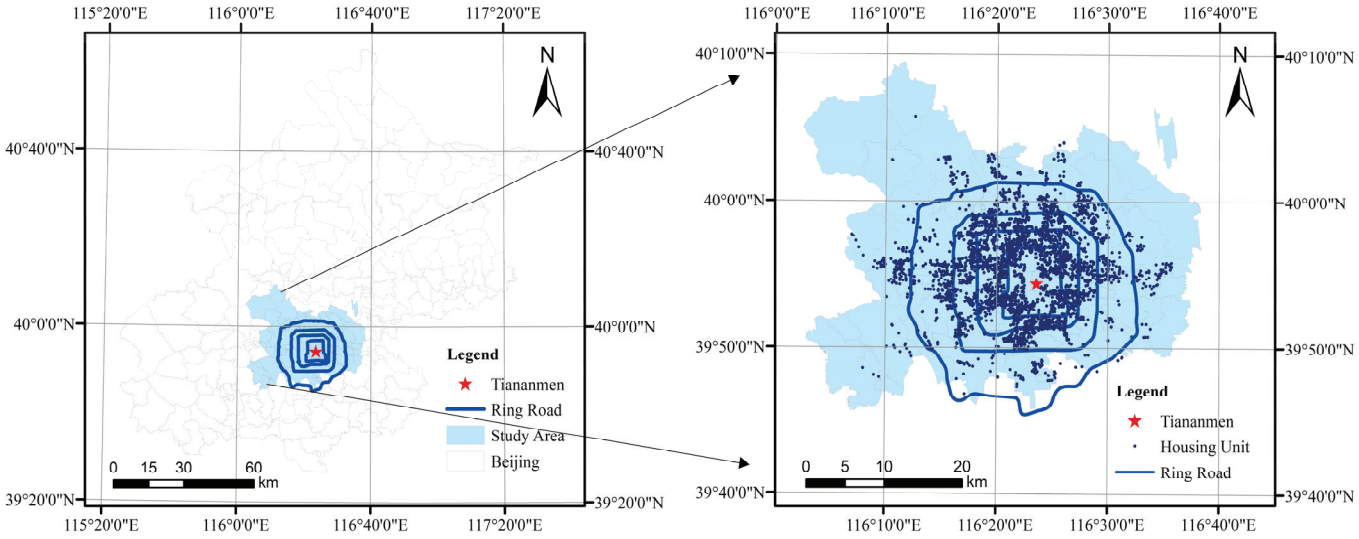


**Figure 2.** The spatial distribution of communities in the six districts of Beijing from 2012 to 2019. Note: the ring roads are the names of ring-shaped highways surrounding Beijing, and the number of rings from the inside to the outside is increasing. For example, the Fourth Ring Road refers to the fourth ring highway from the inside to the outside in Beijing.

We collected 155,845 housing resale transaction data from 2012 to 2019 through *Lianjia*, the real estate brokerage agency with the largest market share of housing resale transactions in Beijing (https://sn.lianjia.com/about/aboutlianjia/ accessed on 9 January 2022). It is worth mentioning that this paper used information from the housing resale transaction market to avoid the endogenous problem of developers simultaneously determining housing prices and property management fee in the new housing market. At the same time, when purchasing resale houses, residents usually visit the house many times through professional real estate brokers, and make decisions very carefully. Therefore, they have a full understanding of the housing characteristics (such as location, and architecture characteristics, etc.). Because of too much missing data for old houses, we chose the average house age (21 years) as the screening criterion, and used data on housing transactions with ages of 21 or less. In the end, this paper selected 155,845 housing resale transaction data with a house age of 21, and these transaction houses were distributed in 3330 communities.

### *3.4. Definition of Variables and Basic Descriptive Statistics*

In terms of variables, the dependent variable is *Ln_price*, which is quantified with the natural logarithm of the unit housing price. We summarize independent variables related to property service characteristics, architectural characteristics, infrastructure characteristics, and community characteristics.

Specifically, the first type of characteristics as related to property service: *D_PS*, a dummy variable, is used to measure whether a property management fee is charged. It is assigned a value of 1 if property management fee is collected, otherwise it is assigned a value of 0; *PS* is used to measure the amount of specific property management fee; *D_top100* is also a dummy variable, judging whether the property service is provided by a top-tier property service company, and the variable is assigned a value of 1 if yes; otherwise, it is assigned a value of 0. The source of this index is the "2020 China Property Service TOP 100 Companies List" (The original source of the list is https://fdc.fang.com/report/13124.html accessed on 9 January 2022) released by the China Index Academy (China Index Holdings Limited, NASDAQ: CIH, https://www.nasdaq.com/market-activity/stocks/cih accessed on 17 January 2022). This evaluation index system has been widely recognized by the industry and has the greatest influence and credibility. The original source of the list is "https://fdc.fang.com/report/13124.html accessed on 17 January 2022". The evaluation index system uses a total of five aspects of 20 indicators to rank property service companies, which are the management scale, business performance, service quality, development potential, social responsibility. According to the ranking of the index system, the "2020 China Property Service TOP 100 Companies List" was obtained. There are 244 property service companies on the list, accounting for 12.4 percent of the total number of companies in the industry. Specific to this study, there are 18,518 resale transactions provided by the top-tier companies, accounting for only 6% of the total sample. Therefore, if the company is on this list, we define it as a top-tier company.

Secondly, architectural characteristics include *Age* (housing age), *Area* (the total area of the house), *Bedroom* (number of bedrooms in the house) and *Living_room* (number of living rooms in the house).

Thirdly, infrastructure characteristics include four variables, which are *Dis_tam*, *Dispark*, *Subway* and *Education*. *Dis_tam* measures the distance from the community to Tiananmen Square; *Dispark* means the distance from the community to the nearest park; *Subway* represents the number of subway stations within 1 km of the neighborhood; and *Education* is used to quantify whether the housing was located within the school district of a key primary school [30,46,47], the definition of key primary schools is referred to [47] and the information is included in POI data) which is important for families with children in primary schools, according to the admission requirements in Beijing. The last type of characteristics is related to neighborhood. *Greenrate* is measured as the ratio between green space and total land area of the complex [48,49]. *Plotratio* represents the intensity of the construction land used in the community.

The specific variable settings and their descriptive statistics are shown in Table 1.

**Table 1.** Variable settings and descriptive statistics.

| Variable Type | Variable Name | Variable Meaning | Descriptive Statistics | |
|---|---|---|---|---|
| | | | Mean | Standard Deviation |
| Dependent variable | *Ln_price* | The natural logarithm of the housing price per square meter | 10.88 | 0.37 |
| Characteristics related to property service | *D_PS* | Whether the community charges property management fee: yes = 1; otherwise = 0 | 0.91 | 0.29 |
| | *PS* | Property management fee of the community (yuan/$m^2$/month) | 1.96 | 1.15 |
| | *D_top100* | Whether the property service company is a top-tier company: yes = 1; otherwise = 0 | 0.06 | 0.24 |
| Architectural characteristics | *Age* | Housing age (years) | 21.47 | 9.06 |
| | *Area* | The total area of the house (square meters) | 80.75 | 37.34 |
| | *Bedroom* | Number of bedrooms in the house | 2.00 | 0.77 |
| | *Living_room* | Number of living rooms in the house | 1.13 | 0.48 |
| Infrastructure characteristics | *Dis_tam* | The distance from the community to Tiananmen Square (km) | 9.05 | 3.78 |
| | *Dispark* | The distance from the community to the nearest park (km) | 1.23 | 0.63 |
| | *Subway* | The number of subway stations within 1 km of the neighborhood | 0.76 | 0.43 |
| | *Education* | Whether there are key primary schools around the neighborhood: yes = 1; otherwise = 0 | 0.10 | 0.30 |
| Community characteristics | *Greenrate* | The greening level of the community (percent) | 0.32 | 0.07 |
| | *Plotratio* | The intensity of the construction land used in the community (percent) | 2.64 | 1.23 |

Note: (1) The variable *price* with "*Ln_*" was logarithmically transformed. (2) The samples contained 155,845 observations in 3330 communities during 2012–2019.

## 4. Empirical Results

This section will introduce the main empirical results from the following three aspects. First of all, we confirm that good service does show a premium in real estate value. In addition, when the service quality is higher or provided by top-tier companies, the premium is greater. Second, the premium of good service quality in real estate value keeps increasing from 2012 to 2019, which is confirmed by the estimated coefficients of the interaction terms (*D_PS* × *Year* and *PS* × *Year*) between the time variable and the property service variables. The last part is that good service quality show more premium, when the serviced houses have a higher price, larger area, younger age, or are further away from the city center.

### *4.1. Good Service Quality Does Show Premium in Real Estate Value*

Since there are no unified regulations on collecting property management fees in the communities in Beijing, we first confirm whether service quality show more premium in real estate value, by comparing the difference price premium of whether or not to

charge a property management fee (*D_PS*). Then, for the sample of communities that charges a property management fee (*D_PS* = 1), we study how the amount of the property management fee show premium in housing prices; that is, whether the premium in housing prices is greater when the quality of property service is better. At the end of the empirical part 4.1, we focus on the sample of communities that charge a property management fee (*D_PS* = 1) again to study whether top-tier service quality have more premium in real estate value.

The regression results of the hedonic price model based on time and Jiedao-fixed effects are shown in Table 2, with robust t-statistics in parentheses. The dependent variable in Columns (1)–(4) is housing prices, which measure real estate value. In the hedonic price model, housing prices are controlled by variables related to property service characteristics, architectural characteristics, infrastructure characteristics, and community characteristics. Judging from the coefficient of determination $R^2$, the basic model can explain more than 77 percent of the difference in dependent variables, indicating that the model is well-fitted and has a certain explanatory power. In general, the empirical results of the main control variables are consistent with expectations.

**Table 2.** Empirical results of good service quality showing premium in real estate value.

| | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| | *Ln_price* | *Ln_price* | *Ln_price* | *Ln_price* |
| *D_PS* | 0.042 *** | | | |
| | (15.793) | | | |
| *PS* | | 0.036 *** | 0.074 *** | |
| | | (60.114) | (42.459) | |
| $PS^2$ | | | −0.006 *** | |
| | | | (−21.840) | |
| *D_top100* | | | | 0.030 *** |
| | | | | (13.765) |
| *Age* | −0.020 *** | −0.014 *** | −0.014 *** | −0.020 *** |
| | (−129.630) | (−84.919) | (−80.392) | (−127.286) |
| *Area* | −0.002 *** | −0.002 *** | −0.002 *** | −0.002 *** |
| | (−54.378) | (−62.767) | (−63.198) | (−52.741) |
| *Bedroom* | 0.041 *** | 0.047 *** | 0.048 *** | 0.040 *** |
| | (35.216) | (39.526) | (40.341) | (33.308) |
| *Living_room* | 0.054 *** | 0.055 *** | 0.055 *** | 0.055 *** |
| | (50.998) | (51.533) | (51.439) | (50.630) |
| *Dis_tam* | −0.041 *** | −0.036 *** | −0.036 *** | −0.042 *** |
| | (−82.299) | (−72.313) | (−72.514) | (−82.297) |
| *Dispark* | −0.036 *** | −0.035 *** | −0.038 *** | −0.036 *** |
| | (−30.028) | (−28.772) | (−30.728) | (−28.951) |
| *Subway* | 0.047 *** | 0.039 *** | 0.038 *** | 0.048 *** |
| | (35.622) | (29.201) | (28.847) | (35.941) |
| *Education* | 0.051 *** | 0.052 *** | 0.056 *** | 0.042 *** |
| | (26.015) | (25.644) | (27.981) | (20.400) |
| *Greenrate* | 0.416 *** | 0.377 *** | 0.363 *** | 0.447 *** |
| | (50.079) | (43.421) | (42.033) | (51.679) |
| *Plotratio* | −0.019 *** | −0.019 *** | −0.020 *** | −0.020 *** |
| | (−38.062) | (−36.642) | (−38.145) | (−37.923) |
| Constant | 10.699 *** | 10.553 *** | 10.503 *** | 10.736 *** |
| | (991.495) | (1025.196) | (1000.539) | (1012.185) |
| *Year-fixed effect* | Yes | Yes | Yes | Yes |
| *Jiedao-fixed effect* | Yes | Yes | Yes | Yes |
| *Observations* | 155,845 | 150,400 | 150,400 | 150,400 |
| $R^2$ | 0.773 | 0.781 | 0.782 | 0.774 |

Note: (1) *** Indicates significance at 1% level. (2) The numbers in parentheses indicate robust t-statistics. (3) We narrow the fixed effect of space from Jiedao to a 2 km × 2 km grid and find that it does not affect the main conclusions of the paper. The empirical results of the grid-fixed effect are shown in Table A1 in Appendix A.

4.1.1. Compared with No Property Service, Houses with Service Do Have Higher Value

According to the regression result shown in Column (1) of Table 2, the coefficient of *D_PS* is 0.042, which means the following: controlling for other characteristics, the housing prices of the communities that charge a property management fee is on average 4.2 percent higher than those of the communities that do not charge a property management fee. Compared with no service, houses with service do have higher value. This may be because the communities where a property management fee is charged are cleaner and safer, hence, residents are willing to pay more for it.

In addition, among the architectural characteristics, housing age (*Age*), housing area (*Area*), number of bedrooms (*Bedroom*), and number of living rooms (*Living_room*) have a significant premium in housing prices. Among these, the estimated coefficients of the age of the house (*Age*) and the area of the house (*Area*) are negative, and the estimated coefficients of the number of bedrooms (*Bedroom*) and the number of living rooms (*Living_room*) are positive. Specifically, for each year a house is older, its unit price decreases by 2 percent; for every 1 $m^2$ of increase in the housing area, the unit housing price will reduce by 0.2 percent; when the bedroom number increases by one, the housing price increases by 4.1 percent; when the living room number increases by one, the housing price increases by 5.4 percent. This shows that newer houses or houses with a smaller area, more bedrooms, or more living rooms, all have greater premium in housing price. Perhaps due to the high housing prices in Beijing and the limited income of residents, residents prefer houses with a smaller housing area. In addition, new houses with more bedrooms and living rooms have a premium in housing prices due to the convenience and comfort of living.

For infrastructure characteristics, the estimated coefficients of the distance to Tiananmen Square (*Dis_tam*) and the distance to the nearest park (*Dispark*) are $-0.041$ and $-0.036$, respectively. This shows that when the distance to Tiananmen Square and the distance to a park are increased by 1 km respectively, housing prices fall by 4.1 percent and 3.6 percent. This shows that the closer the housing is to Tiananmen Square or parks, the greater the premium in housing prices. The coefficients of the number of subway stations (*Subway*) and education facilities (*Education*) are positive, indicating that the number of subway stations and the key elementary schools around the community have a premium in housing price. Within 1 km of the community, for every additional subway station, housing prices will rise 4.7 percent; for each key primary school around the community, the housing price increases by 5.1 percent. This may be because residents pay more attention to transportation and education resources when choosing housing.

For community characteristics, the coefficient of the green rate (*Greenrate*) is positive, and the estimated coefficient of the plot ratio (*Plotratio*) is negative. This shows that the higher the greening rate of the community, the higher the housing price. By analyzing the coefficient of the plot ratio variable (*Plotratio*), it can be seen that relatively uncrowded houses have higher prices. Generally speaking, a greener and less crowded community has more premium in real estate value.

4.1.2. The Better the Service Quality, the Higher the Real Estate Value-Added

According to the regression results in Column (2), we see the following: the coefficient of the property management fee (*PS*) is 0.036, which means that when other variables are controlled, with an increase of 1 in the property management fee, housing prices will rise by 3.6 percent. In other words, the higher the quality of property service, the higher the real estate value-added. This may be because the higher the quality of property service, the residents obtain a better housing experience and are willing to pay more for this. The regression result in Column (3) shows that at the 1% significance level, the coefficient of the property management fee (*PS*) is 0.074, and the coefficient of the quadratic term of property management fee ($PS^2$) is $-0.006$. This shows that the relationship between property service and housing prices is nonlinear. That is, we confirmed that the better the service quality, the higher the real estate value-added.

4.1.3. Top-Tier Service Quality Shows More Premium in Real Estate Value

After regression analysis in Column (4), it can be found that the coefficient of the variable (*D_top100*) is 0.03 at 1% significance level, indicating that the top-tier property service can bring a 3 percent premium in housing price. That is, top-tier service quality shows more premium in real estate value. This is mainly due to the fact that top-tier companies' property service is more scientific, meticulous, and professional, making it easier to meet residents' needs.

*4.2. The Premium of Good Service Quality in Real Estate Value Keeps Increasing over Time*

According to Equations (8) and (9), this paper obtains changes of good service quality's premium in real estate value over time (Table 3). Robust t-statistics are in parentheses. The $R^2$ values of the two models in Table 3 are both greater than 0.77, indicating that the model fits well and has a high degree of interpretability. The estimated coefficient of the interaction-terms (*D_PS* × *Year* and *PS* × *Year*) reflect changes in the premium of service quality in housing prices over time.

**Table 3.** Empirical results of the premium of good service quality in real estate value keeps increasing over time.

| | **(1)** | **(2)** |
|---|---|---|
| | *Ln_price* | *Ln_price* |
| *D_PS* | 0.028 *** | |
| | (4.965) | |
| *D_PS* × *Year* | 0.003 *** | |
| | (2.803) | |
| *PS* | | 0.023 *** |
| | | (18.130) |
| *PS* × *Year* | | 0.003 *** |
| | | (11.204) |
| *Year* | 0.112 *** | 0.109 *** |
| | (99.908) | (166.274) |
| Constant | 10.598 *** | 10.468 *** |
| | (898.055) | (989.059) |
| Control other variables | Yes | Yes |
| *Year-fixed effect* | Yes | Yes |
| *Jiedao-fixed effect* | Yes | Yes |
| *Observations* | 155,845 | 150,400 |
| $R^2$ | 0.773 | 0.781 |

Note: (1) *** Indicates significance at 1% level. (2) The numbers in parentheses indicate robust t-statistics. (3) Only the main control variables discussed in this paper are shown.

Through regression analysis in Column (1) of Table 3, it can be found that the coefficient of whether a property management fee is charged (*D_PS*) and the coefficients of the time-related variables *DPS* × *Year* and *Year* are all positive at the 1% significance level, at 0.028 and 0.003 respectively. These positive coefficients show that compared with no property service, houses with service quality have a price premium increased by 0.3 percent year by year from 2012 to 2019. Similarly, in the regression results of Column (2), the coefficients of property management fee (*PS*) and time-related variables (*PS* × *Year* and *Year*) are also positive at the 1% significance level. What interests us most is the interaction-term (*Year*), and its coefficient of 0.003. This shows that compared with housing transactions in 2012, houses in 2019 have an extra 2.1 percent premium, due to the increasing premium over time. In other words, good service not only shows premium in real estate value, but can also have an increasing premium over time. The reason may be that the income level and quality of life of residents have improved in recent years, causing residents to want a better life and pay more attention to the quality of property service.

*4.3. The Premium of Good Service Quality in Real Estate Value Is Heterogeneous*

We will identify the heterogeneity of service quality's premium in real estate value in this section, from the perspective of housing price, housing area, housing age, and whether the house is further away from the city center. According to Equations (10) and (11), the results of heterogeneity analysis are shown in Table 4, with robust t-statistics in parentheses. From the perspective of $R^2$, the model has great interpretation capabilities.

**Table 4.** Results of the heterogeneity of good service quality's premium in real estate value.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | *Ln_price* | *Ln_price* | *Ln_price* | *Ln_price* | *Ln_price* |
| *D_highprice* × *PS* | 0.027 *** | | | | 0.017 *** |
| | (31.271) | | | | (17.021) |
| *D_highprice* | 0.094 *** | | | | 0.145 *** |
| | (39.242) | | | | (54.744) |
| *D_large* × *PS* | | 0.030 *** | | | 0.006 *** |
| | | (30.743) | | | (5.915) |
| *D_large* | | −0.097 *** | | | −0.096 *** |
| | | (−43.546) | | | (−39.806) |
| *D_old* × *PS* | | | −0.021 *** | | −0.016 *** |
| | | | (−20.245) | | (−16.062) |
| *D_old* | | | −0.046 *** | | −0.006 ** |
| | | | (−18.837) | | (−2.489) |
| *D_suburbs* × *PS* | | | | 0.027 *** | 0.024 *** |
| | | | | (27.008) | (26.132) |
| *D_suburbs* | | | | −0.151 *** | −0.135 *** |
| | | | | (−44.393) | (−43.561) |
| *PS* | 0.022 *** | 0.012 *** | 0.042 *** | 0.024 *** | 0.014 *** |
| | (33.002) | (14.299) | (62.964) | (29.194) | (14.042) |
| Constant | 10.615 *** | 10.618 *** | 10.458 *** | 10.537 *** | 10.514 *** |
| | (1117.656) | (1032.164) | (984.890) | (1018.480) | (1079.082) |
| Control other variables | Yes | Yes | Yes | Yes | Yes |
| *Year-fixed effect* | Yes | Yes | Yes | Yes | Yes |
| *Jiedao-fixed effect* | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 150,400 | 150,400 | 150,400 | 150,400 | 150,400 |
| $R^2$ | 0.806 | 0.775 | 0.780 | 0.784 | 0.815 |

Note: (1) *** indicates significance at 1% level; ** indicates significance at 5% level. (2) The numbers in parentheses indicate robust t-statistics. (3) Only the main control variables detailed in this paper are shown.

According to the results in Column (1) of Table 4, we see that the premium of service quality in real estate value was different between high housing prices and low housing prices. Specifically, property service with high housing price has an extra 2.7 percent premium. The empirical results show that good service quality shows a higher premium with higher housing prices.

In addition, there is a similar conclusion about housing area: the result in Column (2) shows that the premium in housing price is 1.2 percent when serviced houses have smaller area, and the premium is 4.9 percent when serviced houses have larger area. This means good service quality shows more premium, when houses have a larger area.

Column (3) of Table 4 reports the heterogeneous effects between new and old houses, including all control variables, the $R^2$ explained 78.2 percent of the variation in housing prices. The coefficient of the cross-item *D_old* × *PS* in Column (3) was −0.022. The empirical results show that newer houses have an extra 2.2 percent premium in housing price. That

is, the contribution of service quality to real estate value is greater when serviced houses are relatively newer.

In addition to the above grouping by housing price, housing area, housing age, another dimension is based on whether the house is further away from the city center. We use the dummy variable *D_suburbs* to indicate it. The coefficient of the cross-item *D_suburbs* * *PS*, as shown in Column (4), is 0.027 and statistically significant at the 1% level. This means that good service quality shows more premium, when the house is further away from the city center.

## 5. Discussion

Similar to previous studies by scholars, in general, this current study confirms that service quality has a premium in real estate value [9,10,37]. According to their research, service quality increases housing prices by 2.9 percent [21] to 11 percent [9]. Specifically, Dai et al. [9] found that for every 1 yuan/$m^2$/month increase in property management fee, Nanjing's housing prices rise by 11 percent, estimated by a semilogarithmic hedonic price model. Li et al. [10] collected data on 12,137 housing transactions in 3186 closed commercial communities, analyzed them through a semilogarithmic feature price model, and found that an increase of 1 yuan/$m^2$/month in property management fee can bring a 6.8 percent increase in the housing price. Wen et al. [21] divided the community property service quality into five grades through questionnaires: quite good, good, fair, poor, and quite poor, to obtain residents' satisfaction with the service quality, and indicated that improving the property service quality will bring about a 2.9 percent increase in housing prices. Xiao et al. [29] used 18,551 transaction data from 660 communities and analyzed them with a semilogarithmic hedonic price model; every increase in the level of property service causes the housing price to rise 4.2 percent. Liu et al. [37] proposed that the housing prices of the top ten property companies are 9.57 percent higher than those of ordinary property companies. In this paper, we used 155,845 Beijing housing transaction data from 2012 to 2019, and obtained the following through a semilogarithmic hedonic price model: service quality measured by a property management fee and top-tier property service can bring a 3.6 and 3 percent premium to the housing price, respectively.

Different from previous research, we first confirm that compared with no service, houses with service do have higher value, which is ignored by most research. Then, distinguished from one indicator to measure service quality in previous studies, we use two indicators to make the result more complete. The two indicators are property management fee and whether service is provided by top-tier companies. We find that the better the service quality or the service provided by top-tier companies, the higher the real estate value-added. In addition, we consider the changes in premium of good service quality in real estate value over time and the heterogeneity, which are not taken into account by previous research. Our study shows that the premium of good service quality in real estate value keeps increasing from 2012 to 2019. By the end of 2019, China had 848.43 million permanent urban residents, and the urbanization rate had exceeded 60 percent. According to the National Bureau of Statistics, the per capita disposable income of Urban residents in China was 24,565 yuan in 2012 and 42,359 yuan in 2019, a total increase of 72.45 percent in the eight years. With the progress of urbanization, residents have an increasing demand for high-quality property service and urban management in recent years and they are yearning for a higher quality of life. Besides, we find that good service quality shows more premium, when the house has a higher price, larger area, younger age, or is further away from the city center. A possible reason is that more basic public services (such as infrastructure) are placed in the city center than in other areas. Therefore, to make up for the lack of public services, residents far from the city center pay more attention to the property service quality. In other words, public service and property service in the community are linked, and complementary in the field of urban management.

However, this paper has certain limitations, and we will improve theses in the next research. Specifically include the following four aspects: (1) First, some characteristics

are difficult to quantify effectively at this stage (such as residents' subjective feelings of provided service, the demographic composition of the community, community safety, etc.), which are not included in the current empirical model. Thus, our follow-up research will combine subjective surveys to analyze the willingness to pay and heterogeneous demands of residents of different ages or income levels. (2) Second, we will introduce case studies to analyze the relationship between good service and real estate value. (3) Third, we will also establish more indicators to measure the service quality, not just use property management fee. We will establish evaluation indicators for the cleanliness, neighborhood atmosphere, professional quality of property service personnel in the community and so on. (4) In fact, property service companies are generally not replaced all year round. However, we can still find a few special cases that the company is changed. As our current sample is not enough, we are we are researching and collecting more cases. We will use DID model to quantify the change of housing price before and after switching property service company, so as to confirm the causal relationship between service and housing price, which is not included in the current empirical study due to the lack of enough cases and data.

## 6. Conclusions

In order to explore the premium of property service quality in real estate value, this paper selected 155,845 housing resale transaction samples in Beijing's urban six districts from 2012 to 2019 and used a semilogarithmic hedonic price model to conduct empirical analysis. The following are the main conclusions.

In the first part, we confirm that good service quality does show premium in real estate value, using two indicators respectively: property management fee [9] and whether the service is provided by top-tier companies [10]. Specifically, compared with no service, houses with service do have higher value. Secondly, the better the service quality, the higher the real estate value-added. Thirdly, top-tier service quality shows more premium in real estate value. Through the empirical research in this paper, we have found that when the property service quality is measured by property management fee, the premium is 3.6 percent; we used the variation about whether the property service company is top-tier (*D_top100*) to distinguish the qualification of the company, and the premium is 3 percent. In the second part, we have found the premium of good service quality in real estate value keeps increasing from 2012 to 2019. In the third part, we have found that the premium of good service quality in real estate value is heterogeneous. When houses are with a higher price, larger area, younger age, or further away from the city center, good service quality has more premium in real estate value.

These empirical results are of broad policy relevance in the field of land use and urban management. The essence of premium in real estate value is residents' willingness to pay [50], reflecting their real demand for higher quality of service. On the one hand, policymakers should increase the investment in property service in the fiscal expenditures of urban management. Property service is one of the most basic in urban management and the closest to residents, and will play an increasingly important role in urban management. On the other hand, policymakers should integrate basic public services (e.g., infrastructure) with community management, which are complementary to each other. Specifically, the city center is equipped with relatively richer infrastructure and public service resources, so residents in the city center may not have high requirements for high-quality service in the community. However, the public service resources in the suburbs are relatively poor, and residents have higher willingness to pay for the service quality in the community. Our empirical results have proved this, which is that service quality has more premium, when the house is further away from the city center. Furthermore, on the basis of limited land resources [11,51], spatial planning according to residents' demand for property services can promote the city's development [52]. Therefore, basic urban public services (such as infrastructure) and property services in communities should be considered comprehensively and arranged in an overall way, so as to formulate more demand-oriented and targeted urban management and planning policies.

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## Appendix A

We divided the sample into 2 km × 2 km grids to control the grid-fixed effect. Compared with the Jiedao-fixed effect in manuscript, the grid-fixed effect makes the scope of comparison smaller and more effective. It is worth mentioning that both Jiedaos and grids are spatial partitions, and grids are smaller in scope. As can be seen from the regression results in Table A1 of the appendix, compared with the results in Table 2, the coefficient is slightly different, but it does not affect the main conclusion.

**Table A1.** Empirical results of the premium of good service quality in real estate value after control the grid-fixed effect.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Ln_price* | *Ln_price* | *Ln_price* | *Ln_price* |
| *D_PS* | 0.050 *** | | | |
| | (18.465) | | | |
| *PS* | | 0.031 *** | 0.087 *** | |
| | | (49.292) | (45.637) | |
| $PS^2$ | | | −0.009 *** | |
| | | | (−29.156) | |
| *D_top100* | | | | 0.033 *** |
| | | | | (14.242) |
| *Age* | −0.019 *** | −0.015 *** | −0.014 *** | −0.019 *** |
| | (−114.817) | (−83.437) | (−78.349) | (−113.426) |
| *Area* | −0.002 *** | −0.002 *** | −0.002 *** | −0.002 *** |
| | (−54.172) | (−60.959) | (−62.600) | (−52.478) |
| *Bedroom* | 0.043 *** | 0.049 *** | 0.051 *** | 0.042 *** |
| | (36.356) | (40.402) | (42.395) | (34.783) |
| *Living_room* | 0.055 *** | 0.057 *** | 0.056 *** | 0.055 *** |
| | (52.450) | (53.518) | (53.184) | (51.640) |
| *Dis_tam* | −0.035 *** | −0.030 *** | −0.035 *** | −0.035 *** |
| | (−31.422) | (−26.307) | (−30.704) | (−31.017) |
| *Dispark* | −0.032 *** | −0.028 *** | −0.033 *** | −0.032 *** |
| | (−21.551) | (−18.800) | (−21.972) | (−21.086) |
| *Subway* | 0.066 *** | 0.063 *** | 0.058 *** | 0.067 *** |
| | (42.010) | (39.879) | (36.838) | (42.162) |
| *Education* | 0.078 *** | 0.079 *** | 0.083 *** | 0.071 *** |
| | (34.299) | (32.088) | (33.773) | (28.797) |
| *Greenrate* | 0.443 *** | 0.385 *** | 0.365 *** | 0.467 *** |
| | (52.802) | (43.093) | (40.945) | (53.005) |

**Table A1.** *Cont.*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Plotratio* | −0.024 *** | −0.024 *** | −0.025 *** | −0.024 *** |
| | (−47.557) | (−46.030) | (−47.563) | (−45.047) |
| Constant | 10.770 *** | 10.644 *** | 10.710 *** | 10.831 *** |
| | (474.056) | (457.541) | (460.721) | (464.930) |
| *Year-fixed effect* | Yes | Yes | Yes | Yes |
| *Grid-fixed effect* | Yes | Yes | Yes | Yes |
| *Observations* | 155,845 | 150,400 | 150,400 | 150,400 |
| $R^2$ | 0.778 | 0.783 | 0.785 | 0.778 |

Note: (1) *** Indicates significance at 1% level.

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# The Spatiotemporal Non-Stationary Effect of Industrial Agglomeration on Urban Land Use Efficiency: A Case Study of Yangtze River Delta, China

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**Abstract:** All over the world, Industrial agglomeration has become a key to improve the efficiency of urban land use and regulate the process of urbanization. Industrial agglomeration, as a universal economic geographical phenomenon, has been extensively studied, but few scholars have discussed the relationship between industrial agglomeration and urban land use efficiency. Based on this, after classifying the type of agglomeration externalities, our study uses OLS and GTWR models to explore the complex mechanism of interaction between industrial agglomeration externalities and urban land use efficiency, especially the spatiotemporal non-stationary characteristics. We found that the impact of industrial agglomeration externalities on urban land use efficiency is significantly unstable in time and space, and the coexistence, substitution and aging mechanism of agglomeration externalities among different types were also observed. Our research can provide reference for city managers to formulate reasonable industrial policies and enterprises to choose the location. Meanwhile, our research has made some contributions to the academic research on urban land use efficiency.

**Keywords:** industrial agglomeration; urban land use efficiency; spatio-temporal non-stationary; GTWR; Yangtze River Delta

## 1. Introduction

Urban land use efficiency (ULUE) is a comprehensive topic integrating the economy, society, ecology and sustainable development, which has been of high concerned by government departments and scholars [1–3], especially under the background of biodiversity loss [4], soil pollution [5,6], excessive $CO_2$ emission [7–9] and so on. Since 1978, with the rapid advancement of urbanization, China's urban construction land has expanded rapidly [10,11], from 6720.0 $km^2$ in 1986 to 58,355.3 $km^2$ in 2020 (China Urban Construction Statistical Yearbook 2021). The continuous expansion of urban construction land occupies a large amount of agricultural and ecological land [12,13], leading to the increasingly prominent contradiction between regional development, agricultural land protection and ecological conservation and, thus, posing a serious threat to national food security and regional ecological environment [14]. In essence, these problems are directly or indirectly related to inefficient use of urban land [15]. In this context, it is objectively required to improve the efficiency of urban land use efficiency to reduce the occupation of agricultural land [16]. At the same time, it is predicted that the degree of global urbanization will reach 69% in 2050 [17]. In the face of the unstoppable wave of urbanization, how to optimize the urbanization process and achieve sustainable urban development by improving the utilization efficiency of urban land is an urgent issue for all countries [18–22].

Scholars have carried out rich studies on urban land use efficiency, mainly focusing on the connotation, measurement and influencing factors of urban land use efficiency. In

terms of connotation, it generally focuses on the understanding from the perspective of economics, which represents the ratio between the effect of achieving goals and the resources consumed [23]. With the aggravation of habitat destruction and environmental pollution, urban land use must comprehensively consider economic, social and environmental factors to maximize economic, social and ecological utility [24]. Therefore, undesirable outputs must be considered for the evaluation of land use efficiency [25].

In recent years, scholars and government departments have paid more attention to the driving factors and mechanism of urban land use efficiency. There have been abundant studies on the driving factors of ULUE. The most obvious driving factors of ULUE come from the Cobb–Douglas production function. Capital intensity, labor intensity and land productivity are thought to be the direct determinants of ULUE [26,27]. Masini explored the nexus between economic growth and land use efficiency in 417 cities in 17 European countries and found that the richer the city, the higher the land use efficiency [3]. The second group focuses on some key economic and social factors, for example, urbanization and industrialization [28]. Furthermore, the availability of life facilities, such as transportation, electricity and education, is critical to ULUE [29]. In addition, ULUE is also thought to be related to factors like the heterogeneity of firms [30], Development strategies based on "special zones" [31] and so on. Generally speaking, globalization, marketization, urbanization and decentralization are considered to be the most important factors driving the change of ULUE, especially in developing countries [32–35]. Globalization, through foreign investment and international trade, has integrated China's economy into the world economy and participated in global competition, which has greatly increased the demand for land and helped local enterprises develop advanced production technology and management experience [36]. Market-oriented reform has gradually broken the distortion of land market caused by administrative dominance, embodied the economic value of land and improved ULUE [37]. At the institution level, the land reform characterized by marketization has brought about the improvement of land value-added and the efficiency of land use [38]. As one of the important characteristics of urbanization development, it was found that increasing population density can effectively avoid excessive urban expansion [18]. In addition to population, the adjustment of industrial structure is also considered to promote the improvement of ULUE, because it can timeously eliminate backward production capacity and guide investors to turn to high value-added and high-tech industries [34,39–41]. The completeness of infrastructure, especially transportation facilities, affects the layout of enterprises in surrounding cities through the spillover effect, thus improving ULUE [42–44]. As for the decentralization reform, local governments have gained certain political and economic autonomy, which has greatly promoted the development of local industries. However, it is also easy to encourage local protectionism and result in the convergence of industries across the country [32].

In addition to the above driving factors, more and more scholars have begun to emphasize the impact of industrial agglomeration on ULUE [45,46]. The externalities brought by industrial agglomeration can benefit the whole region. In fact, with the development of the industrial division of labor and trade globalization, industrial agglomeration is widespread in both developing and developed countries [47–49]. For example, in China, to cope with the increasing costs of land, labor and other factors, China's industrial layout has shown a very obvious agglomeration feature, especially after its accession to the WTO [50]. As the spatial carrier of industrial agglomeration, the establishment of a large number of development zones further promotes industrial agglomeration and improves the efficiency of urban land use [45,51]. In fact, with limited land resources, only by optimizing industrial layout and structure and improving the efficiency of land use can we achieve economic development goals [52]. Nowadays, it is generally accepted by scholars to divide industrial agglomeration externalities into Marshall externalities, Jacobs externalities and Porter externalities [53,54]. Existing studies have shown that agglomeration externalities have a significant impact on land use efficiency [46,55]. However, there is a lack of a systematic framework, especially from the perspective of three externalities of industrial

agglomeration, to discuss the influence mechanism of industrial agglomeration on ULUE. Moreover, in recent years, with the popularity of variable coefficient models, the characteristics of spatio-temporal non-stationarity of agglomeration externalities have also been observed [55,56]. Then, does the impact of industrial agglomeration externalities on ULUE also show non-stationary characteristics in time and space?

Based on the above analysis, the following problems need to be solved: What are the impacts of different types of industrial agglomeration externalities on ULUE, and how do they work, individually or in more complex relationships? Is this interaction stable in time and space? In order to solve these problems, this study selected the urban agglomeration in the Yangtze River Delta of China as an example to explore the influence mechanism between industrial agglomeration externalities and ULUE by using the GTWR model. While making some contributions to the research in the field of urban land use efficiency, this study can provide meaningful enlightenment for decision-makers to formulate more reasonable industrial policies and also provide a certain reference for enterprises in the location choice. Specifically, the structure of this paper is as follows: the second part constructs the conceptual framework of the influence mechanism of agglomeration externalities on ULUE; the third part presents data and methods; the fourth part presents the results; the fifth part is the discussion; the final part is the conclusion of this paper.

## 2. Mechanism of Industrial Agglomeration Externalities on ULUE

New Economic Geography believes that spatial agglomeration of industries can integrate various market resources, accelerate factors flow, reduce transaction costs through deepening division of labor, improve industrial production efficiency, and promote the sharing of development achievements by neighboring regions through the spatial spillover effect [57]. From the perspective of differences, agglomeration externalities can be divided into three types. The first type is MAR externality, also known as Marshall externality or specialization externality. Specialization externality indicates a situation in which any company benefits from local companies in the same industry, and with the development of a specialization economy, cities will increasingly specialize, and the benefits brought by their own industrial agglomeration will exceed the costs caused by commuting and congestion, improving the overall performance of the industry [58]. Combining the ideas of Arrow and Romer, Gleaser pioneered the MAR model to describe this scenario. The model points out that the agglomeration of the same industry in a region promotes the knowledge spillovers between companies, which accelerates the technological progress of the industry and ultimately promotes economic growth. The resulting agglomeration economy is known as a dynamic externality, which is considered to be an engine of economic growth [53,58–60]. The Marshall externality shows that the geographic agglomeration of industries can increase the efficiency of industrial production, improve the performance of industries in the whole region and improve the local ULUE through three paths: reducing transport costs, creating a labor pool (reducing training costs and counteracting the risk of unemployment) and promoting the exchange and transmission of knowledge [61].

The second type of agglomeration externality is often referred to as the diversity externality or Jacobs externality. Jacobs believes that the exchange and collision of knowledge and ideas between different industries can generate new knowledge and ideas, promote industrial restructuring and give rise to new industries and that the creation of new industries and new jobs can promote a whole set of division of labor, expand the scale of the city and ultimately realize the development of the city, which makes the city full of vitality [62]. Combes takes this a step further, arguing that only technologically connected industries can fulfil the expectations of diversity externalities on urban growth, as only similar sectors can absorb intermediate products and innovative knowledge [63]. The Jacobs externality affects urban land use in many ways, one of which is improving labor productivity [64]. The improvement of labor productivity not only increases the intensity of land inputs and use, but also the income per unit of land. On the other hand, with the phased development of the industry, the transition from vertical to horizontal division of labor will

inevitably occur, resulting in a corresponding development of service industries, especially the diversified agglomeration of productive services, which implies an upgrading of the industrial structure and ultimately promotes the optimization of land use structure. In addition, the agglomeration of diversified industries will be more conducive to technology transmission and knowledge spillover, thus improving the efficiency of land factors [65].

Another important externality of industrial agglomeration was proposed by Porter in 1990, and this type of externality is known as the Porter externality or competition externality [66]. Competition is better for growth, Porter argues, and intense competition in the same market provides an important incentive for innovation, which, in turn, constantly drives industrial upgrading and new processes. If an enterprise or even a country wants to maintain its competitive advantage globally, it must constantly promote innovation, which benefits from the intense competition among enterprises. The more intense the competition, the more conducive it is to the comprehensive development of enterprises and the integration of enterprises into the global economy. Competition among multiple enterprises in the same industry has been proven to be beneficial to the efficiency of land production in urban agglomerations [67]. It is important to note, however, that the effect of competition on growth is non-linear [63]. The Schumpeter model emphasizes this mechanism: intense competition motivates enterprises to make important R&D investments, but if the continuity of innovation is too fast, the return from R&D is low, which reduces the amount of R&D and, in turn, has a negative impact on innovation [68,69].

It should be pointed out that the agglomeration externalities will be uneven in time and space, as the industrial structure will be obviously spatially heterogeneous due to historical and natural conditions. Uneven inter-provincial development exists even in the urban agglomeration of the Yangtze River Delta, which promotes regional integration. Anhui Province, which still has a large proportion of primary industries, is not considered to be well integrated into the integration process of the Yangtze River Delta. In contrast, superior location conditions and more favorable industrial policies can attract various industries to take root in Jiangsu, Zhejiang and Shanghai, and therefore, these regions can have a more diversified industrial structure. In addition, there is always an optimal level of factor agglomeration due to both congestion and agglomeration effects in cities [70]. Excessive agglomeration may have a negative impact on land use efficiency [71]. The theoretical framework of the impact of industrial agglomeration externalities on ULUE is shown in Figure 1.

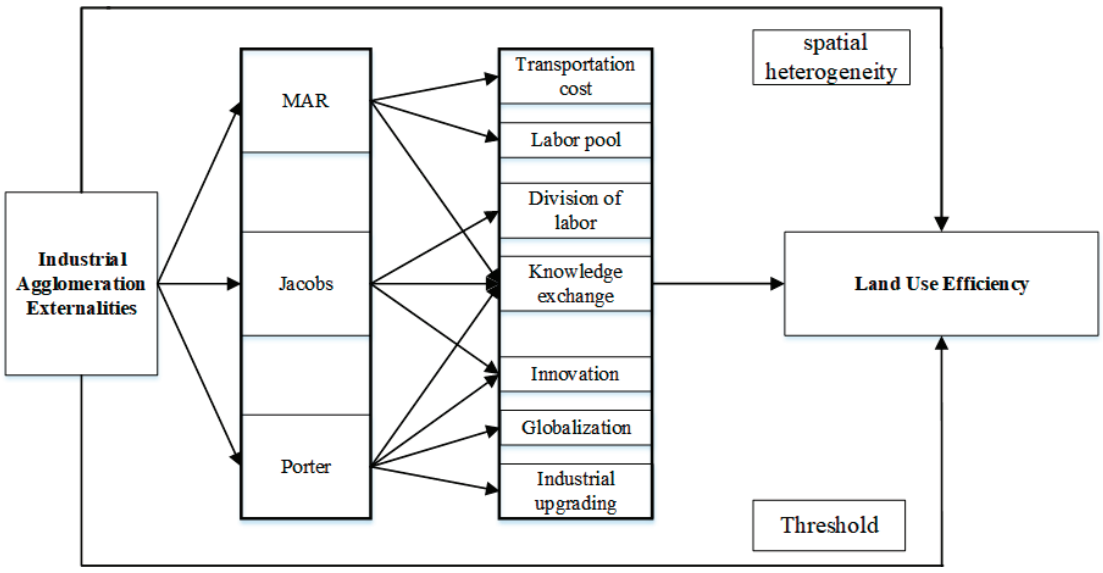


**Figure 1.** Theoretical framework of Industrial Agglomeration Externalities affecting ULUE.

## 3. Methods and Data

### *3.1. Study Area*

Located between 29°20′–32°34′ north latitude and 115°46′–123°25′ east longitude, the Yangtze River Delta region is a flood plain formed before the Yangtze River enters the sea, bearing 41 cities in Shanghai, Jiangsu, Zhejiang and Anhui provinces (see Figure 2). As these regions are adjacent to each other and have similar cultural backgrounds, they have become increasingly economically integrated through human and economic ties. Today, this region has become the largest and most comprehensive economic center in China, as well as one of the six city clusters in the world [72]. As the driving force of China's economic growth, the industrial structure of the Yangtze River Delta is dominated by the second and third industries [73] and shows a high degree of spatial agglomeration [74].

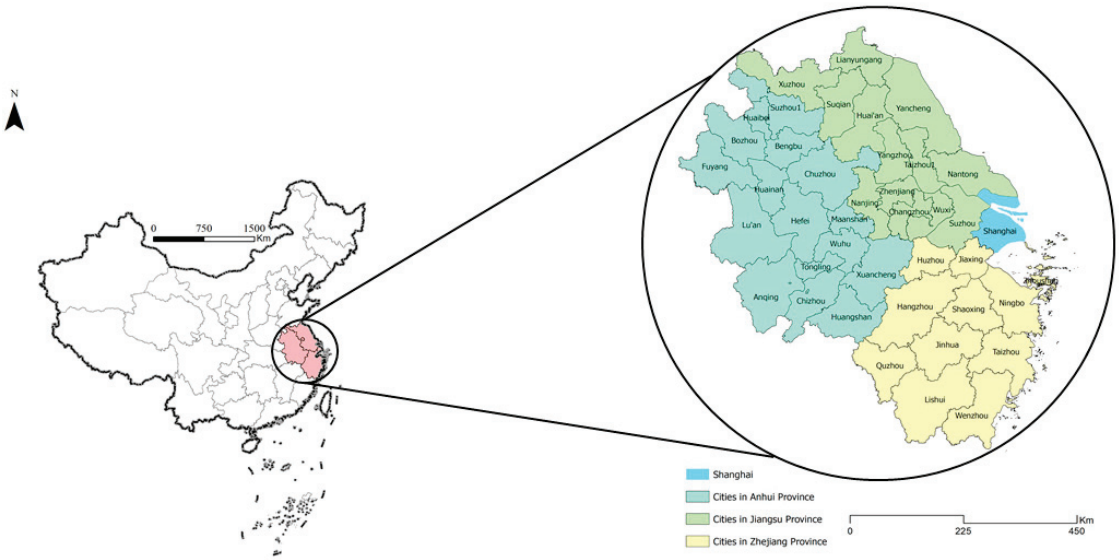


**Figure 2.** Location of the Study Area.

The selection of the Yangtze River Delta urban agglomeration as the research area is mainly based on the following three considerations: (1) the Yangtze River Delta is densely populated and has complete industries. Therefore, a reasonable industrial classification can be carried out to meet the premise of the study; (2) The Yangtze River Delta is composed of three provinces and one city. It is home to both highly developed cities, such as Shanghai, and many underperforming third-tier cities, making the findings more general based on the Yangtze River Delta; (3) Although the Yangtze River Delta city cluster is economically active and industrially prosperous, the unreasonable industrial structure and slow industrial transformation are still important problems plaguing the urban development of the Yangtze River Delta [74]. Therefore, how to carry out industrial layout is a key issue worth studying.

### *3.2. GTWR Model*

The traditional GWR model takes extra spatial dimensions into account on the basis of the ordinary OLS regression, while the GTWR model introduces a temporal dimension on the basis of GWR model. Therefore, the GTWR model can fully consider the non-stationary property of time and space and has incomparable advantages over ordinary OLS fixed coefficient estimation, which can produce more accurate estimation effects. Therefore, this paper adopts the GTWR model to estimate the impact of different externalities of industrial agglomeration on ULUE. The basic form of the GTWR model is as follows:

$$y_i = \beta_0(u_i, v_i, t_i) \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i) x_{ik} + \varepsilon_i \quad (1)$$

where $y_i$ is the observed value; $(u_i, v_i, t_i)$ are the spatiotemporal co-ordinates of the i-th observation point. $\beta_0(u_i, v_i, t_i)$ is a regression constant; $\beta_k(u_i, v_i, t_i)$ is the regression coefficient of the k−th independent variable. $x_{ik}$ is the value of the k-th independent variable at the i-th observation point, and $\varepsilon_i$ is the residual error.

The key of the. GTWR model is to determine the spatio-temporal weight matrix and bandwidth. According to the research method of Huang. et al., the gaussian function is used to calculate the spatio-temporal weight matrix, the specific form is as follows [75]:

$$w_{ij} = exp\left(-\frac{\left(d_{ij}^{S}\right)^2 + \left(\frac{\mu}{\lambda}\right)\left(d_{ij}^{T}\right)^2}{h_{ST}^2}\right) \tag{2}$$

The cross validation ($CV$) method is used to select the bandwidth. When $CV$ reaches the minimum value, the corresponding $b$ is the optimal bandwidth, which is expressed as follows:

$$CV = \sum_{i}^{n} [Y_i - \hat{Y}_i(b)]^2 \tag{3}$$

### *3.3. Variable Selection and Data Processing*

#### 3.3.1. ULUE Evaluation

Before evaluation, it is necessary to define "city". According to the National Bureau of Statistics of the People's Republic of China, a city refers to an urban area with the approval of The State Council of the People's Republic of China for the establishment of a city system. China's National Bureau of Statistics provides two statistical standards for cities' economic and social indicators: Total City and Districts under City. In this study, "City" refers to "Total City", namely, the whole city.

In terms of ULUE measurement, the Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are two mainstream methods to measure urban land use efficiency. Among them, SFA is an estimation method with a specific function form. Generally, it uses the maximum likelihood method for estimation, which has the advantages of not being affected by extreme values and considering residual terms when measuring absolute efficiency [76]. DEA, originally invented by Charnes, is a non-parametric method used to measure the relative efficiency of a set of decision-making units (DMU). Since there is no need to set a specific function form, DEA avoids subjective weighting and is widely used in various performance evaluations [77]. In comparison, SFA has more advantages in measuring productivity, but this model is only applicable to projects with single unit output, and it fails to compare the economic efficiency and environmental efficiency of multi-output projects [78]. In view of this, the DEA method is more advantageous in evaluating the efficiency of land use as a synthesis of economic, social and environmental factors.

However, the classical DEA model does not take into account undesired factors, such as wastewater, exhaust gas and soot, but these factors are widely present in actual production activities and constitute the part that people do not want to produce [25], especially in the context of China's policy of high-quality development and harmonious coexistence between humans and the environment, and undesirable outputs must be considered in the evaluation system of production efficiency. The SBM model can well solve the efficiency evaluation problem of DMU considering undesirable outputs [79], but general SBM cannot distinguish the difference between multiple efficient DMU with an efficiency of 1. Therefore, this paper used a super-efficient SBM model to evaluate the efficiency of each unit in the study area, which is shown below:

$$min\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{\overline{x}}{x_{ik}}\right)}{\frac{1}{r_1+r_2}\left[\sum_{S=1}^{r_1}\frac{\overline{y^d}}{y_{sk}^d} + \sum_{q=1}^{r_2}\frac{\overline{y^u}}{y_{qk}^u}\right]} \tag{4}$$

$$\begin{cases} \overline{x} \geq \sum\limits_{j=1,\neq k}^{n} x_{ij}\lambda_j; \overline{y^d} \leq \sum\limits_{j=1,\neq k}^{n} y_{sj}^d \lambda_j \\ \overline{y^d} \geq \sum\limits_{j=1,\neq k}^{n} y_{qj}^d \lambda_j; \overline{x} \geq x_k \\ \overline{y^d} \leq y_k^d; \ \overline{y^u} \geq y_k^u; \\ \lambda_j \geq 0, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \\ s = 1, 2, \ldots, r_1; q = 1, 2, \ldots, r_2; \\ \sum\limits_{j=1}^{n} \lambda_j = 1 \end{cases} \tag{5}$$

where $\rho$ represents urban land use efficiency (ULUE); $n$ represents decision units; $m$ represents inputs; $r_1$ represents expected outputs; $r_2$ represents undesirable outputs and $x, y^d, y^u$ are elements in the corresponding input matrix, desired output and undesired output matrix.

In this paper, construction Land area (Land), Capital investment in fixed assets (Capital) and Labor in secondary and tertiary industries (Labor) were selected as input indicators. The output value of secondary and tertiary industries (Output value), Road per capita (Road) and the green area of built-up areas (Green area) were selected as expected output indicators. Wastewater, soot and $SO_2$ emissions were selected as undesirable output indexes. All the above indicators, except the green coverage rate of built-up areas, were from the China Urban Construction Statistical Yearbook, and the data of other indicators were from the CHINA CITY STATISTICAL YEARBOOK, with the years ranging from 2005 to 2016 (as shown in Table 1).

**Table 1.** Statistical description of Input-output indicators.

| Composition of Indicator | | Description | Unit | Sources | N | Mean | Max | Min | SD |
|---|---|---|---|---|---|---|---|---|---|
| Inputs | Land | The area of urban built-up area | $km^2$ | CHINA CITY STATISTICAL YEARBOOK | 492 | 191.6 | 2916 | 13 | 402.5 |
| | Capital | The gross investment in fixed assets | 10,000 yuan | | 492 | 14,800,000.00 | 67,500,000.00 | 756,084.00 | 14,200,000.00 |
| | Labor | The number of jobholders in secondary and tertiary sectors | 10,000 people | | 492 | 68.98 | 724.9 | 6.24 | 90.46 |
| Outputs | Output value | Output value of secondary and tertiary sectors | 100 million yuan | | 492 | 2458 | 28,069 | 84.55 | 3351 |
| | Road | The per capita urban road area | $m^2$ | | 492 | 12.78 | 37.95 | 1.43 | 5.957 |
| | Green area | The green ratio of a built-up area | % | China Urban Construction Statistical Yearbook | 492 | 39.67 | 49.78 | 14.18 | 5.176 |
| Undesirable outputs | Wastewater | The volume of discharged industrial wastewater | 10,000 tons | CHINA CITY STATISTICAL YEARBOOK | 492 | 13,105 | 85,735 | 626 | 15,396 |
| | soot | The volume of discharged industrial soot emissions | tons | | 492 | 55,654 | 496,377 | 1925 | 55,725 |
| | $SO_2$ | The volume of discharged industrial $SO_2$ emissions | tons | | 492 | 25,335 | 131,433 | 971 | 20,369 |

3.3.2. Agglomeration Externalities

As discussed above, this paper classifies industrial agglomeration externalities into three categories, namely specialization agglomeration externalities (MAR), diversity agglomeration externalities (Jacobs) and competition agglomeration externalities (Porter). The premise for the correct measurement of industrial agglomeration externalities is to carry out reasonable industrial classification. Combining the data availability with the research carried out by relevant scholars, the basic idea of industrial classification is to classify according to the three industries. On this basis, according to the United Nations Standard Industrial Classification (SIC), the service industries in the tertiary industry are further subdivided into four categories: Producer Services, Consumer Services, Circulation

Services and Social Services [80]. Ultimately, we obtained six broad industrial categories. The six broad industrial categories and their specific sub-industries are shown in Table 2.

**Table 2.** Classification of industry categories and more specific industries.

| Industry Categories | | Specific Industries |
|---|---|---|
| Primary industry | | Agriculture, forestry, animal husbandry and fishery |
| Secondary industry | | Mining, manufacturing, electricity, gas and water production and supply and construction |
| Tertiary industry | Producer Services | Finance, real estate, leasing and business services |
| | Consumer Services | Accommodation and catering, residential and other services, culture, sports and entertainment |
| | Circulation Services | Transportation, warehousing and postal services, information transmission, computer services and software, wholesale and Retail |
| | Social Services | Scientific research and technical services, qualified exploration, water conservancy environment and public facilities management, education, health and social security and social welfare, public administration and social organizations |

(1) Specialization agglomeration externalities (MAR)

Gleaser published Growth in Cities in 1992, which invented the measurement methods of various agglomeration externalities and systematically discussed the mechanism of various externalities on urban economic growth, which is a classic work in the field of industrial agglomeration externalities [53]. The measurement method of industrial specialization proposed by him is essentially the same as the location quotient widely used in economics. Therefore, the location quotient is used to represent the specialization level of industrial agglomeration, and its calculation formula is as follows:

$$LQ_{ij} = \frac{\frac{L_{ij}}{L_J}}{\frac{L_i}{L}} \tag{6}$$

where $LQ_{ij}$ stands for location quotient, $L_{ij}$ represents the number of employments in industry $i$ in region $j$, $L_j$ represents the total number of employments in all industries in region $j$, $L_i$ represents the total number of employments in industry $i$ within the region and $L$ represents the total number of employments in all industries within the region. In general, when $LQ > 1$, it means that the specialization degree of industry $i$ in region j exceeds the average level of the research area. The larger the value of $LQ$ is, the higher the specialization level of industry is. When $LQ = 1$, it means that the specialization of industry $i$ in region j is equivalent to the average level of specialization of industry $i$ across the whole research region. When $LQ > 1$, it means that the industry specialization is below the average level of industry specialization within the study area.

(2) Diversity agglomeration externalities (Jacobs)

The most common way to measure the agglomeration externalities of industrial diversity is to use the Hirschman–Herfindahl index or its reciprocal form, the reciprocal form of which is shown in Equation (4):

$$DI_i = \frac{1}{\sum s_{ij}^2} \tag{7}$$

where $i$ represents industry, and j represents region. If industry in region j is highly concentrated in a certain category, then $DI_i = 1$, and the index will rise as the increase of regional industry diversification occurs. Combes pointed out that industrial diversity works on the premise that sectors are technologically closely related. In other words, inventions in one sector can be incorporated into production in another industry. Therefore, it is necessary to consider whether the sectors are closely related or not [63]. On this basis, Frenken was

the first to decompose the diversity index based on the entropy index and define the concepts of Related Variety (RV) and Unrelated Variety (UV) [81]. Further decomposition of diversity is undoubtedly beneficial for us to have a deeper understanding of the role of industrial agglomeration, and the level of industrial diversity can be expressed as:

$$\begin{aligned} E_T &= \sum_{s=1}^{s} \sum_{i \in s} P_i \ln\left(\frac{1}{P_i}\right) = \sum_{s=1}^{s} \left[ \sum_{i \in s} (P_s / P_s) P_i \left( \ln(P_s / P_i) + \ln\left(\frac{1}{P_s}\right) \right) \right] \\ &= \sum_{s=1}^{s} P_s \left( \sum_{i \in s} \left(\frac{P_i}{P_s}\right) \ln\left(\frac{P_s}{P_i}\right) \right) + \left( \sum_{s=1}^{s} P_s \ln\left(\frac{1}{P_s}\right) \right) = \sum_{s=1}^{s} P_s E_w + E_A \end{aligned} \tag{8}$$

Among them, $\sum_{s=1}^{s} P_s E_w$ is the product of $E_w$ and $P_s$, where $E_w$ represents the entropy indicator of diversity between broad sectors in an economic system, and $P_s$ represents the share of this sector. $\sum_{s=1}^{s} P_s E_w$ measures the industrial connections within each broad sector, namely the degree of diversity of subdivided industries, called Related Variety (RV); $E_A$ is the entropy indicator of diversity between each industry category, called Unrelated Variety (UV). Unrelated Variety (UV) is not completely devoid of correlation; it represents sectoral diversity where industry correlations are relatively weak.

(3) Competition agglomeration externalities (Porter)

For the measurement of the Porter externality, the main method used by scholars is to use indicators such as the number of employments, the number of enterprises and the value added of industries within a city to find the proportion of the number of enterprises or value added of industries per capita in the local area to that of the whole study area. The higher the index value, the greater is the number of enterprises and the more competitive the city [53,82]. We use the ratio of the number of enterprises in industry j in region i to the added value of that industry divided by the value of this proportion in the whole research area, as shown below:

$$C_{i,j} = \frac{\frac{NBE_{i,j}}{Y_{i,j}}}{\frac{NBE_{g,j}}{Y_{g,j}}} \tag{9}$$

where $NBE_{i,j}$ represents the number of enterprises in industry $j$ in region $i$, $NBE_{g,j}$ represents the number of enterprises in industry $j$ in the whole research area and the corresponding $Y_{i,j}$ and $Y_{g,j}$ represent the industrial added value of enterprises engaged in activities of industry $j$ in region $i$ and the whole research area, respectively.

3.3.3. Control Variables

According to the above discussion, urban land use efficiency (ULUE) is mainly influenced by globalization, marketization, decentralization and urbanization. Accordingly, we adopted per mu foreign direct investment (FDI) to represent the impact of globalization on ULUE; labor flow (LF) as a marketization proxy variable [34]; fiscal revenue and the expenditure ratio of local government (DEC) as a decentralization index and population density (POP), industrial structure (IS) and the number of public buses per 100 people (TP) as the urbanization index. In addition, according to the research of scholars, the average salary of employees (ED) was selected to represent the difference of the general economic development level, and the number of college students (EDU) was selected as the characteristic variable of human capital. In order to ensure the consistency of magnitude among variables, the four variables, namely FDI, POP, ED and EDU, were logarithmically treated. All the data above, except the green coverage rate of the built-up area, were obtained from CHINA CITY STATISTICAL YEARBOOK, with the years range from 2005 to 2016. See Table 3 for details of each variable.

**Table 3.** Statistical description of the selected variables.

| Layer | Layer 2 | Variable | N | Mean | Max | Min | SD |
|---|---|---|---|---|---|---|---|
| Dependent variables | | ULUE | 492 | 0.88 | 1.534 | 0.314 | 0.264 |
| Independent variables | | MAR | 492 | 4.526 | 46.06 | 1.255 | 5.958 |
| | | UV | 492 | 1.199 | 1.558 | 0.667 | 0.181 |
| | | RV | 492 | 0.923 | 1.168 | 0.377 | 0.142 |
| | | Porter | 492 | 1.275 | 2.707 | 0.25 | 0.545 |
| Control variables | Globalization | FDI | 492 | 6.232 | 9.951 | 2.52 | 1.034 |
| | Marketization | LF | 492 | 0.136 | 1.841 | 0.0022 | 0.206 |
| | Government behavior | DEC | 492 | 0.664 | 1.174 | 0.0686 | 0.245 |
| | Urbanization | POP | 492 | 7.694 | 9.149 | 5.226 | 0.535 |
| | | IS | 492 | 0.831 | 2.339 | 0.313 | 0.254 |
| | | TP | 492 | 7.573 | 21.05 | 0.43 | 4.386 |
| | | ED | 492 | 10.54 | 11.7 | 9.318 | 0.461 |
| | | EDU | 492 | 10.84 | 13.63 | 7.445 | 1.102 |

## 4. Results

### *4.1. Spatiotemporal Distribution of ULUE*

According to the calculation of the super-efficiency SBM model, the ULUE of 41 prefecture-level cities during 2005–2016 is shown in Figure 3. The annual average value of ULUE fluctuates around 0.88. Among them, Shanghai has the highest ULUE, with an annual average value of 1.11, followed by Zhejiang province, with an annual average value of 0.96. Jiangsu province and Anhui province have a lower ULUE, with an annual average of 0.85 and 0.84, respectively. After more than a decade of development, the gap of ULUE between cities has narrowed, and cities in the Yangtze River Delta are increasingly tending to develop in a balanced way. Cities with a high rank in hierarchy always have high ULUE, for example, Shanghai, Hangzhou and so on. Due to spatial spillover effects, their surrounding cities' ULUE also perform well. Some cities have got high ULUE, even if they do not have the location advantages. The reason is that these cities are well-known tourist cities in China. On the one hand, they can obtain considerable economic income by relying on tourism resources. On the other hand, for the sustainable development of tourism resources, the local governments of these cities have imposed strict restrictions on pollution emissions, so their ULUE performance is generally good. ULUE in the marginal cities of the study area is significantly lower than that in other cities. These cities are poorly located, far from the economic centers, and have a weak industrial base, resulting in poor performance of urban land use efficiency. From 2005 to 2016, the ULUE of prefecture-level cities showed obvious spatial correlation. In the early years, high ULUE values were scattered, and cities with high ULUE values existed in the northern, central and eastern parts of the study area. After 2014, ULUE showed an obvious trend of agglomeration toward the center and the south.

### *4.2. Spatiotemporal Distribution of Three Agglomeration Externalities*

#### 4.2.1. Spatiotemporal Distribution of MAR

Figure 4 shows the temporal and spatial characteristics of MAR. Cities with high MAR values are mainly concentrated in the northern and western parts of the study area, while those in the middle and southern of the study area have low MAR values. The annual mean value of MAR in Anhui province was 7.37, which was much higher than that in other provinces and cities (2.35 in Zhejiang province, 2.80 in Shanghai and 3.00 in Jiangsu province). This is related to the level of development of prefecture-level cities in the region. Anhui province still faces difficulties in integrating into the regional integration of Yangtze River Delta. Its primary industry still accounts for a large proportion and absorbs a considerable part of the labor force [83]. Cities with low MAR values are mainly located in the central and southern part of the study area. Most of these cities are located on the eastern coast of China, which are the first to initiate market-oriented reforms and participate in

global competition. Thanks to geographical conditions and policy support, these cities have attracted different kinds of enterprises to settle in, so their industrial specialization is not high. In addition, it can be seen that after more than a decade of development, MAR values of most cities in the Yangtze River Delta have decreased significantly, indicating that the overall industries of the urban agglomeration in the Yangtze River Delta tend to develop in a diversified way. By 2016, only several prefecture-level cities, such as Ma'anshan, Huainan and Huaibei, showed highly specialized industrial characteristics.

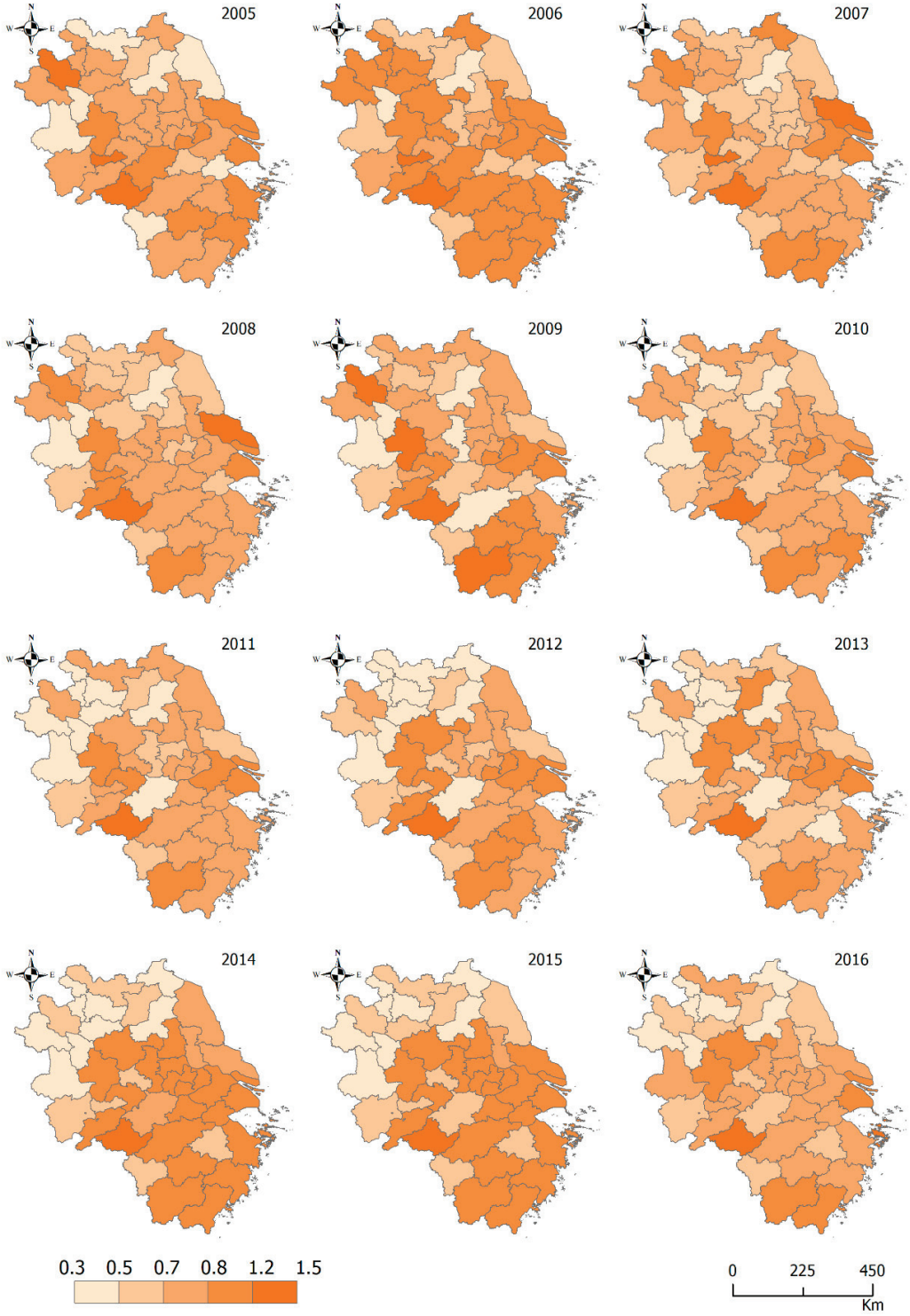


**Figure 3.** Spatiotemporal distribution of ULUE.

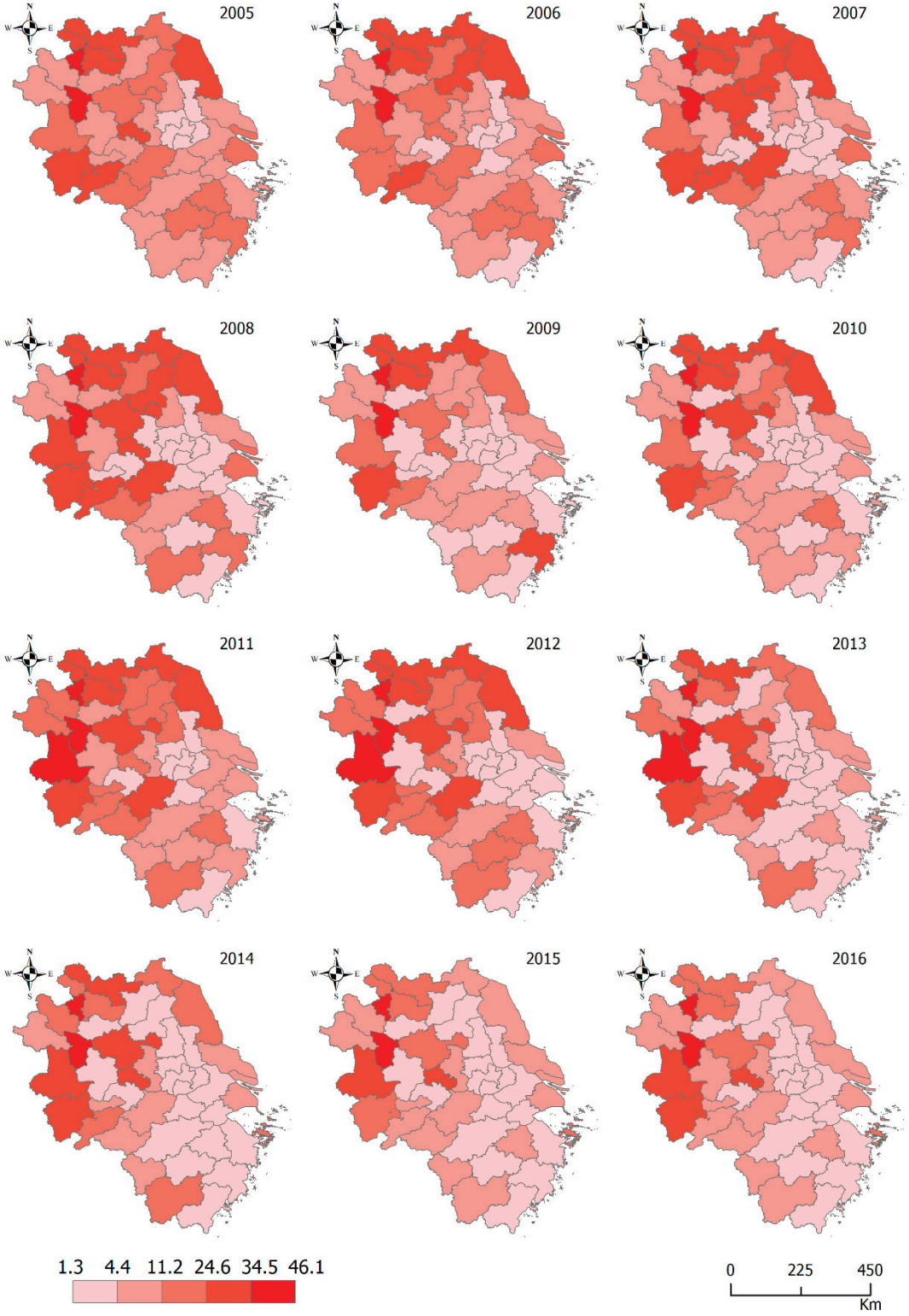


**Figure 4.** Spatiotemporal distribution of MAR.

#### 4.2.2. Spatiotemporal Distribution of UV

Figure 5 shows the spatio-temporal characteristics of UV. In general, the UV difference in the Yangtze River Delta urban agglomeration is small. Shanghai has the highest annual mean UV value of 1.48, followed by Anhui province with 1.25. Jiangsu province and Zhejiang province have relatively close UV values of 1.17 and 1.13, respectively. Specifically,

cities with high UV values are mainly concentrated in Shanghai, the southwest of Anhui province, the northeast of Jiangsu province, the north of Jiangsu province and some cities of Zhejiang Province. After more than a decade of development, UV has not only shifted significantly among the Yangtze River Delta urban agglomerations but has also shown proximity. From 2005 to 2009, the UV high values were significantly concentrated in the north and northeast of the study area, and since 2010, the UV high values have gradually shifted to the southwest, with the UV of Suzhou and Anqing in Anhui province gradually rising, indicating the existence of an inter-provincial industrial transfer phenomenon in the Yangtze River Delta in recent years. Overall, the differences in UV among cities in the Yangtze River Delta have been narrowing, with the annual mean value of UV in the Yangtze River Delta urban agglomeration decreasing from 1.28 in 2005 to 1.17 in 2016. In the past 12 years, the UV gap among provinces has also been narrowing, with Shanghai dropping from 1.52 to 1.50, Jiangsu province from 1.31 to 1.04, Zhejiang province from 1.20 to 1.12 and Anhui province from 1.29 to 1.28. This indicates that the link between the Yangtze River Delta industry sectors has weakened.

#### 4.2.3. Spatiotemporal Distribution of RV

Figure 6 shows the spatio-temporal characteristics of RV. RV fluctuated within the range of 0.38~1.17, with a mean value of 0.92. In terms of provinces, RV fluctuation in Shanghai is the smallest, with an average value of 0.85, a minimum value of 0.80 and a maximum value of 0.92 in 12 years, which indicates that the linkages between industries in Shanghai is the most stable and close. The mean value of RV in Anhui province was the highest in the study range, with a value of 1.00. RV changes in Zhejiang province and Jiangsu province were the most dramatic. The 12-year mean value of RV in Jiangsu province was 0.86, which fluctuated in the range of 0.44~1.12. The mean value of RV in Zhejiang province in 12 years was 0.89, which fluctuated in the range of 0.38~1.11. As can be seen from the characteristics of RV, the industrial structure of Jiangsu and Zhejiang provinces is relatively diversified, but there is a great difference in the tightness of the industrial technology connection between prefecture-level cities. Geographically, RV high values are mainly concentrated in northern Jiangsu province, western Anhui province and central and western Zhejiang Province (e.g., Jinhua and Lishui). RV is generally at a low level in the eastern part of the study area, except Shanghai. High RV values show a trend of migrating to the west, especially after 2008. This shows that Anhui province has begun to pay attention to its own industrial structure and is constantly optimizing its industrial structure, promoting the complementary advantages and joint development of various industries.

#### 4.2.4. Spatiotemporal Distribution of Porter

Figure 7 shows spatio-temporal characteristics of Porter. On the whole, the Porter externality shows obvious center-edge characteristics, and the Porter value in the center of the study area is significantly lower than that in the periphery. On a local scale, the Porter externality shows an obvious spatial agglomeration, forming the "Fuyang-Bozhou-Huaibei-Suzhou1" patch in the northwest, the "Cangzhou-Huangshan-Xuancheng" patch in the west, and the "Wenzhou-Jinhua-Taizhou" patch in the south of the study area. This can be explained by the current situation of the local industry. Wenzhou is the world-famous shoe manufacturing base, which gathers a large number of shoe factories, and the local shoe enterprises are increasingly competitive under the effect of the price mechanism. Yiwu, located in Jinhua, is responsible for the global distribution of small commodities. With the training of the global market and the support of local government, Yiwu's small and medium-sized enterprises have upgraded rapidly and have strong competitiveness. Geographically, the intensity of industrial competition in each province is different. Over a 12-year time span, Shanghai's industrial competition fluctuated the most stably, fluctuating in the range of 0.65 to 0.78, with an average of 0.70. The remaining three provinces experienced a rather severe and unstable industrial competition during the past decade.

However, from an overall perspective, the intensity of the industrial competition in the Yangtze River Delta has eased, with the mean value of Porter dropping from 1.30 in 2005 to 1.28 in 2016, indicating that the industrial competition among prefecture-level cities is in a relatively balanced state and that the strategic promotion of the integration of urban agglomeration in the Yangtze River Delta has been effective.

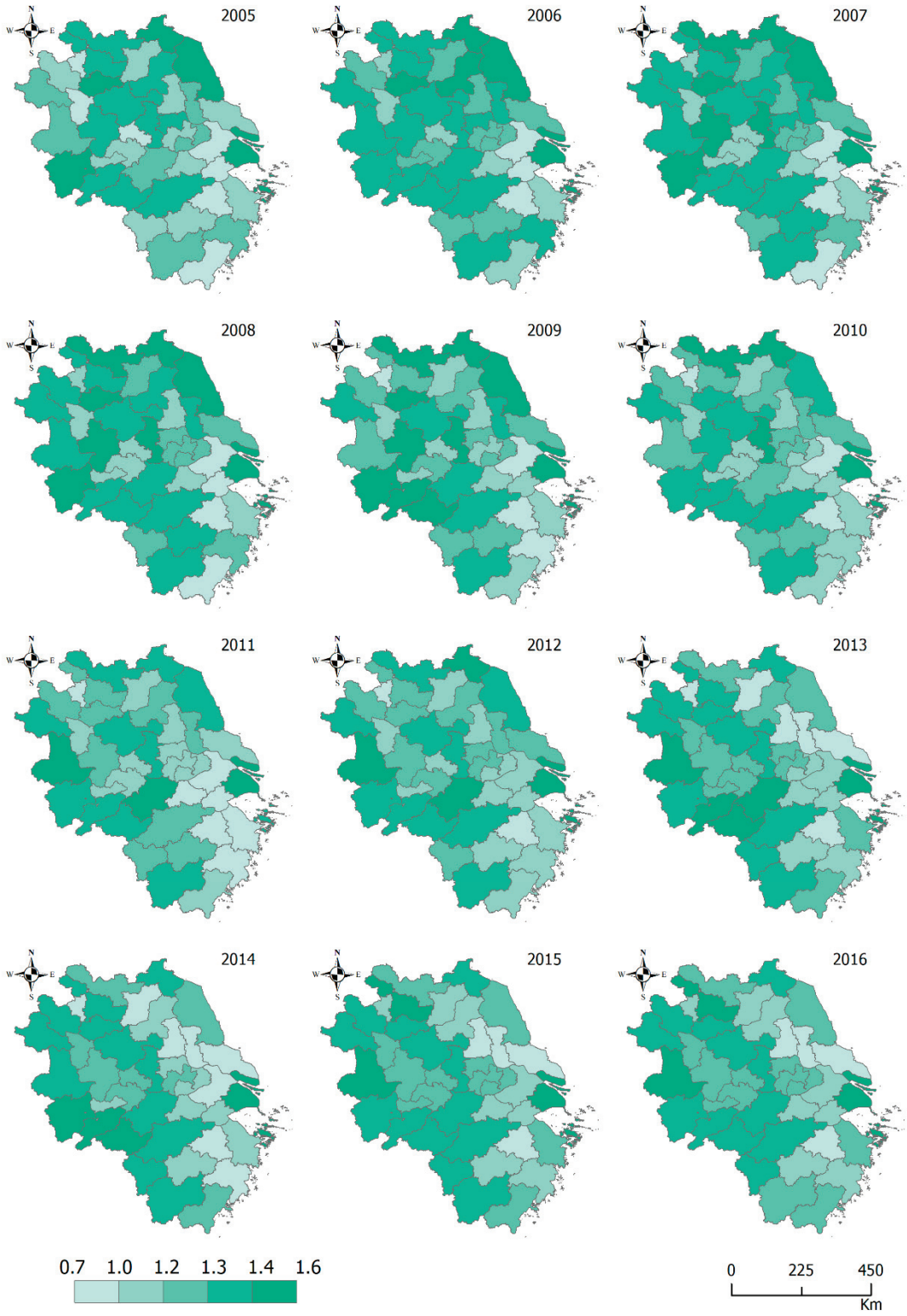


**Figure 5.** Spatiotemporal distribution of UV.

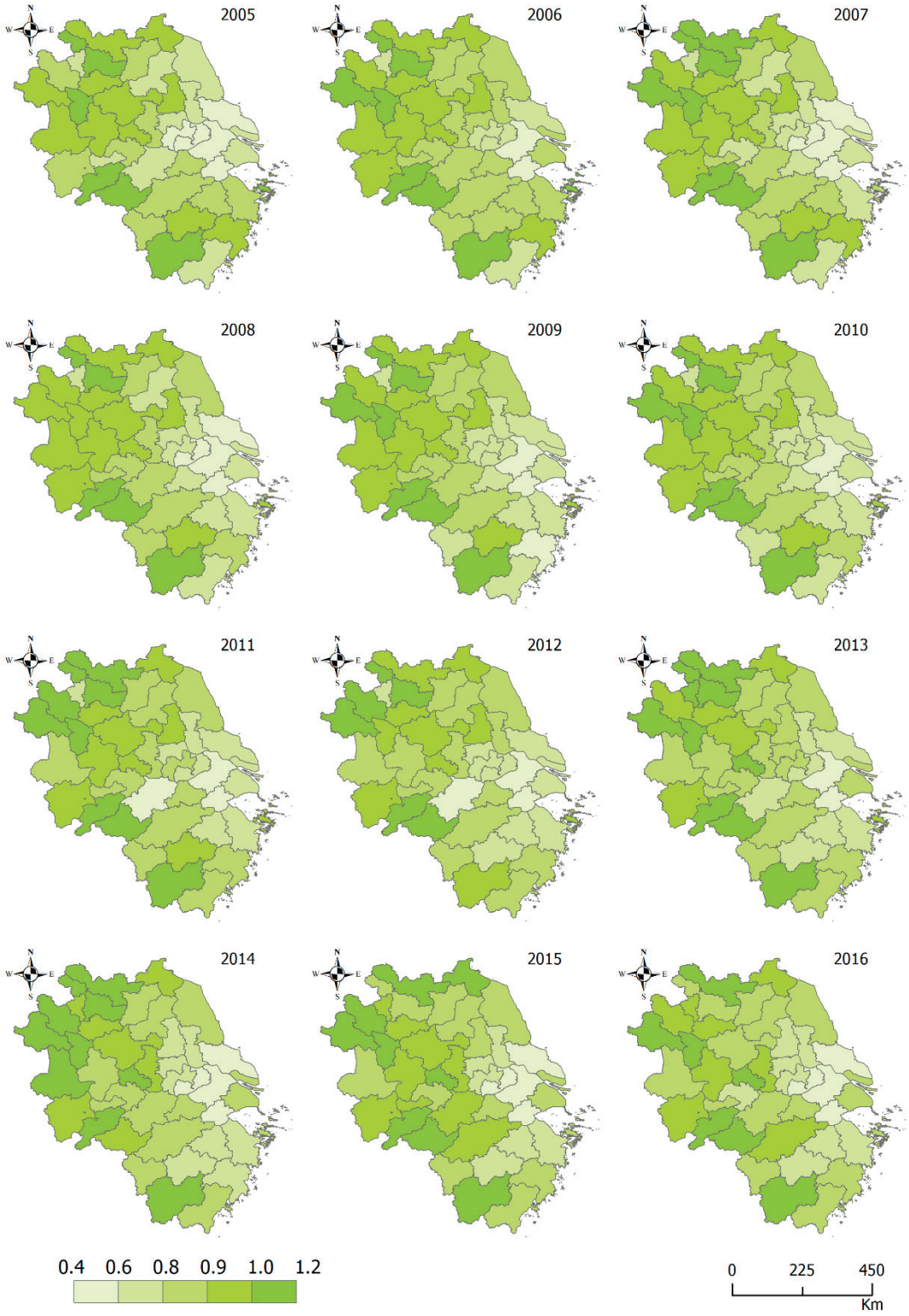


**Figure 6.** Spatiotemporal distribution of RV.

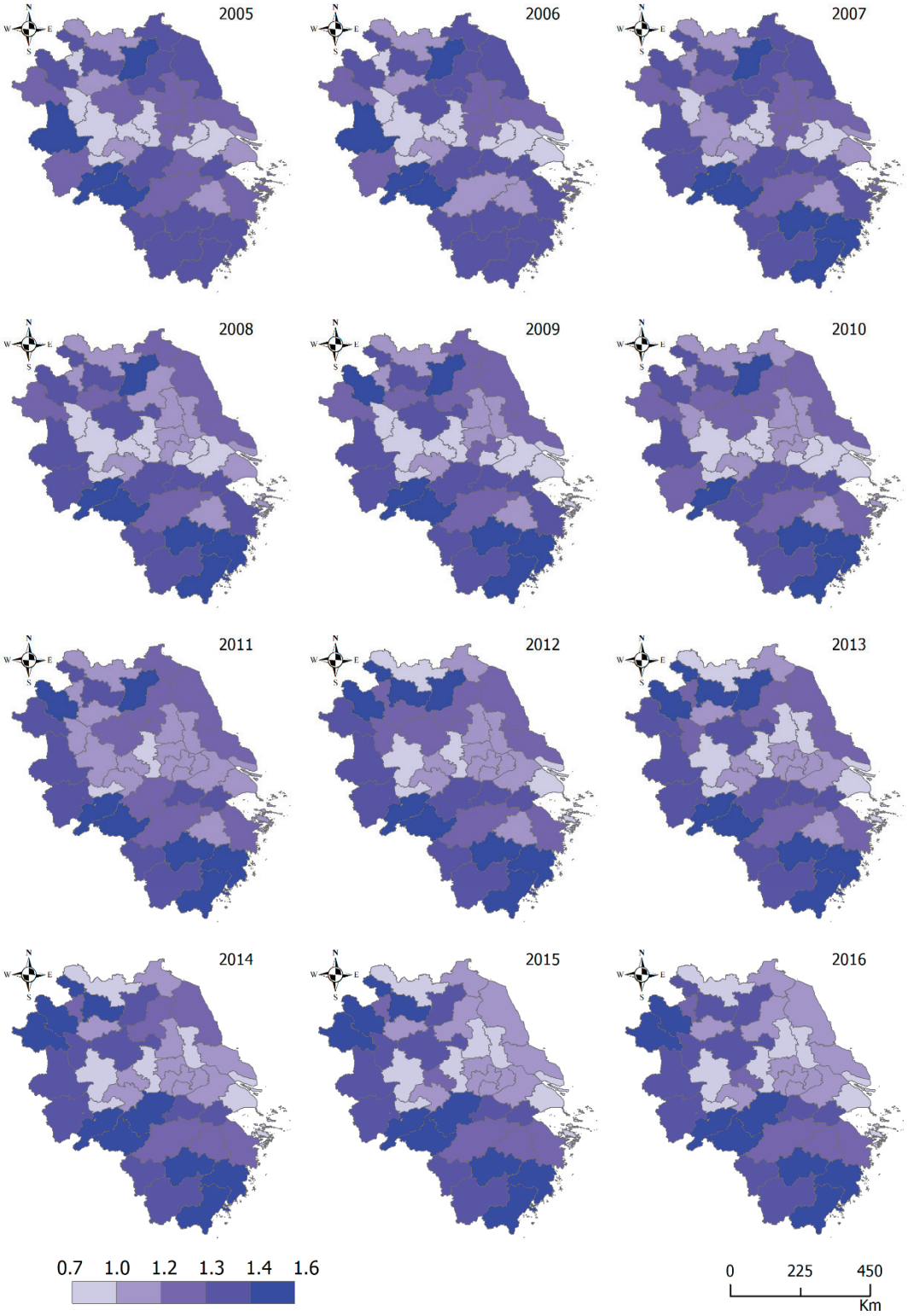


**Figure 7.** Spatiotemporal distribution of Porter.

### *4.3. Spatial Autocorrelation Analysis*

Due to the characteristics of the variable coefficients of the GTWR model, the spatial autocorrelation test of the dependent variable was carried out before modeling. If there is a significant spatial autocorrelation in the dependent variable, then the use of the GTWR model is appropriate. After determining the use of the binary adjacency matrix, we used

Stata17.0 to calculate the global Moran index, and the results are shown in Table 4. It can be seen from the figure that the values of the Moran index are all between [−1, 1], and the absolute value of Moran index has an overall upward trend, with its significance becoming more obvious. This indicates that there is a spatial agglomeration between urban land use efficiency, meaning there is an obvious spatial autocorrelation. Therefore, it is reasonable for us to use the GTWR model for analysis.

**Table 4.** Moran's I test.

| Year | Moran's I | z | *p*-Value * |
|---|---|---|---|
| 2005 | −0.044 | −0.247 | 0.403 |
| 2006 | −0.034 | −0.115 | 0.454 |
| 2007 | −0.019 | 0.081 | 0.468 |
| 2008 | 0.066 | 1.193 | 0.116 |
| 2009 | −0.077 | −0.679 | 0.248 |
| 2010 | 0.090 * | 1.502 | 0.067 |
| 2011 | 0.183 ** | 2.703 | 0.003 |
| 2012 | 0.271 *** | 3.838 | 0.000 |
| 2013 | 0.076 * | 1.298 | 0.097 |
| 2014 | 0.348 *** | 4.833 | 0.000 |
| 2015 | 0.355 *** | 4.906 | 0.000 |
| 2016 | 0.257 *** | 3.638 | 0.000 |

***, ** and * denote significance at the 1, 5, and 10-percent level respectively.

### *4.4. Estimation Results of OLS and GTWR Model*

In order to avoid the influence of multicollinearity, we first calculated the variance inflation factor of each variable, and the VIF value of each independent variable was less than 10, indicating that there was no multicollinearity problem between the variables. Considering that the GTWR model cannot test the significance of variable coefficients, we used Ordinary Least Squares (OLS) and GTWR to study the effects of three agglomeration externalities on ULUE. It can be seen from Table 5 that the three agglomeration externalities have a highly significant impact on ULUE. Among them, the MAR externality and Porter externality, whether put into the regression model alone or together with other externalities, showed negative effects on ULUE. This shows that in a global sense, high industrial specialization and excessive industrial competition are not conducive to the improvement of ULUE. The effect of diversity externalities is unstable. After considering specialization externalities and competition externalities, diversify externalities, or, more precisely, unrelated diversity, show an improved effect on ULUE. This is similar to the findings of most scholars that agglomeration externalities do not act independently [57]. Unrelated Variety replaces Related Variety in making improvements in ULUE, indicating that the technological connections between industries in the Yangtze River Delta urban agglomeration as a whole are still not close enough and that the industrial externalities are limited to large industrial sectors, while specific industries do not benefit from it. The coefficients estimated by the GTWR model are also shown in Table 5. Table 5 reflects the dynamic impact of each variable on ULUE. The maximum, minimum and mean values of the coefficients of MAR externality are 0.15, −0.06 and −0.005, respectively. The maximum, minimum and mean values of the coefficients of the UV externality are 2.17, −1.70 and −0.26. The maximum value, minimum value and mean value of the coefficients of the RV externality are 3.60, −1.33 and 0.47. The maximum, minimum and mean value of the coefficients of the Porter's externality are 0.41, −0.47 and −0.006, respectively. This indicates that the impacts of various agglomeration externalities on ULUE have significant spatio-temporal heterogeneity. In addition, according to the reported GTWR model parameters, $R^2$ is 0.804, which is much higher than OlS's, indicating that the model fits well. Therefore, the GTWR model can be used to deal with the spatio-temporal heterogeneity between agglomeration externalities and ULUE.

**Table 5.** Regression coefficient results of each variable of OLS and GTWR.

| VARIABLES | OLS | GTWR | | |
|---|---|---|---|---|
| | **Coef.** | **Max** | **Min** | **Mean** |
| MAR | −0.012 *** | 0.1508711132 | −0.0607905963 | −0.0052732571 |
| UV | 0.227 ** | 2.1743913471 | −1.6965369279 | −0.2644367352 |
| RV | −0.179 | 3.6012901471 | −1.3257455998 | 0.4657644234 |
| Porter | −0.168 *** | 0.4097858984 | −0.4741365000 | −0.0058395606 |
| FDI | 0.047 *** | 0.3582414797 | −0.0915614750 | 0.0560940909 |
| LF | −0.037 | 2.0845341573 | −2.2141543222 | −0.0683669281 |
| DEC | −0.222 * | 2.1450094485 | −2.0230748214 | 0.0766327641 |
| POP | 0.043 | 0.4790694941 | −0.4903563348 | −0.0364431313 |
| IS | 0.296 *** | 1.4901585525 | −1.0841017332 | 0.1370764120 |
| TP | 0.002 | 0.0473856253 | −0.0255634035 | 0.0011525221 |
| ED | −0.101 *** | 0.2626034279 | −0.4263408446 | −0.0544773004 |
| EDU | −0.054 | 0.2802125440 | −0.3129669496 | −0.0019328456 |
| $R^2$ | 0.186 | 0.804 | | |
| Bandwidth | - | 0.111311 | | |
| CV | - | 23.5291 | | |

***, ** and * denote significance at the 1, 5, and 10-percent level respectively.

### *4.5. Spatiotemporal Impacts of Three Agglomeration Externalities on ULUE*

We combine Figures 8 and 9 to reflect the influence of three industrial agglomeration externalities on ULUE. Figure 8 shows that the impact of the Industrial agglomeration externalities on ULUE has obvious spatial heterogeneity. Figure 9 mainly reflects the trend of time evolution. Our results show that the influence of agglomeration externalities on ULUE has obvious non-stationary characteristics.

Specifically, the regression coefficient of the MAR externality fluctuates in the range of −0.06~0.15, and after more than a decade of development, the role of industrial specialization has been shrinking (the coefficient has become smaller). MAR externalities have shifted significantly in space. Before 2012, positive values were mainly concentrated in eastern Jiangsu province. After 2012, positive MAR values showed a shift towards Zhejiang province and Anhui province, with Hangzhou and Quzhou being the most prominent regions. Thanks to policy conditions and the industrial status, industrial specialization in these two cities made positive improvements to urban ULUE. The negative values of MAR are mainly concentrated in the western part of our study area (Anhui Province), but they tend to be positive.

The spatio-temporal effects of diversity agglomeration externalities are represented by UV and RV in the figure. In terms of regression coefficients, the externality of industrial diversity is the most powerful and unstable externality. Among them, the UV high values are mainly concentrated in some cities in the northeast of Jiangsu province and some cities in Zhejiang province. The geographical distribution of RV and UV shows opposite characteristics, with high values of RV mainly concentrated in the western Jiangsu province and eastern Anhui province. These cities are located in the border area between the two provinces, with frequent economic contacts and active industrial exchanges. Therefore, RV shows an improvement on ULUE. In terms of intensity, RV increased over time (the overall color became darker), while UV weakened (the color became lighter).

The regression coefficient of the Porter externality fluctuated between −0.47 and 0.41. The spatio-temporal heterogeneity of the Porter externality is particularly obvious. In general, positive Porter values are concentrated in the eastern part of the study area, while negative Porter values are concentrated in the western part of the study area and occupy most of the area. After 2012, the Porter coefficient showed an obvious spatial transfer. Jiangsu province, Zhejiang province and Shanghai gradually benefited from industrial competition, while industrial competition in Anhui province showed an obstacle to ULUE.

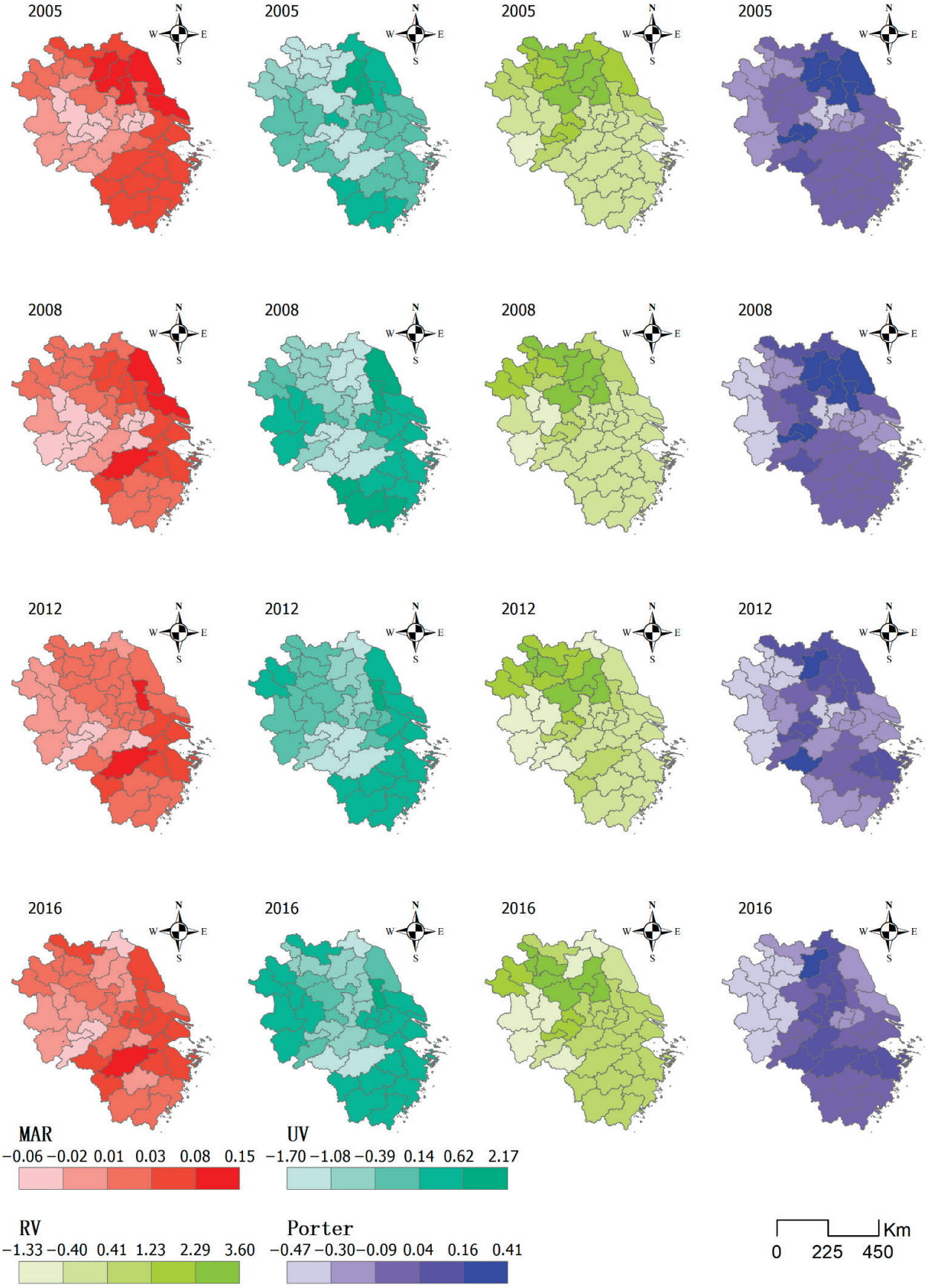


**Figure 8.** Spatiotemporal distribution of Porter.

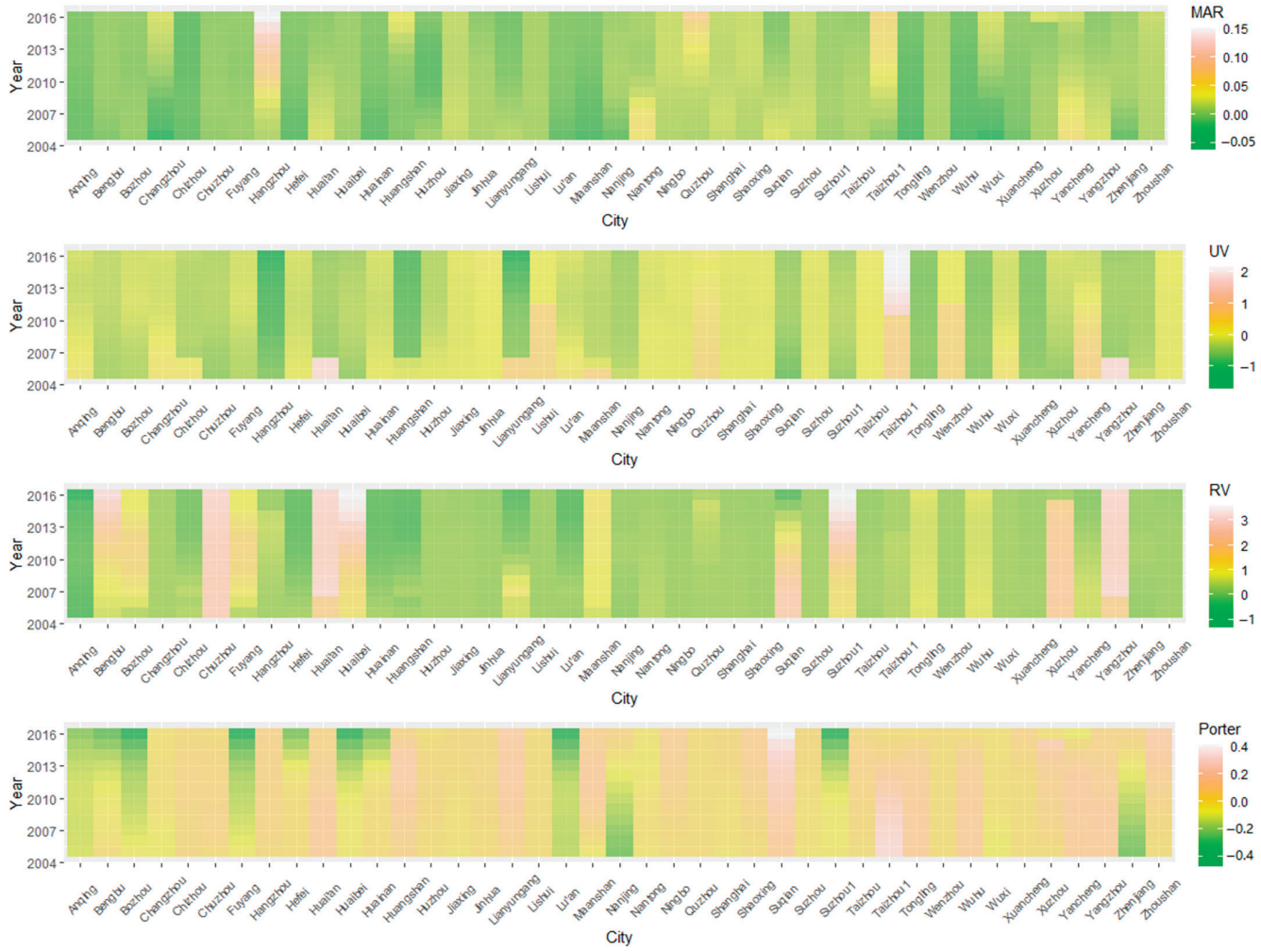


**Figure 9.** Annual Regression Coefficients of Three Agglomeration Externalities.

Our results also show that each city may be affected by multiple types of agglomeration externalities, such as Shanghai, which benefits from both industrial specialization externalities and industrial competition externalities.

### *4.6. Impacts of the Control Variables on ULUE*

This study selected population density (POP), transport infrastructure (TP), human capital (EDU), economic development level (ED), foreign direct investment (FDI), marketisation level (LF), industrial structure (IS) and decentralization (DEC) as the control variables for the GTWR model. The mean regression coefficients of the control variables for each year from 2005 to 2016 are shown in Figure 10. The results show that high population density and differences in economic development are important causes of urban underutilization of land. Economic development levels have a negative impact on the ULUE. In other words, economic development constitutes a threat to ULUE, indicating that the growth of the Yangtze River Delta urban agglomeration may be crude, and therefore, we are concerned that the development of the Yangtze River Delta over the past decade or so is not consistent with the connotation of high-quality development. Foreign direct investment and industrial structure are important drivers, leading to steady improvement, suggesting that engaging in global competition, learning advanced technology and guiding industrial transformation are important directions for the Yangtze River Delta's future urban development strategy. Marketisation (LF) has experienced a negative to positive change over the 12-year period, indicating that the Yangtze River Delta is becoming in-

creasingly market-oriented, market operations are becoming more regulated and various factors of production can circulate freely. Decentralization shows a clear inverted 'U' trend, indicating that local fiscal incentives can indeed motivate local governments to develop industries, but a performance assessment-centered system and blind imitation may lead to disorderly competition among local governments, resulting in a convergence of industrial structures and duplication of construction [32,84].

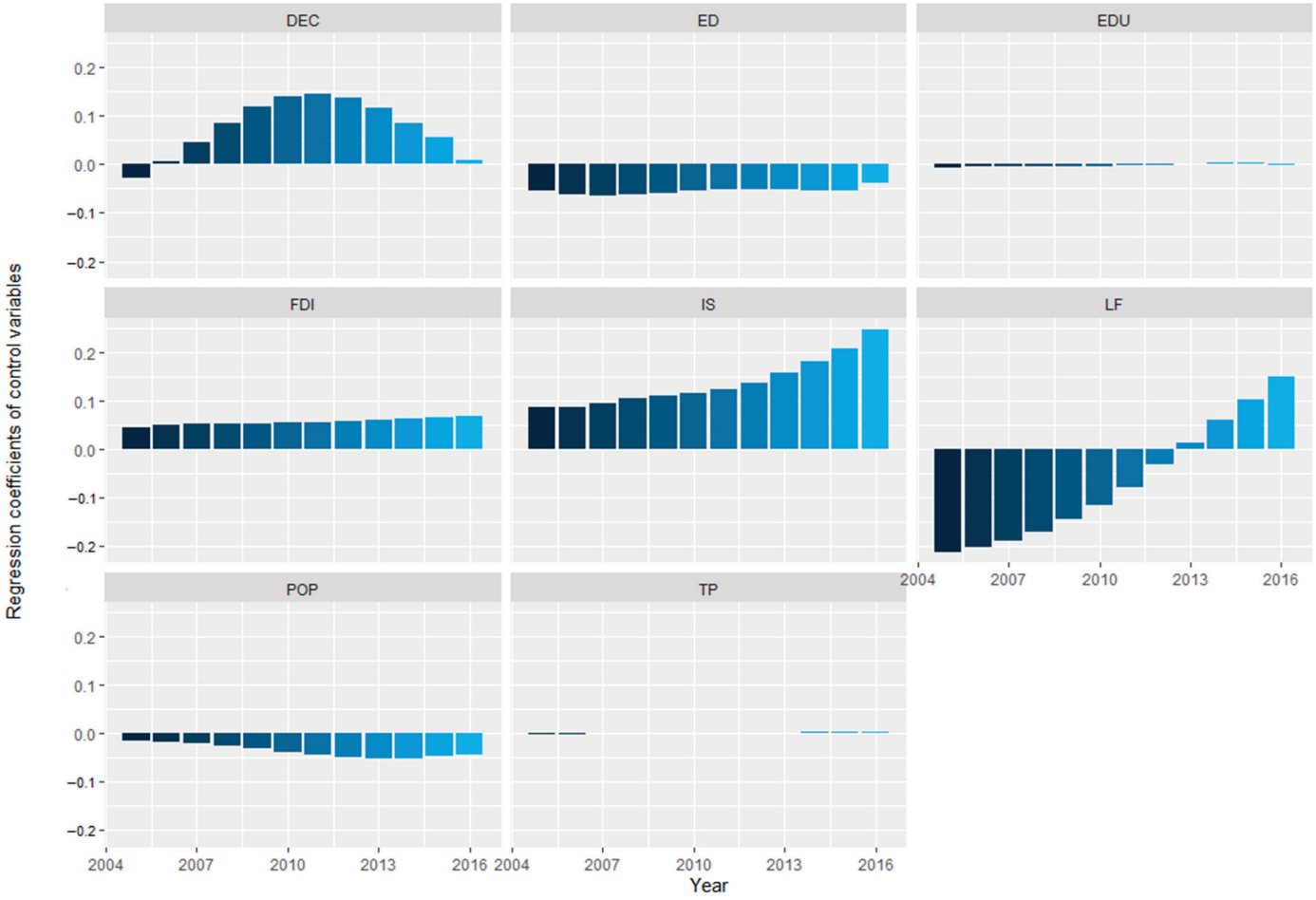


**Figure 10.** Regression coefficients of control variables.

## 5. Discussion

We selected 2005, 2008, 2012 and 2016 as representatives to discuss the relationship between the three agglomeration externalities on ULUE.

As for The Marshall externality, we observed that, in general, it gradually played a negative role in the improvement of ULUE in Jiangsu and Zhejiang provinces over time. However, two exceptions attracted our attention, namely, Hangzhou and Quzhou. Industry has always been an important engine of urbanization and the main channel to absorb employment in Hangzhou. In 2012, The Hangzhou Municipal Government issued several Opinions of the Hangzhou Municipal People's Government on Accelerating the Industrial Transformation and Upgrading and Promoting the Sustainable and Healthy Development of the Real Economy, providing a large amount of funds to enterprises meeting the requirements to help traditional industries upgrade to modern industries. In recent years, with the widespread application of advanced information and communication technology, especially the settlement of Alibaba, Hangzhou's Internet information industry has made great development. Hangzhou has developed a distinctive industrial system dominated by modern industry and the Internet industry, which plays a key role in the overall performance of Hangzhou. The situation of Quzhou can be explained by its specific

industrial structure. Paper making and chemical industry are the two leading industries in Quzhou. The companies engaged in paper making and chemical industry absorbed a large number of the labor force, which makes Quzhou's industry highly specialized. For Anhui province, the role of the Marshall externality is gradually strengthened, and the sign tends to become positive over time. For example, the Marshall externality of Huangshan has played a positive role in the improvement of urban ULUE, which indicates that a specialized agglomeration mode has the potential to improve urban ULUE in Anhui province in the future. The current situation of Anhui province can be explained from the theory of industry cycle. According to industry cycle theory, the benefits an industry gets from the local environment are closely related to its life cycle stage. For new industries, innovation is crucial, and the Jacobs externality plays an important role in this stage. As the period of strong expansion passes, the technological innovation of products becomes difficult, and the industry reaches a more mature stage. At this point, products tend to be homogeneous and will compete in the local market with price advantages, at which point the performance of enterprises becomes more dependent on Marshall externality [85]. In comparison, Jiangsu, Zhejiang and Shanghai regions have advantages in economic strength and openness. Therefore, the growth of local cities will not completely depend on some mature industries. Comparatively speaking, traditional industries in Anhui province still have a large market, which means that Anhui province can gain advantages from professional industrial agglomeration. These local dominant industries can reduce factor costs in the form of economies of scale and participate in market competition at lower prices. With the strengthening of this trend, the Marshall externality gradually shows an improvement effect on ULUE.

As for the externalities of diversity agglomeration, our study revealed an important phenomenon, that is, the effect of UV on the improvement of ULUE on the whole becomes weaker over time, while the effect of RV on ULUE becomes stronger over time. In addition, from the perspective of the time trend, another phenomenon that can be observed is that in addition to Taizhou1, UV almost had negative effects on the improvements of ULUE, while RV had an opposite effect. This is basically consistent with the prediction of Freken et al. [81], that technology spillovers only occur between related industry sectors, and the extent of spillovers is limited between unrelated sectors. Therefore, UV, which represents the diversified pattern of industry sectors, has a poor performance, while RV, which represents the diversity of specific industries, has a positive performance. Diversity externalities with negative signs are likely to be caused by infrastructure. The key is whether firms can benefit from local infrastructure. Although physical infrastructure in cities is shared by all industries, much of the infrastructure is built for specific industries. Therefore, the more diverse a city's industrial mix, the more difficult it is to provide tailored solutions for each industry, which can well explain why diversified agglomeration externalities do not improve the performance of a large city, such as Shanghai and Hangzhou. However, the diversity of industries can be beneficial for a region as long as they are not too fragmented [63]. Therefore, we can find the positive effects of diversity externalities in other cities, such as Taizhou1, Bengbu and Huaibei. Although the performance of these cities is not as good as that of Shanghai and Hangzhou, their industries are supported by complementary infrastructure. Even with an imperfect industrial structure, its local firms can still benefit from diverse agglomeration externalities.

The temporal and spatial heterogeneity of the Porter externality is particularly obvious. For ULUE improvements in Jiangsu, Zhejiang and Shanghai, Porter externalities play a positive role, while for ULUE of almost all cities in Anhui province, the effect of the Porter externality is obviously negative, and the negative effect showed an intensified situation. In fact, the smooth realization of China's economic transformation is largely attributed to the introduction of market competition, which has brought remarkable economic growth to the country [86]. However, competition is not as orderly as people think. In China, there is a special form of "race to the bottom" competition, which means that too much competition is not conducive to growth [87]. One possible explanation is that the industrial structure

in these regions is still dominated by traditional low-tech industries, consisting of many relatively small companies, and that the companies operating in these industries are characterized by traditional management systems and simple internal organizational models. As a result, these companies are primarily concerned with exploiting cheap labor rather than raising productivity levels and introducing technological and organizational innovations. Therefore, competition among local enterprises will be based on price and cost-cutting (especially labor costs) rather than product quality. In addition, fierce local competition also squeezes the profits of enterprises and reduces their investment in innovation, which may have a negative impact on local economic development. In our opinion, another possible reason is that in order to maintain advantages in local competition, local enterprises block their core technologies rather than exchange them, which will lead to market segmentation. Therefore, the Porter externality will also show a negative impact on urban development. However, the Porter externality will play a positive role when it is linked with globalization and local government fiscal capacity. When local governments have greater economic autonomy to support and promote related industries to participate in global competition, the Porter externality can significantly promote growth, which can explain why the. Porter externality shows positive effects in Jiangsu, Zhejiang and Shanghai [88].

Our study also proves that different types of agglomeration externalities have aging mechanisms [58]. The effects of the Marshall and Porter externality are not sustainable. In our cases, the prominent MAR values of Hangzhou and Quzhou underwent a rapid decline within four years, and their prominent role disappeared within a decade. However, diversity agglomeration externalities can play a lasting role. Even after a decade, its prominent position is still very obvious, such as Huai'an and Yangzhou. This is consistent with Jacobs's own speculation that a diversified industrial structure is better for the city's long-term development.

Furthermore, we find that to some extent, the contribution of these three agglomeration externalities to ULUE are substitutable for each other. It means that if the MAR externality plays an obvious role on ULUE, then the Jacobs and Porter externalities will play a relatively weak role in this city, such as Hangzhou. If the Porter externality plays an obvious role, the corresponding effects of the MAR and Jacobs externalities are not so strong, such as Yancheng. Therefore, one possible policy implication is that regions should formulate strategies for industrial distributions according to their own conditions, rather than taking advantages of all types of agglomeration externalities.

The results of the study should provide insights for policy makers. Specifically, it can be divided into the following points:

(1) Selectively cultivating agglomeration externalities according to the status quo of local industries. Although agglomeration externalities have been proven by many scholars to be beneficial to urban development, not all agglomeration externalities can be beneficial to local economic activities. Specialization, diversity or competition externalities may not affect or even hinder the development of the city. For cities with incomplete infrastructure, it is still recommended to focus on cultivating some related industries, rather than advocating a balanced development of each industry.
(2) Following the laws of industry cycle and giving support to enterprises in industrial transformation. Industrial transformation is still a trend within the Yangtze River Delta urban agglomeration, but in the process of industrial transformation, the environment faced by each economic subject will undergo drastic changes, and the agglomeration externalities that previously played an important role in urban development may become an obstacle to development. To this end, local governments need to provide subsidies to enterprises within their capacity to promote the smooth transformation of local enterprises.
(3) Regulating market order and achieving healthy competition. Local governments should pay attention to the internal development of local enterprises and impose severe sanctions against monopolies, vicious competition and other behaviors that

destroy the market environment, so as to guide the free flow of production factors and cultivate the international competitiveness of enterprises.

(4) Looking to the future and purposefully cultivate diversified industries. Diversified industries help cities develop in the long run, but many cities do not have the resources to do so now. To this end, local governments should take a progressive reform approach on the basis of respecting basic economic laws and develop diversified industries with the purpose to lay a foundation for long-term urban development.

## 6. Conclusions

This paper introduces the effect of industrial agglomeration externalities on urban land use efficiency. By using OLS and GTWR models, we prove the complex mechanism between industrial agglomeration externalities and urban land use efficiency. Our study shows that (1) The impact of three types of industrial agglomeration externalities on urban land use efficiency is unstable both in time and space; (2) The three industrial agglomeration externalities do not function independently, meaning that they often occur simultaneously or are replaced by each other; (3) Different agglomeration externalities have different aging mechanisms, and diversity externalities have the most lasting effect. Our study is helpful for city managers to make reasonable industrial decisions, and it can also provide useful references for enterprises to choose their sites.

The contribution of this study is to explore the impact and mechanism of industrial agglomeration on urban land use efficiency, especially at the temporal- and spatial-level, which further strengthens the complex relationship between urban land use efficiency and industrial development. On the one hand, it is one of the important development directions of the existing urban land use efficiency research. On the other hand, it can provide useful theoretical and practical guidance for urban industrial development planning.

Admittedly, the current study still has several research limitations. Due to limited data availability, we excluded some meaningful indicators when calculating urban land use efficiency, for example, greenhouse emissions and cultivated land erosion. Due to the change of the statistical caliber, panel data can only support the research span of 12 years, which means that it is difficult to observe the long-term mechanism of agglomeration externalities on urban land use efficiency. The consideration of industrial heterogeneity is still insufficient in this study. Even though we made a more careful division of the tertiary industry, the existing data do not allow us to pay more attention to the second industry, which affects the accuracy of the results to some extent. In future studies, research design can be more subtle, for example, by carefully considering and contrasting the interactions between each of the two aggregate externalities. In addition, due to the geographical adjacency of each observed object, the application of spatial econometric methods should also be considered.

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# The Impacts of Regional Cooperation on Urban Land-Use Efficiency: Evidence from the Yangtze River Delta, China

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**Abstract:** Urban land-use efficiency (ULUE) has been increasingly recognized as an issue of land-use management across the world in the last century as the globe experienced unprecedented rapid urban expansion. However, although a large body of studies was dedicated to analyzing the driving forces of ULUE, literature was rarely focused on the impacts of regional cooperation on ULUE. To bridge the knowledge gap, we used the Chinese trailblazer of regional cooperation–Yangtze River delta (YRD)—as a case to reveal the impacts of regional cooperation on ULUE. Social network analysis and a super efficiency SBM model with undesirable outputs were used to measure regional cooperation and ULUE, respectively. Furthermore, the impacts of regional cooperation on ULUE were examined by using the geographically and temporally weighted regression model. The results show that regional cooperation in the YRD strengthened from 2009 to 2016, among which Shanghai was the core node city in the YRD. Only seven cities maintained good ULUE with a stable trend during 2009–2016. The regression results indicated the positive impacts of regional cooperation on ULUE, which was more evident in the southern cities of the YRD. The potential mechanism to explain the impacts of regional cooperation on ULUE includes co-building transportation facilities and joint development zones. These findings provide insightful implications for improving ULUE by strengthening regional cooperation in Chinese cities.

**Keywords:** regional cooperation; urban land-use efficiency; impacts; geographically and temporally weighted regression; Yangtze River delta

## 1. Introduction

The world has witnessed unprecedented urban expansion during the last century [1,2]. Global urban land has increased by 58,000 km$^2$ from 1970 to 2000. If the trend is to be continued, global urban land area is projected to increase by 1.2 million km$^2$ in 2030, tripling the amount circa 2000 [3]. Unfortunately, rapid urban expansion has been accompanied by inefficient urban land use, which more frequently takes place in developing countries [4–6]. Inefficient urban land use indicates extensive land development that is characterized by high coverage of the urban built-up area with low yield in a region. According to the report on China's land use situation by Wang, et al. [7], 45% of urban land is used inefficiently, and approximately 5% of it is vacant. Furthermore, inefficient urban land use has resulted in considerable loss of cultivated land and ecological land, imposing challenges for food security and environmental protection [8–10]. Therefore, the concerns about ULUE and its driving forces have attracted great attention from decision-makers, scholars, and planners across the world.

ULUE was defined as the yield per unit of urban land area with respect to social and economic activities [11]. There is a plethora of studies related to ULUE, which can be categorized into two main streams. The first stream is measuring ULUE through the lens of economic, social, and environmental output [12,13]. An increasing body of studies found

that most cities show an increasing trend of ULUE with technological progress [14]. At the urban agglomeration scale, the world-class urban agglomerations are inclined to have better ULUE than nation-class and region-class urban agglomerations [15,16]. At the city scale, developed cities are generally characterized by higher land-use efficiency [17,18]. In terms of land types, residential land has been used effectively as compared to industrial land [19]. The second stream is exploring the driving forces of ULUE. Existing literature found that land market [20], land-use structure [21], socio-economic development [22], local government behavior [23], and public policy [24] imposed positive impacts on ULUE. However, existing literature was focused on the effect of endogenous factors of a city on ULUE, particularly from the perspective of socio-economic determinants. By contrast, exogenous factors resulting from the interaction among cities, such as regional cooperation, were chronically overlooked in previous studies.

Regional cooperation is likely to be an instrument in affecting land-use efficiency [25,26]. Regional cooperation is regarded as any kind of formalized trans-local, international, or bi-lateral cooperation between local authorities and their communities [27]. It is well-known as the modes of "twin city strategy" [28], "city-helps-city schemes" [29], and "inter-city integration agenda" [30], which is an efficient way to facilitate the linkages of economic, social, and institutional affairs among cities for alleviating urban competition [31]. Inevitably, regional cooperation seems to have profound impacts on regional land-use management [32]. On the one hand, industrial development cooperation among cities over a physical space (e.g., cross-jurisdictional economic development zones) promotes industries from scattered distribution to a cluster pattern [33]. This gains the industrial agglomeration effect, which is beneficial for industrial yield but also saves industrial land resources. On the other hand, cooperative spatial planning for a city-region regulates disordered urban land development through formulating spatial zones and planning ordinances [34]. By establishing coordination mechanisms for land development, intensive land development could be implemented in the region. For example, the Pearl River Delta Urban Cluster Coordination Plan proposed a spatial zone with "one core area, three belts, and five axes" to prevent urban sprawl. Nevertheless, although regional cooperation is increasingly acknowledged as a driver affecting urban land use, the impacts of regional cooperation on ULUE remain rarely explored.

To bridge the knowledge gap, we used the Chinese pioneer of regional cooperation—YRD—as a case to explore the impacts of regional cooperation on ULUE. This paper was dedicated to two issues: (1) what are the characteristics of regional cooperation and ULUE in the YRD; (2) how regional cooperation imposes impacts upon the ULUE. We used social network analysis and a super efficiency slack-based measure (SBM) model with undesirable outputs to measure the intensity of regional cooperation and ULUE, respectively. Furthermore, the impacts of regional cooperation on ULUE were examined by using geographically and temporally weighted regression (GTWR). Thus, this article proceeds as follows. Section 2 following the introduction presents a conceptual framework about the definitions, dimensions, and potential impacts of regional cooperation on ULUE, which provided the theoretical premise for this study. Section 3 introduces the study area of YRD, data source, and research methods. Section 4 demonstrates the results, including regional cooperation, ULUE, and the impacts of regional cooperation on ULUE. Section 5 shows the mechanism related to the impacts of regional cooperation on ULUE, policy implications, and limitations. Section 6 is the conclusion. The present work has two potential contributions. On the one hand, a conceptual framework was established to clarify how regional cooperation imposes impacts on ULUE, providing a new lens on the driving forces of ULUE. On the other hand, the empirical analysis was conducted to examine the conceptual framework about the impacts of regional cooperation on ULUE and to further discuss the possible explanations for the differences in the impacts among cities.

## 2. Conceptual Framework

Regional cooperation is defined as the coordination made by the governments, society, and markets to reduce negative externalities from economic globalization and intercity competition [35]. According to Zhang, et al. [36], regional cooperation can be summarized as three dimensions: economic cooperation, social cooperation, and institutional cooperation. Firstly, economic cooperation reflects the agglomeration of economic activities for a city-region [37]. It is considered to be the initial form of cross-border regional integration [38,39], which focuses on promoting the flow and recombination of production elements among regions. In recent years, due to the fewer land quotas, more big cities are keen on seeking physical space for industrial development with surrounding less-developed cities. More economic cooperation modes are emerging, such as co-building industrial development zones, and developing infrastructures. Secondly, social cooperation is related to social welfare to improve social interaction, which helps support economic contact. It aims to integrate multiple participants (e.g., enterprises, the public, governments, and non-governmental organizations) to share better social services in terms of science, education, culture, public health, and entertainment. For example, the case of Ningbo-Zhoushan-Taizhou (Zhejiang province) city-regional cooperation shows that in parallel with economic cooperation, a range of social cooperation in realms, i.e., human resources, credit information, and healthcare is set to enhance social wellbeing. Thirdly, institutional cooperation bridges territorial authorities in forms of urban planning, urban management, and institution construction [36]. Existing literature shows that it is an efficient way to be initiated by subordinate governments with the active involvement of superior governments [40]. It can not only ensure that the local authorities make great efforts for the mutual interests, but also enable the superior government to play its regulatory role, as well as provide support and preferential policies for the cooperation.

ULUE includes two concepts–structure efficiency at the macro level and margin efficiency at the micro level. The former is focused on the degree of planned land use, which reflects the effects of public policy on land use. The latter is focused on the output of land per unit area, which reflects the productive capability of land resources. In this paper, ULUE was used to measure the input-output relationship at the micro level, reflecting the transformation capability from resource consumption to economic, social, and environmental benefits. Generally speaking, the dimensions of land input often refer to production elements, including labor, land, and capital [41]. According to Xie, et al. [42], technology is the other important dimension of land input. The dimensions of land output were initially focused on economic and social benefits [25,43]. However, due to the worsening environmental issues across the world, negative environmental externalities of land use have attracted great attention. They are often regarded as undesirable outputs from land development. For example, the wastewater and solid waste from the secondary and tertiary industries are defined as undesirable outputs.

The potential impacts of regional cooperation on ULUE are concluded as follows (Figure 1). First, economic cooperation improves ULUE through joint development zones (JDZs) and co-building transportation facilities. China's development zones were initially designed to attract foreign direct investments and promote regional economic development [44,45]. JDZs usually attract high-added-value industries [46] by supporting extensive land, abundant labor, and sufficient raw materials. The process promotes intensification of land use and upgrading of industrial structure, which is conducive to gaining an agglomeration effect [22]. As mentioned by Duranton and Puga [37], "sharing, matching, and learning" among cooperative firms fosters agglomeration externalities. In addition, economic cooperation is concomitant with coordinated planning of transportation facilities, i.e., a joint port, a regionally integrated railway network with identical railway gauges, regional shipping companies, and an integrated highway system [47]. The co-building transportation facilities are committed to facilitating land development along the routes and quickening production-element exchange among cities. Second, social cooperation is an efficient way to optimize land-use strategy. On the one hand, an important approach of

social cooperation is building social infrastructure, such as research institutions, universities, cultural institutions, and healthcare facilities [48,49]. Those infrastructures are likely to be distributed along with the sites of economic cooperation, i.e., urban core, industrial parks, and economic development zones. Such a strategy ensures a compact land-use pattern. On the other hand, the enhancement of cooperation in social services contributes to increasing social interaction and driving human and social capital. The process leads the urban population to concentrate in urban areas, which intensifies urban density. Third, institutional cooperation acts as a guide in urban land use from government behavior through coordinated urban management and cooperative spatial planning. Coordinated urban management refers to a series of governance rules formulated by cities to regulate land developmental order, including planning ordinances and spatial governance zones [34]. This takes account of urban land development intensity and density in different cities, which is beneficial for reducing ineffective land use. Cooperative spatial planning is dedicated to depicting a concrete spatial structure of the core, axe, belt, and network among cities. By implementing these cooperative regional plans, land-use patterns will be stipulated, which prevents disordered urban land use. In sum, we suppose that regional cooperation will pose positive impacts on ULUE according to the conceptual framework.

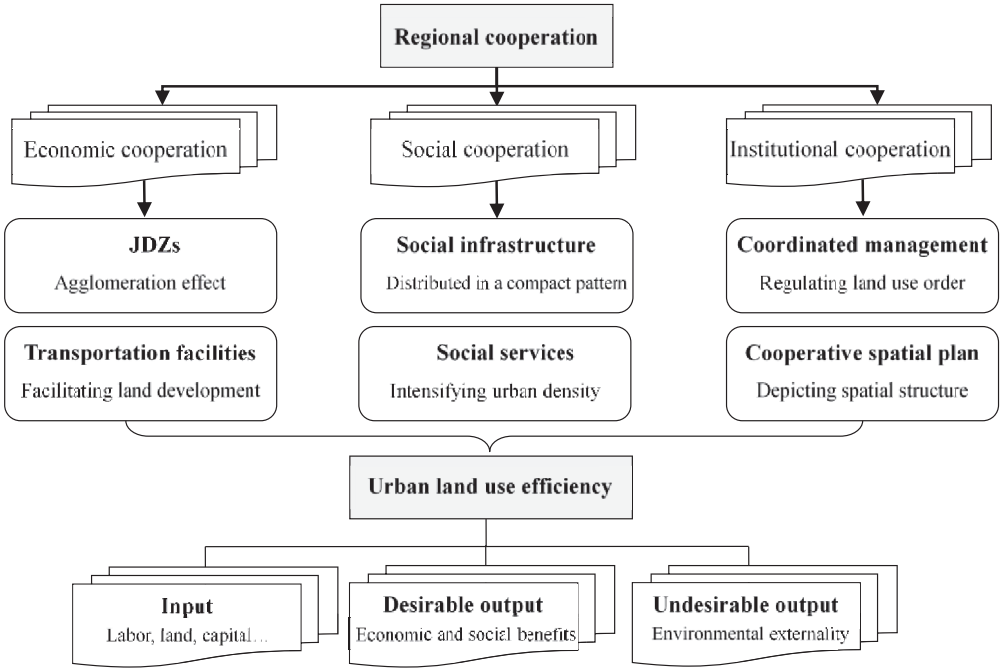


**Figure 1.** Conceptual framework.

## 3. Data Source and Methodology

### *3.1. Study Area*

The Yangtze River delta is located downstream of the Yangtze River, which belongs to the middle coastline of China (Figure 2). The proposal of YRD Regional Planning was approved in 2010, stipulating its realm and including 16 core cities with an area of 113,852 km$^2$, including Shanghai, Nanjing, Suzhou, Wuxi, Changzhou, Zhenjiang, Yangzhou, Taizhou (Jiangsu province), Nantong, Hangzhou, Ningbo, Huzhou, Jiaxing, Shaoxing, Zhoushan, and Taizhou (Zhejiang province). As an economic growth engine, the YRD only takes 2.03% of China's urban district area but harnessed 17.23% of the nation's gross domestic product (GDP) in 2020. The GDP per capita is 144,397 Yuan, indicating the high level of economic development in the YRD. With the deepening of regional integration, the YRD has evolved into one of the most integrated urban agglomerations in China. In 2003, 16 cities in the YRD took the first step of regional cooperation by signing the proposal of urban linkage development in the YRD. Currently, regional cooperation in the YRD has expanded from

economy, transportation, and tourism to culture. Along with an increasingly important role in regional cooperation, its ineffective land use is becoming evident [50]. The growth rate of urban land (3.53%) was much higher than that of the urban population (3.24%) from 2009 to 2016 [51], revealing ineffective urban land use in the YRD. Therefore, it is necessary to explore whether ULUE is related to regional cooperation in the YRD.

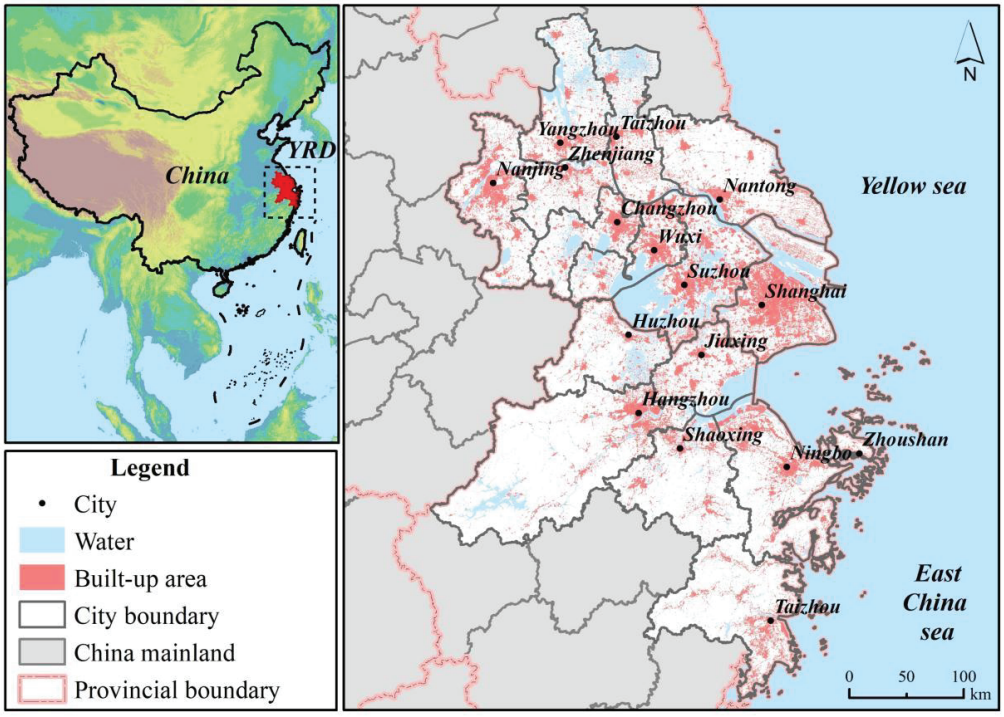


**Figure 2.** Location of the YRD.

### *3.2. Data Source*

Media data and statistics yearbooks were used in this work. Firstly, media data of intercity cooperation news between 2009 and 2016 was collected from local government official websites. The data was the most comprehensive and systematic records, involving the joint actions of governments at all levels, government-affiliated institutions, enterprises, private organizations, and non-governmental organizations for coordinated development [32]. It has been widely applied to measure the intensity of intercity cooperation [29,36]. For the data collection, target city names were entered as keywords on a local government website to search for official news about regional cooperation [29,36]. For instance, Nanjing and Shanghai were used as keywords on Shanghai and Nanjing's official websites to search for cooperation news between the two cities, respectively. We defined 240 news keywords search combinations and obtained 5299 pieces of news after excluding the irrelevant cooperation news. Secondly, statistical data regarding prefecture-level cities for the period 2009–2016 were obtained from the China city statistical yearbook and the China city construction statistical yearbook from 2010 to 2017. Most statistical indicators were extracted from China city statistical yearbook, including the proportion of employees in secondary and tertiary industries (%), total investment in fixed assets (10,000 Yuan), the proportion of secondary and tertiary industries in GDP (%), the average salary of employees (Yuan), industrial wastewater discharge (10,000 t), industrial $SO_2$ emissions (t), and industrial smoke/powder/dust emissions (t). Park area per capita ($m^2$) and urban area ($km^2$) were extracted from China city construction statistical yearbook.

*3.3. Methodology*

3.3.1. Social Network Analysis

Social network analysis was a set of methods to quantitatively analyze the structure and attributes of social relations [52]. Social network analysis in urban studies could reveal intercity relations and spatial interaction [53,54]. During the analysis, urban agglomeration was considered as the overall network, and each city within was regarded as a node in the network. As one of the network structure indexes, centrality measured the influence of nodes in the complex network, including degree centrality, betweenness centrality, and closeness centrality [55,56]. In this study, degree centrality was used to analyze the structural characteristics of regional cooperation, which indicated the number of linkages for a node. The higher the degree centrality of a node, the more connections it had with other nodes, and further reflected the strong regional cooperation [32,36]. The degree centrality of each city in the regional cooperation network of the YRD was analyzed using UCINET. The following equation shows the degree centrality of node *i* to its adjacent nodes:

$$C_D(N_i) = \sum_{j=1}^{g} x_{ij} (i \neq j)$$

where $C_D(N_i)$ represents the degree centrality of node *i*; *g* refers to the amount of nodes in the network; $x_{ij}$ refers to the sum of linkages between node *i* and node *j*.

3.3.2. Super Efficiency SBM Model with Undesirable Outputs

Data envelopment analysis has been widely adopted to measure the land-use efficiency of decision-making units with multiple inputs and outputs [26,57]. To compensate for the slack problem of input and output, Tone [58] proposed the SBM model based on non-radial and non-angle by putting the slack variables directly into the objective function. In addition, considering the negative environmental consequences induced by production and life, undesirable outputs were taken into account [59]. The model can crack the issue in efficiency evaluation that decision-making units are simultaneously efficient with the value of 1 [60]. Therefore, we applied the super efficiency SBM model with undesirable outputs to measure ULUE. There were *n* decision-making units with *m* input indicators, $S_1$ desirable output indicators, and $S_2$ undesirable output indicators. The inputs, desirable outputs, and undesirable outputs were represented as $x \in R^m$, $y^g \in R^{s_2}$, $y^b \in R^{s_2}$, respectively. The vectors X, $Y^g$, $Y^b$ were expressed as $X = (x_{ij}) \in R^{m \times n}$, $Y^g = (y_{rj}) \in R^{s_1 \times n}$, $Y_b = (y_{rj}) \in R^{s_2 \times n}$. Therefore, the super efficiency SBM model with undesirable outputs for evaluating decision-making units $\left(x_0,\ y_0^g,\ y_0^b\right)$ is as follows [61]:

$$\min \alpha^* = \frac{\frac{1}{m}\sum_{i=1}^{m}(\overline{x}/x_{i0})}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s1}\left(s_r^g/y_{r0}^g\right)+\sum_{r=1}^{s2}\left(s_r^b/s_{r0}^b\right)\right)}$$

$$\text{s.t.} \quad \begin{cases} \overline{x} \geq X\lambda \\ \overline{y^g} \leq Y^g\lambda \\ \overline{y^b} \geq Y^b\lambda \\ \overline{x} \geq x_0, \overline{y^g} \leq y_0, \overline{y^b} \geq y_0^b, \lambda > 0 \end{cases}$$

where $\alpha^*$ is the efficiency value of decision-making units $\left(x_0,\ y_0^g,\ y_0^b\right)$; $\lambda$ is the weight vector; $s^g$ and $s^b$ correspond to the slacks in desirable outputs and undesirable outputs, respectively.

The following indicators were selected to measure the input and output of land use. Descriptions of the indicators are shown in Table 1.

**Table 1.** Variables of input and output.

| Variable Types | Dimensions | Definitions |
|---|---|---|
| Input | Land | Urban area ($km^2$) |
| | Labor | Proportion of employees in secondary and tertiary industries (%) |
| | Capital | Total investment in fixed assets (10,000 Yuan) |
| | Technology | Proportion of secondary and tertiary industries in GDP (%) |
| Output | Desirable output | Average salary of employees (Yuan) |
| | | Park area per capita ($m^2$) |
| | Undesirable output | Industrial wastewater discharge (10,000 t) |
| | | Industrial $SO_2$ emissions (t) |
| | | Industrial smoke/power/dust emissions (t) |

3.3.3. Geographically and Temporally Weighted Regression

GTWR was used to examine the impacts of regional cooperation on ULUE. The GTWR model was developed by Huang, et al. [62], which is better to describe the temporal and spatial relationship between dependent variables and independent variables. In the GTWR model, spatial or temporal variations of ULUE were taken into consideration, which is superior to common regression models–ordinary least squares (OLS) and temporally weighted regression (TWR) [63,64]. In fact, location and time are both important determinants of ULUE. On the one hand, location is an important factor since ULUE is often affected by the spatial spillover effect of peripheral cities [24,57]. On the other hand, there are temporal effects, such as inflation related to the economic output. In this study, OLS and TWR were also used to compare the performance of model fitting. The GTWR model is specified in the following equation:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i$$

where $i$ denotes city; $(u_i,\ v_i,\ t_i)$ refers to the spatial-temporal coordinates (longitude, latitude, time) of city $i$; $Y_i$ refers to the explained variable; $X_{ik}$ refers to the k-th explanatory variable; $\beta_0$ refers to the constant term; $\beta_k$ refers to the regression coefficient of the k-th explanatory variable; $\varepsilon_i$ is a random error term. The estimation of $\beta_k(u_i, v_i, t_i)$ can be expressed as:

$$\hat{\beta}_k(u_i, v_i, t_i) = \left[X^T W u_i,\ v_i, t_i X\right]^{-1} X^T W u_i, v_i, t_i Y$$

where $W(u_i, v_i, t_i) = diag(W_{1uvt},\ W_{2uvt}, \ldots,\ W_{nuvt})$ refers to the spatio-temporal weight matrix, which is used to determine the influence of other sample points on the regression sample point. This paper used the Gaussian function method to determine the spatial-temporal weight matrix:

$$W_{ij}^{ST} = exp\left[-\left(d_{ij}^{ST} / b_{ST}\right)^2\right]$$

where $d_{ij}^{ST}$ is the spatial-temporal distance, $d^{ST} = \lambda dS + \mu dT$, $\lambda$ and $\mu$ represent the weight of space and time distances, respectively; $b_{ST}$ is the bandwidth, and the cross validation ($CV$) method is generally used to determine the optimal bandwidth. The expression is:

$$CV = \sum_i^n \left[Y_i - \hat{Y}_i(b)\right]^2$$

When $CV$ is the minimum value, the corresponding $b$ is the optimal bandwidth.

Dependent variables, independent variables, and control variables are shown in Table 2. ULUE of a city was defined as the dependent variable. The amount of news about regional cooperation was used to indicate regional cooperation, which was defined as the independent variable. Four control variables, including GDP per capita, the proportion

of fiscal expenditure in GDP, population density, and science expenditure, were added to control the impacts of economic development, government investment, population, and technology on urban land use.

**Table 2.** Variable definitions and descriptive statistics.

| Variable Types | Variables | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|
| Dependent variable | Urban land-use efficiency | 0.94 | 0.27 | 0.40 | 1.59 |
| Independent variable | Number of news about regional cooperation | 41.40 | 25.76 | 6 | 120 |
| Control variables | GDP per capita (Yuan) | 85,054.75 | 29,391.30 | 33,166.00 | 199,017.00 |
| | Proportion of fiscal expenditure in GDP (%) | 11.39 | 3.69 | 7.14 | 24.64 |
| | Population density (Person/km$^2$) | 821.67 | 409.09 | 411.80 | 2286.70 |
| | Science expenditure (10,000 Yuan) | 354,797.34 | 601,108.78 | 21,057.00 | 3,417,109.00 |

## 4. Results

### *4.1. Degree Centrality of the Cities in the YRD*

Figure 3 demonstrates the degree centrality of 16 cities within cooperation networks in the YRD. Regional linkages in the YRD have intensified during the research period as the degree centrality of 16 cities increased from 568 in 2009 to 893 in 2016. Besides, the network structure of the YRD shows as an increasing agglomeration. In 2009, the YRD formed four groups from north to south, including Nanjing-Yangzhou-Zhenjiang-Changzhou-Taizhou (Jiangsu province), Changzhou-Wuxi-Nantong-Suzhou-Shanghai, Hangzhou-Huzhou-Suzhou-Jiaxing-Shanghai, and Hangzhou-Shaoxing-Ningbo-Zhoushan-Taizhou (Zhejiang province). Jiangsu province and Zhejiang province strengthened their ties within the province, respectively, in the following years, and all cities actively cooperated with Shanghai. In addition, increasing cross-provincial cooperation has been achieved between Hangzhou, Ningbo, Huzhou, Jiaxing, and Nanjing, Suzhou, and Wuxi, in which the sum of linkages increased from 29 to 76 within eight years. This is reflected by the more frequent information exchange, regional survey, and scientific cooperation in terms of cooperative industrial development and urban management. Finally, in 2016, taking Nanjing-Wuxi-Suzhou-Shanghai as the intersection, the YRD formed two large network circles with the other five cities in Jiangsu province and seven cities in Zhejiang province, respectively.

The degree centrality of 16 cities can be classified into three types. The first type is Shanghai, which leads substantially in the degree centrality. The average centrality of Shanghai reaches 101, far exceeding that of other cities. The second type includes Nanjing, Zhenjiang, Yangzhou, Nantong, Hangzhou, and Huzhou. The average degree centrality of these cities ranges from 45 to 60, indicating the relatively active roles of these cities in regional cooperation. The other nine cities belong to the third type, whose degree centralities are less than the average. Among them, Wuxi (25), Zhoushan (22), and Shaoxing (22) have the lowest degree centrality.

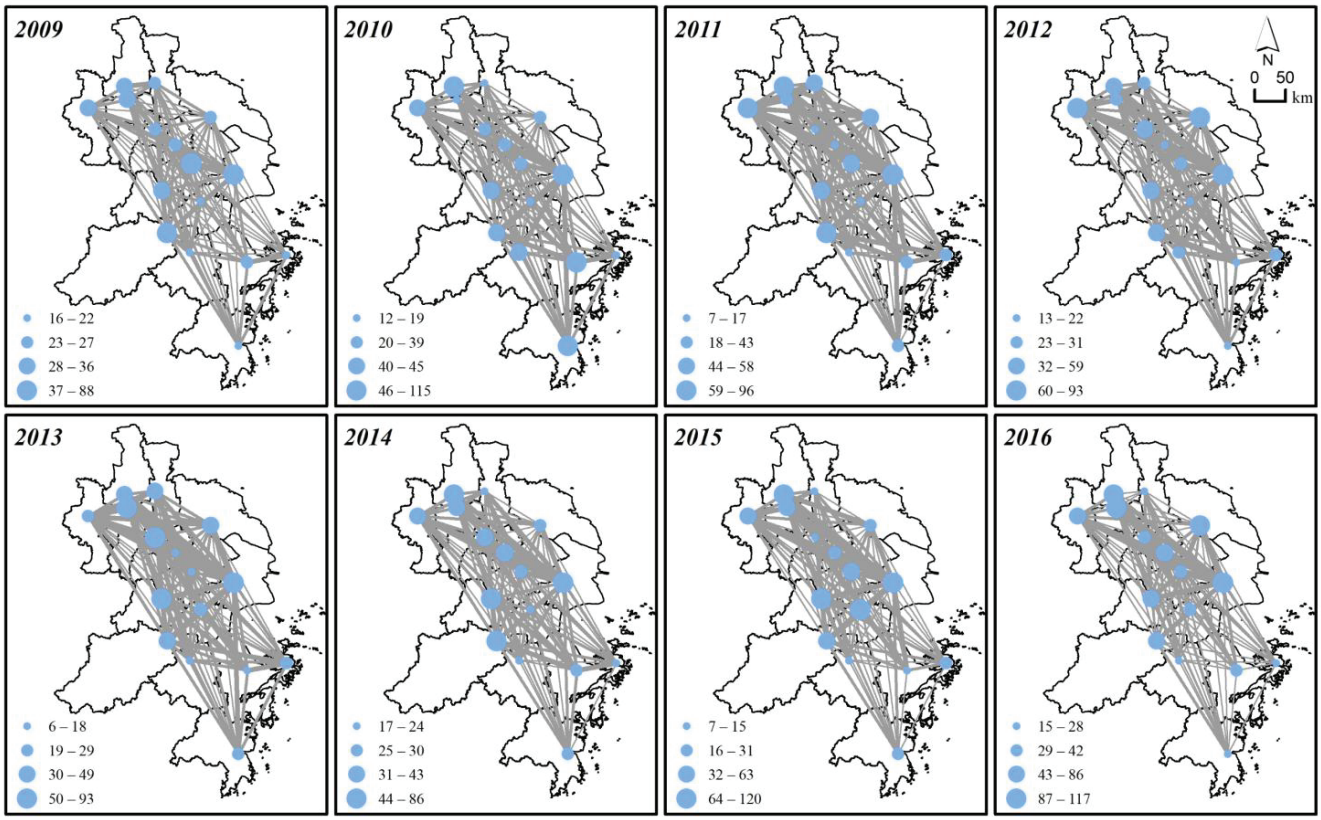


**Figure 3.** Regional cooperation network and degree centrality in the YRD.

### *4.2. ULUE Changes in the Cities of the YRD*

The ULUE of 16 cities from 2009 to 2016 is shown in Figure 4. The overall ULUE in these cities remains low; only seven cities are characterized by effective land use, and the other nine cities remain in an ineffective state of land use, when considering the average ULUE of 1 as the threshold for effective land use. Among them, Zhoushan (1.445) ranks first, and Ningbo (0.608) ranks last. From the temporal scale, the ULUE of 16 cities shows a slight decline, with an annual decline rate of 0.89%. Geographically speaking, cities in the middle of YRD have relatively high ULEUs from 2009 to 2016.

The characteristics of ULUE change vary across these cities. Shanghai, Yangzhou, Nantong, Hangzhou, Huzhou, Jiaxing, and Zhoushan remain in a high ULUE from 2009 to 2016. ULUEs of these cities are both above 1, reflecting the highest ULUE in the YRD. These cities balance the economic, social, and environmental benefits of land development yield, and make efforts to control urban land expansion. Nanjing, Changzhou, Zhenjiang, Taizhou (Jiangsu province), and Ningbo are featured by a slight increase in ULUEs from 2009 to 2016. ULUEs of these cities mainly range from 0.5 to 1. In particular, the land-use efficiency of Changzhou improves significantly, with an annual growth rate of 7.3%. The economic yield of land use is high, while social and environmental yield remains in a medium range. Suzhou, Wuxi, Shaoxing, and Taizhou (Zhejiang province) are featured by "multi-peak" fluctuation falling. ULUEs of these cities decrease from 2009 to 2016, with the decline range between 0.5 and 0.9. Especially in Taizhou, the annual decrease rate of ULUE achieves 10.8%. Suzhou and Wuxi have high industrial energy consumption and pollution emission, leading to considerable negative environmental output and the weakening of ULUE. The descending ULUE in Shaoxing and Taizhou (Zhejiang province) is attributed to their higher proportion of employees in secondary and tertiary industries, higher total investment in fixed assets, and lower average salary of employees, in comparison to land development.

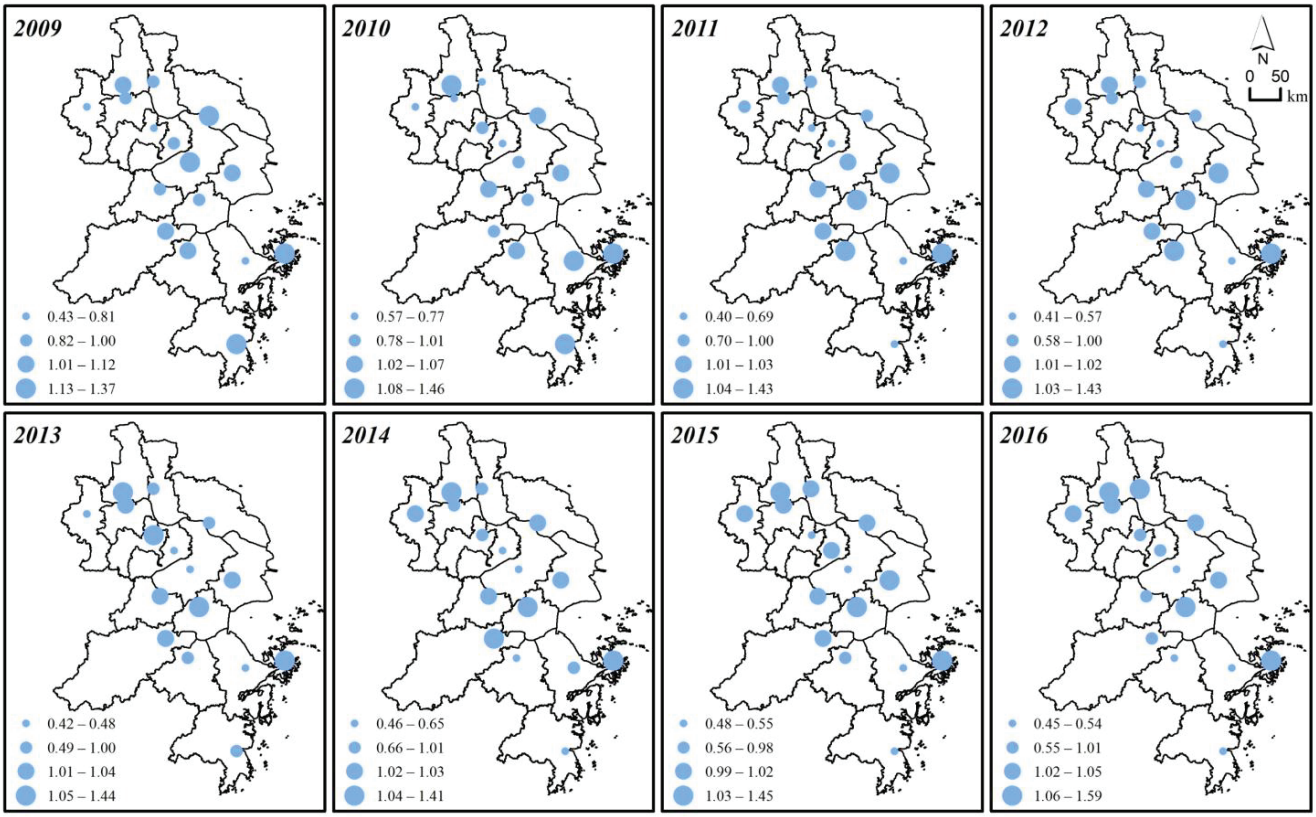


**Figure 4.** ULUE change from 2009 to 2016.

### *4.3. The Impacts of Regional Cooperation on ULUE*

The model fit of two traditional models (OLS and TWR) and GTWR are compared after the tests of multicollinearity and spatial autocorrelation (Table 3). It should be noted that the percentage of explanation of variance has increased from 37.21% in the OLS and 39.03% in the TWR to 76.44% in the GTWR. Besides, adjusted $R^2$ values increase from 0.3460 in the OLS and 0.3653 in the TWR to 0.7547 in the GTWR. It reveals that the GTWR model is the best, even if the differences in degrees of freedom with the reduction in AICc (from −19.5304 for the OLS and −15.7549 for the TWR to −67.9987 for the GTWR) are taken into account. By comparing the residual sum of squares (RSS), the decreased value further indicates that the GTWR shows a better regression fitting than the OLS and TWR models.

**Table 3.** Comparison results of OLS, TWR, and GTWR models.

| Regression Types | AICc | $R^2$ | Adjusted $R^2$ | RSS |
|---|---|---|---|---|
| OLS | −19.5304 | 0.3721 | 0.3460 | 5.8581 |
| TWR | −15.7549 | 0.3903 | 0.3653 | 5.7326 |
| GTWR | −67.9987 | 0.7644 | 0.7547 | 2.2155 |

The regression results of the GTWR are presented in Figure 5. The minimum, median, mean, and maximum coefficients of regional cooperation are 0.0021, 0.0057, 0.006, and 0.0108, respectively. This indicates a positive impact of regional cooperation on ULUE in the cities of the YRD. Meanwhile, the mean coefficients of regional cooperation are varied in the YRD, showing that the impacts of regional cooperation on ULUE vary among 16 cities. In general, the mean regression coefficients are large in the southern cities of the YRD, medium in the middle cities, and small in the northern cities. The mean regression coefficients of Ningbo, Zhoushan, and Taizhou (Zhejiang province), which are the top three cities in the YRD, are above 0.8. Wuxi and Changzhou results are also prominent in the northern YRD, with mean regional cooperation coefficients of 0.0063 and 0.0062, respectively. By contrast,

those in Taizhou (Jiangsu province), Zhenjiang, Shanghai, Yangzhou, and Nanjing remain at low levels, with scores below 0.005. The mean regression coefficients in the other seven cities ranges from 0.005 to 0.0063.

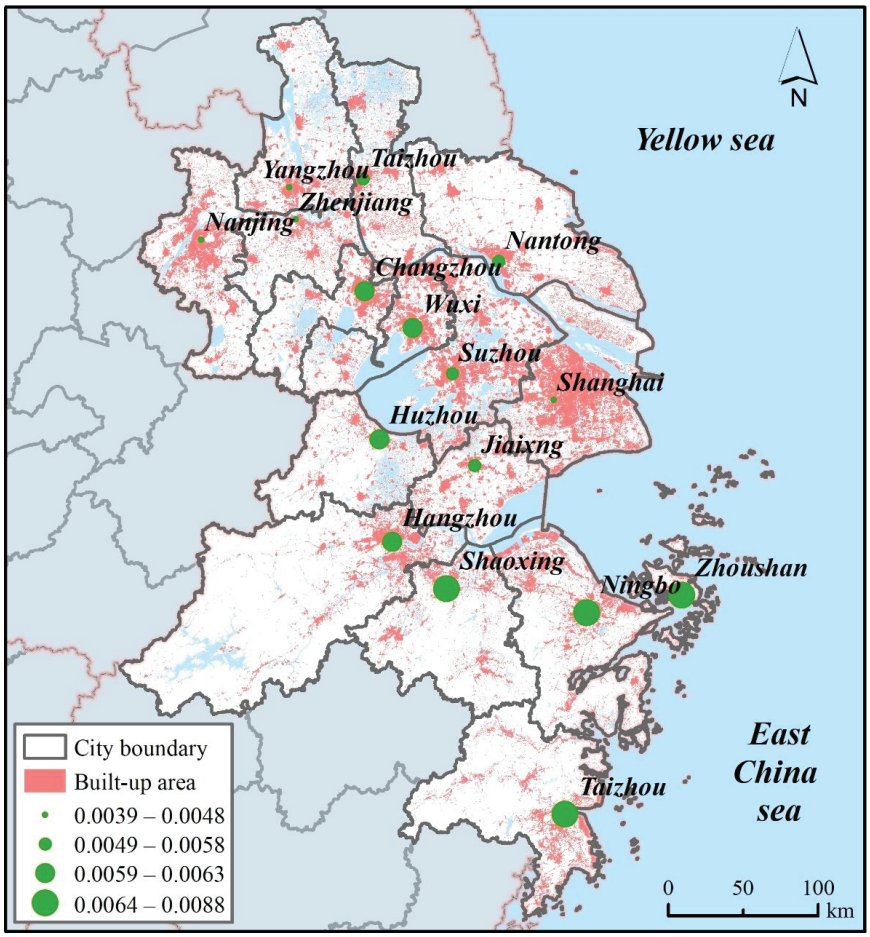


**Figure 5.** Distribution of the mean regression coefficients.

## 5. Discussion

### *5.1. The Influence Mechanism of Regional Cooperation on ULUE*

#### 5.1.1. Improvement of ULUE by Co-Building Transportation Facilities

Our findings reveal that the mean regression coefficients of regional cooperation in Ningbo and Zhoushan are the highest in 16 cities of the YRD. The possible explanation is that co-building port facilities improve ULUE, which is inferred from a large amount of regional cooperation news about the Ningbo-Zhoushan Port between Ningbo and Zhoushan. The Ningbo-Zhoushan Port is one of the largest ports and the first port in the world with an annual cargo throughput of more than 1 billion tons. It was merged with Ningbo Port and Zhoushan Port in 2006. The positive effect of the Ningbo-Zhoushan Port on ULUE benefits are its spatial plans, efficient land-use mode, and high economic output. First, cooperative spatial plans contribute to compact land patterns. In 2006, Ningbo-Zhoushan Port Management Committee was established to regulate the major construction projects of Ningbo-Zhoushan Port integration. Local governments planned a comprehensive road network as "2 rings, 10 radials, 4 links, and 4 avenues" to gain the agglomeration effect in the Ningbo-Zhoushan Port. The master plan of Ningbo-Zhoushan Port (2014–2030) designed the spatial pattern of "1 port, 4 cores, and 19 districts", which clarified functional positioning, respectively. Second, a series of strategies were adopted to promote effective land use in the Ningbo-Zhoushan Port. On the one hand, local authorities revitalized a large number of deserted islands in Zhoushan and built related infrastructure.

The successive development of fishing villages, i.e., Jintang, Shulanghu, Huangzeshan, and Liuheng to core parts of Ningbo-Zhoushan Port contributes greatly to land economic yield. On the other hand, the Ningbo-Zhoushan Port was committed to developing intermodal systems to save transportation costs and ease traffic tension. For example, Meishan Port was opened as a free-trade zone of the Ningbo-Zhoushan Port, to play an important role in international trade in 2010. Third, the Ningbo-Zhoushan Port took advantage of increasing returns to scale to develop the port industry and port service industry. It expanded the scale of the port area from 2009 to 2016 by means of increasing the number of berths and lengths of wharves. In 2015, there was an increase to 170 large berths of 10,000 t class and 100 extra-large deep-water berths of 50,000 t class, which evolved into the busiest port for large ships in China.

#### 5.1.2. The Positive Effects of JDZs on ULUE

As an important form of economic cooperation, the positive effects of cross-border industrial parks on ULUE can be confirmed by the regression coefficient of Wuxi and Changzhou, whose mean regression coefficients are prominent in the northern cities of the YRD. According to the news about regional cooperation, the news amount of JDZs in Wuxi and Changzhou leads other cities substantially. Since 2006, Jiangsu province has initiated the steps on the construction of cross-border industrial parks through north–south cooperation, to accelerate the industrialization process of northern Jiangsu and promote the industrial upgrading of southern Jiangsu. Wuxi and Changzhou are keen on cooperating with cities in northern Jiangsu and constructing industrial parks jointly, such as Wuxi-Xinyi industrial park, Xishan-Fengxian industrial park, Xinqiao industrial park, Yuehai industrial park, and Linjiang industrial park. According to Luo and Shen [40], such modes of JDZs in Wuxi and Changzhou play a crucial role in coordinating urban economy and industrial cooperation among cities. This is beneficial for improving ULUE.

Jiangyin economic development zone is a typical case of JDZs, which is a provincial development zone jointly established by Jiangyin (in Wuxi) and Jingjiang (in Taizhou, Jiangsu province) in 2003. Compared with other JDZs in Jiangsu province, which were initiated by some local enterprises for cross-border investment and conflict resolution, it has obtained the involvement of provincial governments, i.e., preferential policies, financial support, and management services. Such features provided new possibilities to guarantee intensive land development and land economic output. On one hand, joint land development is achieved by transferring industries, labor, and raw materials among cities, upon which land will be saved. On the other hand, the endowment of provincial government power may attract enterprises and maintain the smooth process of industrial production.

### *5.2. Policy Implications and Limitations*

Detecting the impacts of regional cooperation on ULUE can provide policy implications for intensive urban land development. Firstly, joint land development among cities is an effective way to improve ULUE, such as the modes of co-building transportation facilities and JDZs. Due to the limited built-up land quotas in most cities in the YRD, joint land development can save built-up land quotas for multiple cities but also motivate related industries in a region to gain an agglomeration effect. Indeed, a few pioneer projects of joint land development were launched in the YRD and improved ULUE. For example, the Caohejing development zone has established a park with a planning area of 105 $km^2$ in Yancheng and a zone with a planning area of 15 $km^2$ in Haining, which saved Shanghai's built-up land quota and stimulated industries to unitive parks in Yancheng and Haining. Our study also confirmed that the establishment of massive joint land development projects helps to improve ULUE in the cities of southern Jiangsu. The policy implication can be applied in cities in the Pearl River Delta and Beijing-Tianjin-Hebei urban agglomeration.

Meanwhile, joint land development as an instrument for transferring and upgrading industries helps economic yields of land use. Recently, the YRD is experiencing large-scale industrial relocation from big cities to surrounding cities, which provides the opportunity

for joint land development among cities. On the one hand, joint land development projects in surrounding cities can relocate manufacturing industries from big cities to support economic development. On the other hand, it can provide more land for big cities to develop financial services, high-tech, and other industries to promote land-use benefits when manufacturing industries have been relocated. This strategy is particularly propitious to core cities, such as Shanghai and Hangzhou. In these, large-scale development of residential and commercial land indicates more economic and social yields than industrial output, which promotes ULUE.

Besides, local governments should be aware of the important role of cooperative spatial plans in improving ULUE, as revealed by the planning efforts in co-building transportation facilities and JDZs. Firstly, a cooperative spatial plan delimits the urban growth boundary in the urban agglomeration, which aims to restrain the disorder development and uncontrolled urban sprawl. It will prevent the inefficient development of urban land use. Secondly, spatial planning often portrays a spatial structure for compact land-use patterns, such as "points, axis, belts, and networks", to guide the intensive land use. Thirdly, spatial planning can accelerate land, labor, and raw materials to industrial parks or development zones. Under the circumstances, overheated industrial land development and redundant facility construction are restrained.

There are some limitations to be further addressed. Firstly, the cities of the YRD were taken as a case to examine the hypothesis that regional cooperation is positively correlated with ULUE, due to the data unavailability. However, although the confirmation of the hypothesis in the case study may be typical, it is also to be verified in other regions, considering the differences in intercity cooperation and ULUE among regions. Secondly, while we preliminarily clarified the impacts of regional cooperation for economic, social, and institutional affairs on ULEUE in the conceptual framework, we failed to quantitatively explore the impacts from the perspective of different thematic areas of regional cooperation. Actually, regional cooperation could be further subdivided into many areas, including industrial development, infrastructure construction, urban planning, etc. [36]. Therefore, the impacts of multiple dimensions of regional cooperation on ULUE can be further explored.

## 6. Conclusions

The issue of what imposes impacts on urban land-use efficiency has attracted great attention from planners and governors across the world. Unfortunately, although a large body of literature was focused on analyzing the driving forces of urban land-use efficiency, those related to regional cooperation were rarely explored. To address the knowledge gap, we used the YRD, China as a case to examine the impacts of regional cooperation on urban land-use efficiency. Firstly, we developed a conceptual framework to uncover the potential impacts of regional cooperation on urban land-use efficiency. Secondly, official news about intercity cooperation was used to indicate regional cooperation through social network analysis. Urban land-use efficiency was measured through the super efficiency SBM model with undesirable outputs. Finally, geographically and temporally weighted regression was used to examine whether regional cooperation affects urban land-use efficiency.

The results show that regional cooperation increased from 2009 to 2016, indicating more frequent linkages among the cities in the YRD. Shanghai plays a leading role in the regional cooperation network in the YRD. Less than half of the cities in the YRD have good urban land-use efficiency. Shanghai, Yangzhou, Nantong, Hangzhou, Huzhou, Jiaxing, and Zhoushan maintain high land-use efficiency during 2009–2016, while Suzhou, Wuxi, Shaoxing, and Taizhou (Zhejiang province) feature low land-use efficiency, showing a declining trend. The regression results show a positive relationship between regional cooperation news and urban land-use efficiency, which verifies our hypothesis that regional cooperation will improve urban land-use efficiency. This impact in the southern cities of the YRD is more evident than that in the northern. The potential mechanism to explain the impacts of regional cooperation on improving urban land-use efficiency includes

co-building transportation facilities and joint development zones. Therefore, cities are supposed to explore joint land development to save built-up land quotas and promote industrial transfer and upgrading. Besides, cooperative spatial plans can be regarded as local governments' instruments to guide intensive land use.

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Review

# A Review of Spatial Mismatch Research: Empirical Debate, Theoretical Evolution and Connotation Expansion

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**Abstract:** At present, widespread urban expansion, regeneration, and transformation have inevitably led to the spatial separation of residence and employment, and negatively affected the employment welfare of the subjects concerned, which needs to be traced back to the theory of spatial mismatch to explore possible solutions. The theory of spatial mismatch has been proposed for more than sixty years, and its theoretical connotation has been continuously expanded through the heated debate on its objective existence. However, due to the lack of understanding of its expansion process and the essence of its theoretical connotation, its theoretical meaning is ambiguous and fails to truly guide its role in practice. Based on the structural analysis of the connotation of spatial mismatch, this study summarizes the theoretical evolution and empirical development of spatial mismatch from four levels: "objects of concern-influencing factors-spatial relations-consequential effects". It is found that after half a century of evolution, the study of spatial mismatch has formed a relatively perfect theoretical and methodological system, and in the process of expansion, spatial mismatch has been given a deeper meaning, which can provide an important theoretical and practical reference for solving the separation of residential and spatial resources and the resultant welfare loss effects.

**Keywords:** spatial mismatch; empirical debates; theoretical evolution; connotation expansion

## 1. Introduction

The transformation and development of territorial and urban systems, whether it is incremental expansion or spatial reconfiguration of the stock, inevitably brings about the restructuring of urban industries and land use, and in turn brings about a trend of spatial separation of residence and employment [1,2]. This separation is considered to be the main cause of the employment and income difficulties of some groups, and this dilemma is even more acute for the disadvantaged groups having explicit barriers to mobility and access to the separated employment resources [3]. How to deal with the residence-employment separation and the consequential employment difficulties has been identified as goals for cities and communities. In this regard, there is an urgent need to trace theories and find possible solutions.

The theoretical basis for the study of residential-employment spatial separation and the resulting job losses can be traced back to the spatial mismatch hypothesis developed in the late 1960s [4]. At that time, technological innovation, rising land prices in urban centers, and declining transportation costs combined to bring about a massive and sustained suburbanization of metropolitan America. While the rapid growth in labor demand (particularly in manufacturing and retail for low-skilled, blue-collar workers) has shifted from the inner city to the suburbs, Black ethnicity has been passively segregated in the inner city due to suburban housing market discrimination, or actively segregated in the inner city due to "residential stickiness", resulting in a spatial separation of Black people from suitable jobs

in the suburbs, and then a decline in income and even unemployment [5,6]. In Kain's article "Residential Segregation, Black Employment, and Metropolitan Dispersal", Kain found and tested that "the spatial separation of inner-city black neighborhoods from suburban jobs in the Chicago and Los Angeles metropolitan areas induces high unemployment rates among inner-city blacks" [4]. This finding was then refined into the spatial mismatch hypothesis and its implications were clearly defined: the subject concerned is on inner-city Blacks, the influencing factors are the suburbanization of employment in metropolitan America and racial discrimination in the housing market, and the relationship manifests itself as a spatial separation of residence and employment, resulting in high unemployment, low incomes, and long commutes for inner-city Blacks.

Soon after the spatial mismatch hypothesis was put forward, empirical studies using different indicators, methods, and studies on different groups have intensively debated the objective existence of spatial mismatch [5–8]. With the continuous expansion of spatial mismatch research in terms of groups concerned, influencing factors, and spatial relationship metrics, more and more scholars have moved from objective existence examination to asking about the mechanisms of spatial mismatch [9–12], and have devoted themselves to extracting and summarizing from empirical studies and constructing theoretical models to upgrade spatial mismatch hypotheses into theories [13–18]. Meanwhile, scholars in various countries have combined spatial mismatch research with country-specific scenarios such as public housing allocation, public transport development, urban spatial planning, and slum upgrading, making spatial mismatch theory widely used [19–24]. In a word, spatial mismatch has been studied for more than half a century, and has gone through different stages of theoretical hypothesis, objective existence debate, and hypothesis rising into theory; its connotation has been enriched and its application has been expanded. However, there are few studies to sort out the whole process of the development of spatial mismatch theory and to refine its theoretical essence, making the current research on spatial mismatch biased in the following two aspects: one is to confuse spatial mismatch with housing segregation, job accessibility, and job-housing separation, and the other is to focus on the analysis of the spatial structural relationship between housing and employment at the macro level of aggregation, ignoring the impact on the relevant groups in terms of employment participation, wage income, and other labor market dilemmas. As a result, most of the current studies point to macro spatial distribution issues such as the balance of employment and residence, as well as urban planning, and lack sociological perspectives on issues such as social justice and spatial equity, which deviates from the original purpose and essence of spatial mismatch theory.

Many urban spaces in the developing world, represented by China, are currently in a period of rapid sprawl. The resulting urban spatial alienation and separation of residence and employment is a phenomenon that has become obvious. The disadvantaged groups who cannot afford the high housing prices in the city center and are gradually moving to the urban periphery are facing similar spatial barriers to employment and welfare deprivation as the Blacks in the inner cities of the United States, and failure to address these problems in time will likely lead to spatial injustice and social imbalance [1,25]. In the face of this emerging reality, it is necessary to clarify a series of questions such as "which groups are affected by spatial mismatch, what are the manifestations of spatial separation, to what extent does the separation lead to welfare loss for the groups concerned, and what are the real causes of spatial mismatch" in order to find answers to these issues. This requires a return to the theory of spatial mismatch itself and a reconsideration of the practical and theoretical propositions that it implies. In fact, since its first formulation by Kain, the spatial mismatch hypothesis has illustrated the theory elements, including the group concerned, influencing factors, spatial relationship manifestation, and consequential effects hierarchically. Therefore, this study aims to analyze the hierarchical elements of the spatial mismatch theory, and to sort out the whole process from the debate to the continuous expansion of its theoretical elements, as well as to reaffirm its theoretical value in solving the increasingly prominent spatial and social injustice of many cities.

## 2. The Debate on the Objective Existence of Spatial Mismatch

Once the spatial mismatch hypothesis was formulated, studies were conducted to examine the validity and generalizability of the hypothesis using empirical statistical methods. A number of studies revolved around several levels of the initial definition of spatial mismatch, seeking to falsify it in terms of the limitations of the indicator methods used, the non-dominant influence of spatial distance, and the fact that the subjects concerned were not restricted to inner-city Blacks. Many studies, on the other hand, have more or less confirmed spatial mismatch along Kain's lines, and since the 1990s there have been a number of reviews that support spatial mismatch, with a long-running debate between the verifying and disproving sides over the objective existence of spatial mismatch.

### *2.1. Falsification of Spatial Mismatch*

Although Kain's research on the relationship between residential segregation of Blacks and their employment has pioneered a new research direction, his study has been questioned since its inception, with some scholars questioning the objective existence of spatial mismatch from the perspectives of the validity of the selection of indicators and the scientific nature of the model construction, e.g., the Quarterly Journal of Economics published three consecutive papers discussing the rationality of his research methodology and the credibility of his findings with Kain [26–28]. At the beginning of the second half of the 1980s, more studies questioned the objective existence of spatial mismatch in terms of the importance of spatial distance, arguing that the spatial barriers to employment resulting from the geospatial separation of residence and employment had a minimal effect, and that racial mismatch [7], transportation mismatch [29], skill mismatch [30], information mismatch [31], and even policy mismatch [32] mainly account for the employment loss of disadvantage Blacks (Table 1). Other studies have found that suburban areas may face similar spatial mismatch problems as inner cities [33], and that Whites trapped in inner cities for economic reasons also are affected by spatial mismatch [8], suggesting that there are more possibilities for the spatial mismatch hypothesis than just a simple formulation of the initial definition.

**Table 1.** Representative literatures of the various mismatch types.

| Mismatch Type | Representative Literatures | Main Conclusions |
|---|---|---|
| Racial Mismatch | Ellwood (1983) [7] | Barriers to employment for Blacks do not stem from spatial factors, but rather from racial issues arising from skin color |
| Transportation Mismatch | Ong & Miller (2005) [29] | Heavy reliance on the slow public transport is the real reason for the long commute times for residents of inner cities |
| Skill Mismatch | Stoll (2005) [30] | The mismatch between lower-skilled inner-city minorities and traditional lower-skilled jobs in the suburbs could explain a large proportion of the Black-White employment gap |
| Information Mismatch | Parks (2004) [31] | Good social relations in the family can improve employment outcomes for migrants, especially for women |
| Policy Mismatch | Chapple (2006) [32] | Many policy measures to improve the links between minorities and suburban job opportunities have not significantly improved their employment outcomes |

### *2.2. Confirmation of Spatial Mismatch*

Most empirical studies still confirm the objective existence of spatial mismatch, especially since the second half of the 1980s when American urban sociologists re-emphasized the theoretical assumption of spatial mismatch in the face of the persistence of poverty clusters and high unemployment rates among inner-city residents. Keith R. Ihlanfeldt was probably the most active researcher on spatial mismatch during this period, publishing several empirical studies on employment suburbanization and the Black-White wage gap [33], employment accessibility and the employment rates of Black youth [34,35], and employment accessibility and the employment earnings of Hispanic youth [36], all of whose results

fit the description of the spatial mismatch hypothesis. Other scholars' findings, controlling for variables such as individual characteristics, family characteristics, neighborhood characteristics, local unemployment rates, and population growth, all confirm to a greater or lesser extent the objective existence of spatial mismatch [37,38]. Most of the review studies since the 1990s have also supported the objective existence of spatial mismatch. Kain sorted out the impact of housing market discrimination on Black employment and wage levels from the perspective of labor economics, and responded to empirical studies questioning spatial mismatch in each case [39,40]. Some scholars have analyzed the results of different or even contradictory empirical studies from a methodological perspective [41,42]. More scholars have found through the review that with the expansion of the object of spatial mismatch research, the maturity of research methods, and the enrichment of influencing factors, the debate about whether spatial mismatch exists objectively is no longer meaningful [43–45].

The continuing debate over the objective existence of spatial mismatch is related to the inconsistent understanding of the connotations of the spatial mismatch hypothesis. As spatial mismatch was initially proposed to emphasize the adverse effects of space and distance on the labor market outcomes of inner-city Blacks, the early connotation of spatial mismatch was relatively clear but narrowly defined: the subject of the study was Black ethnicity, and the main influences on Black employment disadvantage were necessarily derived from spatial factors in the context of residential segregation and employment suburbanization. Studies questioning the objectivity of spatial mismatch have argued that any inconsistency with these four levels of representation falsifies spatial mismatch. Differences in the subjects, influences, and measures of spatial mismatch can lead to arguments about spatial mismatch. It is important to note, however, that while Kain focused on inner-city Black ethnicity at the beginning of the spatial dislocation proposal, he did not deny the spatial mismatch faced by other groups, particularly vulnerable groups. Although Kain emphasized the role of space as well as distance in the labor market outcomes of Black ethnicity, he clearly recognized how space was interconnected and embedded with social structures, racial discrimination, and labor market functioning.

## 3. Expansion of the Research Scope of Spatial Mismatch

A growing number of studies have realized that spatial mismatch itself was from the beginning not only about how space interacts with the labor market, but about how space is related to race, transport, skills, social relations, occupational segmentation, and other elements that influence labor market outcomes, and that spatial mismatch needs to be understood and constructed in a broader context [40,45]. With further suburbanization, changes in demographic characteristics, housing market reforms, and economic restructuring, and urban sprawl, scholars have begun to reassess the diametrically opposed findings on spatial mismatch by placing them in the new socio-economic context and working to expand the possibilities of spatial mismatch in terms of the group concerned, influencing factors, indicator methods, spatial relationships, and consequential effects.

### *3.1. Expansion of the Group Concerned*

Black inner-city Americans face employment vulnerability from the separation of residence and employment, as do other minorities in inner cities. Employment suburbanization can also negatively affect the employment rates of inner-city Hispanic and Latino workers [36,38,46], and even inner-city Whites experience employment vulnerability due to the separation of residential-employment space [47]. Youth are more vulnerable to job market fluctuations due to their lack of employability skills and transportation options [48], and the employment participation rate of ethnic minority youth in particular declines significantly due to reduced employment accessibility [35,37]. Female workers also present frequent employment disadvantages due to occupational segmentation and family responsibilities in the process of suburbanization of employment [49]. Other disadvantaged groups, such as immigrants [50], low-skilled [51], low-income groups [52,53], entry-level

workers [54], individuals recently released from prison [55], and welfare-recipients [56], have entered the study of spatial mismatch in America.

Since then, scholars in other countries have found that not only disadvantaged groups, but also ordinary workers may face employment disadvantages arising from spatial mismatch. Groups such as city dwellers, community dwellers, and general commuters have also become the subject to be included in the study of spatial mismatch [57]. However, subsequent studies have argued that there may be considerable differences in the spatial separation of residence-employment and the resulting negative labor market impacts for different groups, i.e., the spatial separation of residence and employment may not necessarily face spatial mismatch, as some groups may rely on transport as well as personal capabilities to compensate for the threats posed by spatial separation. Therefore, disadvantaged groups remain the focus of spatial mismatch research, but only that the types of disadvantaged groups vary over time and depending on their locations. In China, disadvantaged groups living in low-income settlements such as subsidized housing, urban villages, and old neighborhoods are the main targets of spatial mismatch studies [58–60].

### *3.2. Complication of Influencing Factors*

Since the late 1990s, spatial mismatch research has shifted from simply examining spatial mismatch to disentangling the influences that trigger it. Early scholars had mainly attributed spatial mismatch in US metropolitan areas to the suburbanization of employment and the residential-employment separation under housing market segregation [4,5]. Later, a growing number of studies have argued that it is important to focus not only on the spatial separation of residence and employment, but also on the processes of connection or barriers between employment opportunities and workers [45,61], i.e., what prevents ethnic minorities such as inner-city Blacks from supplying labor to suburban areas where labor demand is growing. Residential immobility, commuting barriers, and job searching barriers form three major barriers to spatial mismatch: (1) In the context of suburbanization and urban spatial reconstruction, the lack of residential mobility makes it spatially difficult for ethnic minorities, such as Blacks, to move closer to jobs and increases their employment possibilities [62]; (2) The lack of cars and the inaccessibility of public transport in situations where residence is far from employment result in barriers to commuting [36]; (3) Weaker access to employment information and inefficient job searching behavior may exacerbate the employment vulnerability of the groups concerned in the absence of the separation of their residence and employment [63]. The current widespread urban sprawl, urban renewal in many developing country cities, such as the reconstruction of city centers, shantytown renovation, new town development, and the construction of affordable housing in suburbs, have shifted a large number of vulnerable groups to the urban periphery, inevitably leading to the spatial separation of vulnerable groups from the job-rich central areas. Meanwhile, the combination of barriers to migration caused by high property prices in central areas, barriers to commuting caused by poor transport facilities in the suburbs, and barriers to job search caused by a lack of access to employment information leads to spatial mismatch [1,58,64].

Therefore, the research which were originally presented to falsify the objective existence of spatial mismatch shown in Table 1 have turned out to help the expansion of spatial mismatch theory at last (Figure 1). Employment suburbanization and residential segregation bring about the physical manifestation of residence-employment spatial separation on one hand. On the other hand, a series of factors, such as race, transportation, employment skills, employment information, etc., may create residential immobility, commuting barriers, and job searching barriers to aggravate the dysconnectivity between residence and employment. In a word, spatial mismatch is a phenomenon that reflects the loss of employment welfare due to the spatial distance of residence from employment and the lack of connectivity between residence and employment. Spatial mismatch is caused by a combination of factors such as restricted residential migration, imbalanced public transport policies, lack of individual mobility, selective discrimination in the job

market, and poor access to employment information, all of which are superimposed on the changing spatial structure of the city. Overall, research on the factors influencing spatial mismatch has evolved in two respects: firstly, from focusing on the factors influencing the distance of the relevant subject from employment (residential segregation) to the lack of connection between residence and employment (residential immobility, commuting barriers, job searching barriers); and secondly, by interconnecting and embedding these factors with space and understanding spatial mismatch from a broader perspective of spatial inequality, emphasizing the essential link between space and factors such as race, poverty, transport, and individual characteristics rather than separating them out and considering only spatial distance, so as to resolve the debate between spatial mismatch and racial mismatch, transportation mismatch, skills mismatch, information mismatch, etc.

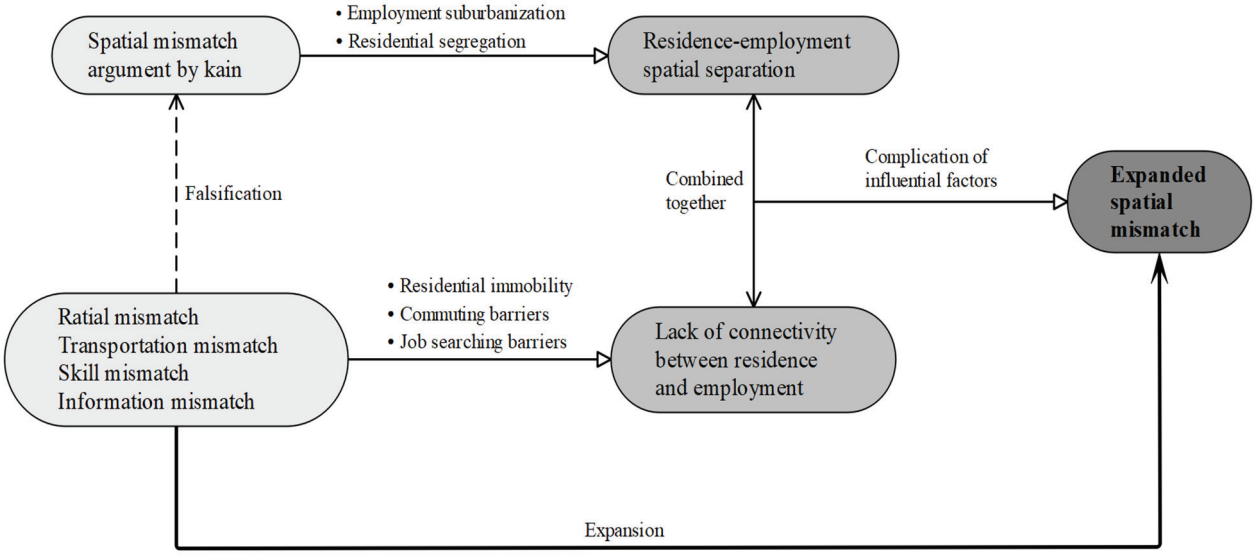


**Figure 1.** The complication of influential factors of spatial mismatch.

### *3.3. Diversity in the Manifestation of Spatial Relations*

To confuse spatial mismatch with residential segregation, residential-employment separation, and lack of accessibility is in fact to confuse the measurement of spatial mismatch with the manifestation of spatial separation. No matter segregated in inner city but employment decentralized or relocated in suburbs but employment concentrated in city centers, both manifest the residence-employment spatial separation. However, spatial separation is only a pre-stage of spatial mismatch, which occurs when spatial separation results in employment loss for the group concerned. Appropriate indicators and methods to accurately measure spatial separation are the prerequisite for testing spatial mismatch. Job accessibility is an indicator commonly used to characterize the spatial relationship between residence and employment. It is literally easy to understand, but its accurate measurement is very difficult. Over the years, research has developed a number of indicators to measure spatial relationships. These indicators can be divided into two main categories: those that indirectly reflect job accessibility and those that directly reflect job accessibility (Table 2).

**Table 2.** Category of spatial relationship measurement indicators.

| Categories | Specific Indicators |
|---|---|
| Indirectly reflecting job accessibility | Residential Segregation<br>Residential suburbanization<br>Employment suburbanization |
| Directly reflecting job accessibility | Commuting-based job accessibility: commuting time, commuting distance, commuting costs, etc.<br>Employment-based job accessibility: ratio of job to residence |

3.3.1. Indirect Indicator of Job Accessibility

(1) Residential segregation

Using residential segregation to reflect the separation of Blacks from employment was the indicator originally used in the spatial mismatch test. This is related to the initial emphasis on racial discrimination in suburban housing markets and the resulting residential segregation leading to impaired employment status for Blacks [4,5]. The logic behind this was that residential segregation would prevent the group concerned from being closer to employment growth opportunities and therefore affect their employment status. However, the degree of residential segregation can indirectly measure the separation from employment and can be seen as a crude institute for job accessibility, as residential segregation does not show the relationship between residential area and job distribution and can lead to biased results.

(2) Residential suburbanization

Residential suburbanization is also an indirect way of reflecting the job accessibility [11,65]. The logic behind it is that inner-city Blacks are less accessible to job opportunities than suburban Blacks, and the lack of job opportunities can lead to higher unemployment, longer commuting distances, and lower wages. Earlier studies have examined spatial mismatch by comparing differences in employment participation, commuting, and wages between inner-city Blacks and suburban Blacks, but the findings vary considerably. This may be related to the simple city-suburban ring dichotomy: employment opportunities are unequal within the simple delineation of city-suburban areas, and the boundaries of city-suburban areas are constantly changing and blurring over time.

(3) Employment suburbanization

The degree of employment suburbanization is usually measured as a ratio of the number of jobs outside the inner city to the total number of jobs. The spatial mismatch can be tested by comparing the differences in the number of jobs in inner city and suburban areas and linking them to differences in the income status of Black in inner cities and suburbs [21]. However, some studies have suggested that discussing all job numbers in general would lead to bias, and that the proportion of certain jobs suitable for certain groups should be used, such as the proportion of manufacturing, retail, and service jobs suitable for Blacks [38]. It is important to notice that using this indicator is still subject to the simple city-suburban ring dichotomy and that wage earnings will vary according to the profitability, labor market supply and demand conditions of different zones, which need to be carefully excluded from the study.

3.3.2. Direct Indicator of Job Accessibility

While the first three indicators have their own use logic, they can only indirectly reflect job accessibility to characterize the spatial relationship between residence and employment. Some studies have suggested the need to directly measure job accessibility, i.e., to directly reflect the proximity of the employed population to job opportunities.

(1) Commuting-based job accessibility, such as commuting time

If the accessibility of jobs is low for a particular group, a longer commute is required for employment. While Ellwood argues that commute time is the best direct indicator of job accessibility, two contrasting conclusions have been reached by testing the relationship between commuting time and Black youth employment, with some studies that concluded no significant effect [7] and others that concluded that there was a significant effect [34,35]. The differences in empirical results may be related to sample selection bias, endogeneity of residential choices, and differences in commuting distances, commuting tools, and commuting nodes. Studies have also suggested that accessibility is a concept that involves physical, psychological, economic and social features, which makes the measurement of it invalid using traditionally place-based accessibility related to the costs needed to reach a destination [66]. Thus, explicit indicators, such as surface for vehicular traffic only,

pedestrian accesses, percentage of accesses without architectural barriers, etc., are used to measure the commute-based accessibility directly [67,68].

(2) Employment-based job accessibility, such as employment to residence ratio

Direct measures of job accessibility can also be made by directly reflecting the matching of potential employers of different geographical units with potential jobs in the vicinity, i.e., employment to residence ratio [69]. However, a range of methodological challenges may also affect the accurate measurement of job accessibility, including measurement bias issues using all jobs rather than vacant jobs, labor market segmentation issues using all jobs without distinguishing jobs suitable for low-skilled workers, including the failure to consider job market competition from residents of neighboring communities seeking jobs in their own community and from residents of their own community working in other communities, as well as the failure to consider issues such as distance decay effects due to the spatial mobility of employed people [70]. In this regard, some studies have created functions that express job vacancies, labor market segmentation, employment competition, and the degree of spatial obstruction between two locations in order to measure spatial accessibility of jobs more accurately [71–74]. The scale is also a key issue to be considered in the accessibility measurement, since the level of accessibility of cities or metropolitan differs greatly with that of regional, local, and individual [75]. Accessibility of 15-min neighborhood level is often used responding to the current urban restructuring that much more employment activities are supposed to be done in the 15-min neighborhood instead of in city scale. There is a higher accessibility if it guarantees an adequate supply of jobs and basic services within the 15-min neighborhood [76].

### *3.4. Extension of Consequential Effects*

It is always emphasized that spatial mismatch is formed when spatial separation of employment from residence and the resulting adverse labor market outcomes occurs in both stages. Spatial mismatch was first proposed through research which found that inner-city Blacks had higher unemployment rates due to geospatial mismatch from employment resources. As the research progressed, indicators of labor market outcome status such as employment participation, commuting, and income, as the main manifestations of the consequences of spatial separation, gradually became important indicators of the consequences of spatial separation in the test of spatial mismatch. Employment participation is the most commonly used indicator to characterize labor market outcomes, and where job accessibility is high, employment rates are relatively high [77,78]. Commuting distance, time, and cost were also another indicator of early empirical evidence of spatial mismatch. It was later suggested that distance, time, and cost alone do not fully represent the burden imposed on commuting, and that a combination of commuting costs may be a better option, taking into account the degree of inaccessibility and other unforeseen problems in commuting [79]. The wage income indicator was developed as a result of research that found that Black Americans in inner cities may shift from higher-wage jobs to lower-wage jobs in response to the spatial mismatch caused by suburbanization of employment, and that these Blacks may have no change in employment participation and a shorter commute, but significantly lower wages and earnings [80]. When conducting spatial mismatch tests, there are multiple combinations of how indicators are selected to reflect spatial separation as well as reflect labor market outcomes (Figure 2). This combination of different indicators, combined with the methodological challenges faced in the use of the indicators, has led to differences in the empirical results and the debate on the objective existence of spatial mismatch [81]. However, integration with labor market outcomes has been emphasized by spatial mismatch since its inception, and this is exactly where it distinguishes from macro-spatial pattern studies.

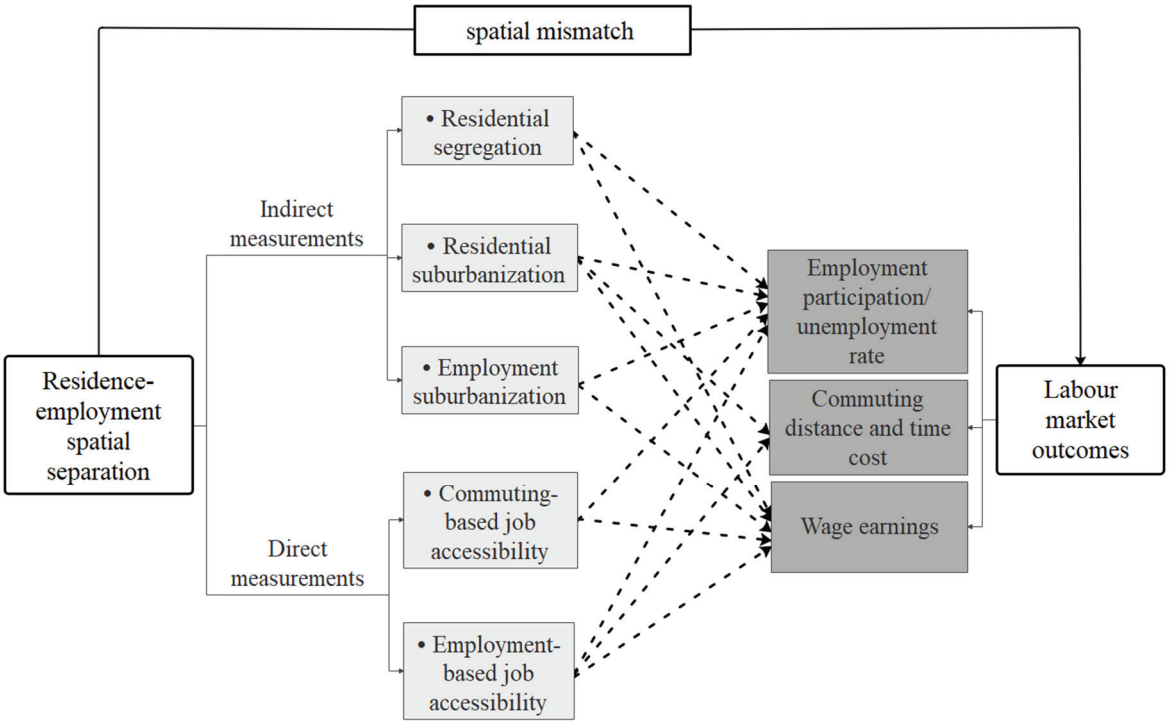


**Figure 2.** The measure of Job Accessibility and Spatial Mismatch.

In addition to impaired employment well-being resulting from the separation of residential and employment resources, residential misalignment with other spatial resources may also lead to a range of spatial welfare losses; the latter has become a powerful direction for the expansion of spatial mismatch research. The groundbreaking research in this area continues to be produced by Kain, who in 2004 raised concerns about the mismatch between disadvantaged groups and public service resources such as education and the resulting disadvantages. By using the example of public schools in Texas, he found that much of the Black-White achievement gap could be attributed to the continued residential segregation of Blacks in the inner city and the spatial inaccessibility of highly productive schools [40]. Public service resources include shopping and commercial services, health care, educational and cultural services, sports and green spaces, etc. The accessibility of public service resources is unequal across communities and is clearly linked to residential location [82]. With the suburbanization in the United States, there is a clear tendency to allocate public service resources to higher-income suburban communities. In China, the accessibility of public green space to different social classes varies and the excessive daily commute to kindergartens leads to a residence-kindergarten spatial mismatch [83]. In the UK, the accessibility of primary healthcare provision needs to be improved [84]. These studies have expanded spatial mismatch from the spatial relationship between employment and residence to public service provision. However, there is a need to further deepen the theory of spatial mismatch to guide how to bridge the gap from accessibility to public service resources to loss of public service benefits.

In other words, when spatial mismatch was first proposed, it was mainly focused on the spatial separation of residence and employment and the loss of employment welfare from the perspective of labor economics. Subsequently, most studies in the US, the UK, and other western countries also followed this line of thought, emphasizing the labor market consequences as a level that must be attended to in the study of spatial mismatch. However, with the intervention of disciplinary fields such as sociology and planning, spatial mismatch is not only used to express the separation of the spatial relationship between residence and employment, but the spatial relationship between residence and public service resources has also entered the realm of spatial mismatch research. Spatial

mismatch can be used to express the spatial relationship between multiple subjects, can be applied to areas other than the labor market, such as the study of the spatial relationship between residential areas and public service resources and the resulting loss of spatial welfare. This can dovetail with current hot issues such as spatial equality and social justice, thus continuously enrich and deepen the connotation of spatial mismatch and maintaining the vividness and lasting power of the theoretical value of spatial mismatch.

## 4. Study on the Mechanism of Spatial Mismatch: From Hypothesis to Theory

In the face of the intricate empirical research methods and results, some scholars have emphasized the importance and necessity of conducting normative research on spatial mismatch at the theoretical level [13–15]. However, it was not until the late 1990s that theoretical models related to spatial mismatch began to emerge. At the present, there are two main types of normative studies explaining the mechanism of spatial mismatch: the labor market effect model constructed from the perspective of commuting, and the search-match model constructed from the perspective of job search.

### *4.1. Description of Labor Market Effect Model*

The fact that commuting may discourage the unemployed from searching for jobs in distant zones or accepting long-distance jobs (low expected net wages after removing commuting costs) has long been a major concern of empirical studies of spatial mismatch, but theoretical studies of the commuting perspective have emerged relatively late. Coulson et al. (2001) constructed a basic version of a spatial mismatch model explained in terms of commuting, where differences in the entry costs of firms in different locations and differences in the commuting ability of potential workers lead to different spatial frictions in the search matching process between potential workers and firms and ultimately to equilibrium [85]. There are more vacancies in the suburbs than in the inner city, suburban dwellers work mainly in the suburbs, some inner-city dwellers who endure long commutes work in the suburbs, and inner-city dwellers are more likely to have reverse commutes, lower wages, and higher unemployment rates than suburban dwellers. Subsequent studies have taken into account housing market discrimination and depicted the equilibrium pattern of urban structure under employment suburbanization and housing market distortions: housing market discrimination confines Blacks to living in the inner city and discourages some Blacks from accepting suburban jobs, making the labor pool of inner city larger than the suburban, resulting in impaired welfare for Blacks at both fixed-wages and flexible-wages [14]. The model does not explain the effect of spatial mismatch on the unemployment rate. Subsequent studies have solved for the effects of employment suburbanization and housing market distortions on Black unemployment by assuming that labor demand is exogenous to the wage level: Black labor tends to be supplied in the inner city regardless of the minimum-wage setting or the efficiency-wage setting, resulting in higher black unemployment in the inner city than in the suburbs [86].

### *4.2. Description of Search-Match Model*

The job search process can reflect the spatial relationship between residence and employment, and the spatial distance between residence and employment may manifest itself in negative effects in terms of access to job information, job search intensity, and job search costs. Distance may reduce access to information about job opportunities, which may reduce the efficiency of job search and the likelihood of successful employment. When the expected benefits of search for potential workers are lower than the difference in commuting costs between workers and the unemployed, a spatial mismatch equilibrium tends to develop. Unemployed people living away from employment centers have lower search efficiency and higher unemployment rates [87]. Living away from the employment center, social networks are less effective in disseminating and sharing employment information, and search efficiency may be further reduced, and unemployment may be further increased [88,89]. Distance may reduce job search motivation and job search intensity,

which in turn affects employment participation levels: employment participants who live away from employment centers are less stressed about housing, less motivated to search for jobs, and do not search as frequently, increasing their short-term utility but losing long-term benefits, and may lower long-term employment possibilities and wage incomes. Spatial mismatch may also be the result of active behavioral choices by labor market participants [90]. High search costs may discourage inner-city residents from searching jobs in job-intensive suburban areas, thereby affecting employment participation levels: inner-city residents weigh search efficiency against search costs to choose their search area, and when search costs are too high in suburban areas, inner-city residents lose their incentive to search for jobs in suburban areas and unemployment increases; at the same time, high search costs reduce the bargaining ability of inner-city residents, making inner city residents bargain for lower wages in the suburbs than suburban residents [91].

Normative research can clarify the mechanism of spatial mismatch and sort out the messy results of spatial mismatch empirical studies, so as to help spatial mismatch hypothesis rise into spatial mismatch theory [92]. However, normative research has emerged late, and these theoretical models are mostly after, rather than ahead of, empirical research, resulting in a certain disconnect between normative and empirical research. For example, the exploration of factors influencing spatial mismatch in empirical research has transitioned from emphasizing residential segregation to focusing on barriers to residential migration, but so far there is a lack of normative research conducted from the factors of barriers to residential migration.

## 5. Conclusions and Discussions

### *5.1. Conclusions*

Through the process of spatial mismatch from "hypothesis formulation, objective existence debate, theoretical connotation expansion, hypothesis into theory", it is found that the process of spatial mismatch research development is essentially a process of continuous re-conceptualization of spatial mismatch theory. Kain's groundbreaking research focused on the adverse effects of space and distance on the employment of Blacks in inner cities in the United States, which was later described by scholars as the spatial mismatch hypothesis when distilling Kain's findings, resulting in a rather clear but narrow definition of spatial mismatch in the early years. The initial definition of spatial mismatch was too narrow, which led to a long debate on the objective existence of spatial mismatch. As the understanding of spatial mismatch deepens, research is no longer limited to testing spatial mismatch and debating the objective existence of spatial mismatch but begins to enrich and expand the connotation of spatial mismatch at different element levels. This has led to a general understanding of the current connotation of spatial mismatch, namely that the misalignment or inconsistency between residence and the location of job opportunities combined a series of geospatial barriers to employment together results in the disadvantageous position of the relevant subject in the labor market, describing the spatial relationship between residence and employment, focusing on the resulting spatial barriers and the labor market disadvantage of the relevant subject, with the complex factors that trigger spatial mismatch not explicitly specified but implied.

Residential segregation and poor transportation may also lead to a misalignment between residence and the location of public service resources, creating spatial barriers to access and enjoyment of public service resources by the relevant groups, reducing the accessibility of public service resources, and bringing about a loss of public service welfare for the relevant subjects. The use of spatial mismatch to express the spatial separation between residential areas and public service resources and the resulting loss of welfare makes spatial mismatch more possible. Spatial mismatch is a comprehensive reflection of the unequal spatial opportunities in accessing employment resources and public service resources such as education, health care, and green spaces, and its essence is to reveal the survival and living conditions of the relevant subjects in the changing spatial structure of the city from the perspective of the spatial separation between the place of residence and the

relevant resources. It is in the ongoing debate on the objective existence of spatial mismatch, in the practice of focusing on a wider group of people concerned, in the continuous improvement of the method of measuring spatial relations, and in the attempt to apply spatial mismatch to areas other than the labor market that help to give the theory of spatial mismatch deeper connotations, making it still a living theoretical value today (Figure 3).

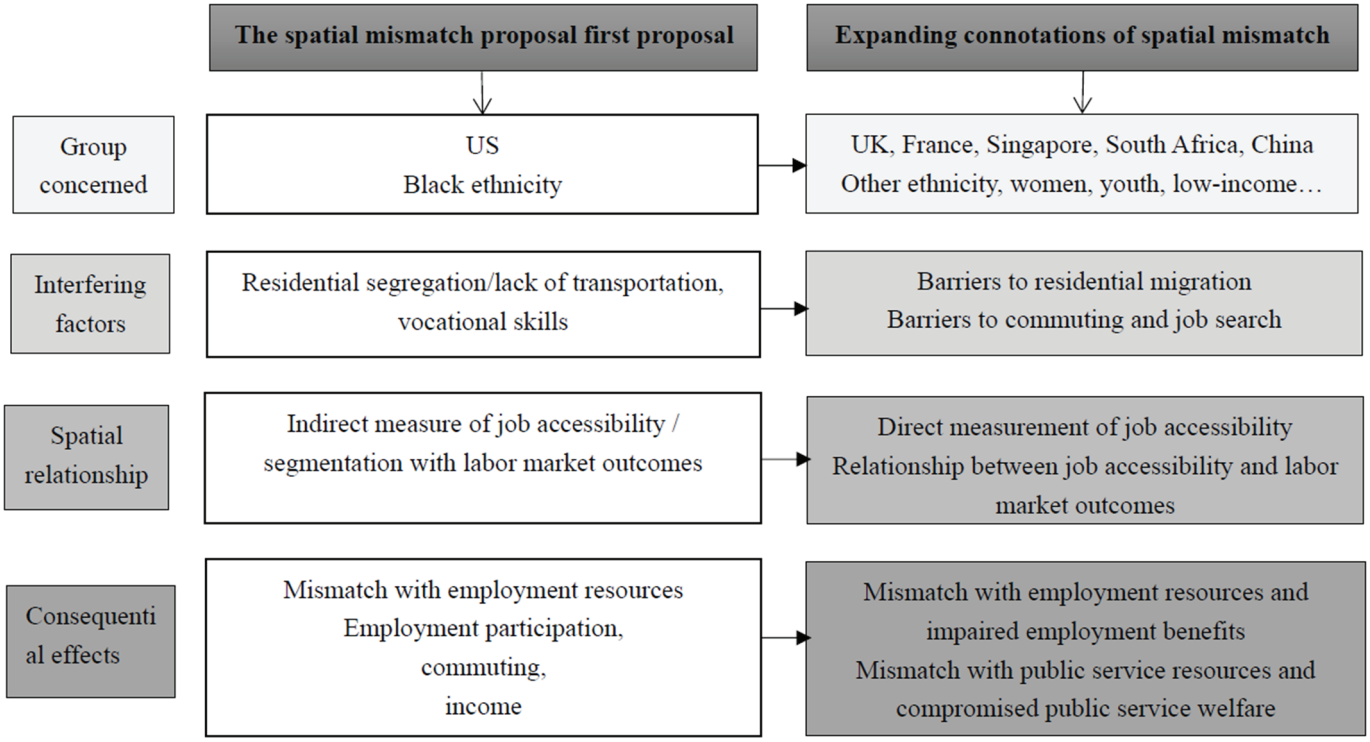


**Figure 3.** The Connotative Expansion of Spatial Mismatch Theory.

### *5.2. Discussions, Limitations and Future Research Directions*

The evolution and expansion of the connotations of spatial mismatch theory did not happen overnight. Some are still at a discovery stage, such as in the accessibility of public service resources and the resulting welfare-consequential effects. Some have yet to be examined in depth, such as action mechanisms that lead to the separation of residence from employment and prevent the group concerned from coping with this separation through migration. Some have not been fully applied, such as the improved indicators for measuring job accessibility to overcome methodological challenges and the test method for spatial mismatch. Under the current trends of "urban restructuring and spatial separation have become inevitable", "the pursuit of social equality and spatial justice", and "reflecting the differences of subjects and caring for humanistic demands", it is a challenge and a future direction for spatial mismatch research to focus on the welfare loss of the relevant subjects from the perspective of spatial mismatch and analyze the deep-seated causes and mechanisms of spatial mismatch.

As for limitations, firstly, the spatial mismatch theory itself has been detailly analyzed to help better understand the roots of the spatial mismatch theory and its potential and next evolutions. However, actions and interventions and policy implementations that oriented to edit and improve the spatial mismatch have not been paid enough attention. Therefore, this article is useful for scholars. While for city planners and administrators, it can provide theoretical preparation but cannot provide practical methods and policies about how to design and deliver services that are easily and conveniently available. Secondly, spatial mismatch theory reveals the spatial separation and the consequential adverse effect on the group concerned, but how the group concerned will react to such adverse effect have not been included in this research. Since the possible residential, employment, and travel

actions of the group concerned draw main references to the governors, the miss of possible action studies may also decrease the practical value of this research to some extent. Anyway, the specific practice for overcoming spatial mismatch of different countries differs since the influential factors and spatial separation manifestations are inconsistent. In addition, taking considering that, focusing on the intervention policies of spatial mismatch may dilute the live of logic about analyzing the hierarchical elements of spatial mismatch, this acritical have studied spatial mismatch theoretically, not applicably.

The spatial mismatch in the United States stems from the suburbanization of metropolitan employment and the segregation of the housing market in the late 1960s, manifesting itself in long commutes to suburban employment while living in the inner city. The spatial mismatch in many countries outside the United States, on the other hand, stems mainly from the transformation of the economic system and changes in the spatial structure of the city, manifesting itself in the concentration of employment in the central city and living in the urban periphery. Although the spatial mismatch in various countries is quite different in terms of its background and manifestation, its essence is always due to the spatial separation between residence and employment, resulting in barriers to employment and income for the subjects concerned. The current widespread urban expansion, renewal, and transformation in developing countries have inevitably led to the spatial separation of residence-employment and negatively impacted the employment welfare of the relevant subjects, and it is urgent to analyze and explore possible solutions from the perspective of spatial mismatch. The measurement of the spatial relationship between residence and employment cannot be confined to the macro level of aggregation. It is necessary to closely associate spatial separation with labor market outcomes, analyze the impact of spatial separation of residence and employment on the labor market, and then extend it to areas such as public service provision. In this way, the essence of spatial mismatch theory is grasped, and the scope of its application is expanded, so that it continues to maintain its vivid theoretical and applied value.

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# Integrating ANNs and Cellular Automata–Markov Chain to Simulate Urban Expansion with Annual Land Use Data

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**Abstract:** Accurately simulating and predicting the urban expansion process, especially in expeditious urbanization areas, is an important aspect of managing limited land resources and adjusting flawed land use policies. This research was conducted on the basis of a high-temporal-resolution land use dataset to precisely model urban expansion in a rapidly developing zone by integrating the Artificial Neural Network (ANN), cellular automata (CA), and Markov Chain (MC). An urban suitability index (USI) map was created using ANN and fed to CA–MC to identify possible changed-to-urban cells. Two ANNs, multiple-layer perceptron (MLP) and long short-term memory network (LSTM), were implemented as simulation models for comparison. Due to its ability to capture more temporal information, LSTM outperformed MLP in modeling urban expansion dynamics over a short temporal interval. The simulated results were validated by (fuzzy) kappa simulation and the results revealed that the combination of ANN and CA–MC can precisely model the urban development locations due to its strength in revealing the nonlinear relationship between the expansion process and its drivers. The same model was applied to southern Auckland, and the compared results show that the most simulated variance is caused by the land use policies implemented by different types of governments.

**Keywords:** urban expansion; artificial neural network; multiple-layer perceptron; long short-term memory network; cellular automata

## 1. Introduction

Since the economic reform in the late 1970s, China has been experiencing rapid economic development and urbanization, driven partially by a dramatic increase in the urban population [1–5]. However, the fast but unsustainable urban development in the past few decades has caused many pressing issues that have become obvious in recent years. The massive and chaotic urban expansion has led to the inefficient and irrational use of limited land resources, polluted the environment, damaged or destroyed the sensitive ecosystem, and degraded agricultural and forest land [6–9]. Naturally, much research has been conducted to monitor and model such changes [10–14].

Current urban expansion modeling is limited by a coarse temporal resolution owing to a lack of suitable data. Many empirical studies selected a temporal increment of five-year intervals or longer for the urban expansion model, due to the normal life cycle to form a new urban area from an existing one [8,9,12,15,16]. However, this temporal resolution does not allow urban expansion in rapidly developing cities to be detected in a timely manner, especially in some industrial districts [13,17]. Thus, it is impossible to assess the unanticipated effects of land use policies abruptly promulgated by central and local governments [3,18,19] or to remedy the problems arising from them. Therefore, a shorter temporal interval is highly desirable in modeling and analyzing urban land use changes to reveal more frequently updated details both spatially and non-spatially, and hence to better

explain the dynamic process within a rapidly growing urban area [20]. Another impactful issue, besides land use policy, is the transportation factor, including both already-built transportation facilities and transport planning, which could also exert significant effects on the urban expansion process. Early in 2004, Wegener and Fuerst [21] explored the interactions between transport planning and land use changes by implementing several models. In 2013, Wegener provided a more detailed explanation of the integrated models of urban land use and transport and discussed how to improve the models to simulate the most appropriate level of spatial resolution and substantive disaggregation [22]. Based on this research, Dingli et al. [23] conducted a systematic review of the socio-technical factors that impact urban transportation performance, hence modeling the urban land use status. All these previous studies demonstrated the critical role of the transportation factor. However, transport planning is always performed for a long time gap, which may reduce its impact when the simulation time is relatively short. To offer compensation for this, this research uses several proxy factors as transportation factors to include this important aspect.

Another issue in urban expansion modeling is the limited predictive ability of individual models. For the past two decades, static-data-analysis-based urban expansion research has been performed via advanced simulation modeling processes due to progress in geospatial technology. Such models as Cellular Automata (CA) [10,24–26], the Multi-Agent Model [27,28], the Land Transformation Model [29], and SLEUTH [30] have added the spatial scope into the urban expansion simulation processes. In 2015, Dr. Roger White, Dr. Guy Engelen, and Dr. Inga Ulgee, with their excellent book "Modeling Cities and Regions as Complex Systems: From Theory to Planning Applications", especially pointed out that to simulate the "complex, adaptive, self-organizing" urban system precisely, the traditional land use change models must be carefully incorporated with the spatial dynamics of human–environment interactions. They also provided a framework to combine the raw types of ANNs with CA to model population dynamics and economic activities [31,32]. In 2022, Kim et al. [33] and Yi et al. [34] also pointed out that CA models could combine with machine-learning-based algorithms to enhance simulation accuracy and provide more reliable results. From their work, in line with many other studies in the urban expansion modeling field, all simulation models need to capture the complex nonlinear relationships between various driving factors and urban expansion parcels, via the "bottom-up" model approach and different transition rules. Among these models, Cellular Automata with Markov Chain (CA–MC) is found to be one of the most popular CA-based models since it can easily predict the urban expansion demand based on the Markov Chain (MC) and implement the analytic hierarchy process (AHP) and logistic regression (LR) processes into the land use change iteration process to build the urban suitability index map. It can also allocate the amount of urban land spatially based on CA by taking fewer variables into consideration than other models. However, the self-adaptive ability of CA–MC to model the nonlinear relationships between drivers and the urban dynamic process is still not completely reliable [16,26,35].

Reliability can be improved by replacing AHP and LR with an Artificial Neural Network (ANN). ANNs can more efficiently consider the complex nonlinear relationships between the dependent and independent variables than AHP and LR, since they have advantages in simulating urban expansion dynamics [36,37]. Because of their self-learning ability, the unknown relationships among variables can be addressed with the automatic approximation of nonlinear functions by the ANN, which is better than linear-based regression models [38]. Moreover, due to its self-organizing and adaptive approach, the integration of an ANN can make the CA–MC more self-adaptive than the traditional models [39,40]. Therefore, ANNs have been integrated into many other spatial simulation models to simulate urban expansion, despite the difficulties in properly parameterizing and optimally configuring an ANN model [8,9,41,42]. Xu et al. [43,44] incorporated an ANN with CA–MC to simulate the urban expansion process in both the U.S. and Auckland, New Zealand, and to predict future possible urban building areas. Results from these

studies have demonstrated that such innovative integration can improve the accuracy of simulations. To provide more detailed information on the ANN-based CA–MC and improve simulation accuracy, the major objective of this paper is to integrate two ANNs into CA–MC for the modeling of spatiotemporal urban expansion dynamics in a rapidly developing area and to assess the model's capability.

The remainder of this paper is organized as follows: In Section 2, we describe the study area, explain the data used, and describe the methodologies that we have proposed to build the ANN–CA–MC model. After this, the results present the possible future urban expansion in both spatial and quantitative scopes. The model's results are further compared with a previous study to indicate the different expansion processes for developing and developed countries. Some limitations of this study are also discussed in this section. Finally, we conclude with the results and offer some future research directions. By doing this, we wish to reveal that a high temporal resolution of data could lead to a better result. Still, the model must have the ability to capture such characteristics. Furthermore, with the results, we seek to provide insightful information and a planning tool for the urban planners and decision makers that could be applied to compare the simulated results with land use plans to modify their work more effectively.

## 2. Data and Methods

### *2.1. Study Area*

The Liangjiang New District of Chongqing, southwest China, was chosen as the study area because it has been experiencing rapid growth since 2009. It comprises three industrial zones (Longxing, Yufu, Shuitu), two duty-free ports (an airport and a harbor), plus several counties (Figure 1). Characterized by an area of 1172 $km^2$, it has been designated as the first hinterland development and a showcase zone for southwest China. Thus, this district plays a very critical role in regional economic development. It enjoys both local and national incentivized land use policies, as well as a high level of investment and a well-designed future development plan. All these political advantages have led this area toward unprecedented urban development, utilizing a significant amount of land resources. The projected population inside this area was 3.5 million within a 350 $km^2$ built-up urban area by 2020. However, the actual amount of the built-up areas has already surpassed the planned value, since the number had already reached 344 $km^2$ in 2014, indicating that the average annual growth rate for the urban land is at 7.5%. Thus, further development will have to rely on a more intensive use of the land. Therefore, it is critical to judiciously model, allocate, and plan new urban areas in the future.

### *2.2. Data*

The National Annual Land Use Survey Database was used in this study, in which land use was mapped at different levels by the China Ministry of Land Resources. The database is in an annual temporal resolution and obtains data from a national–province–city multi-scaled land use transformation monitoring approach involving both remote sensing and field survey data. With this temporal resolution, the land use change can be periodically monitored so as to plan urban growth effectively. We simplified the data from the original 25 classes into 9 categories (farmland, orchard, forest, grassland, transport, water bodies, bare land, urban land, and other land uses).

In addition, for every grid cell in question during the modeling, its neighborhood effects in different years were also calculated because they would affect the cell status in future years. Other urban expansion drivers were all proxy factors, such as nearby existing urban areas, the distance to different types of roads, and utilities. They were also considered as independent variables for every cell during the simulation (Table 1).

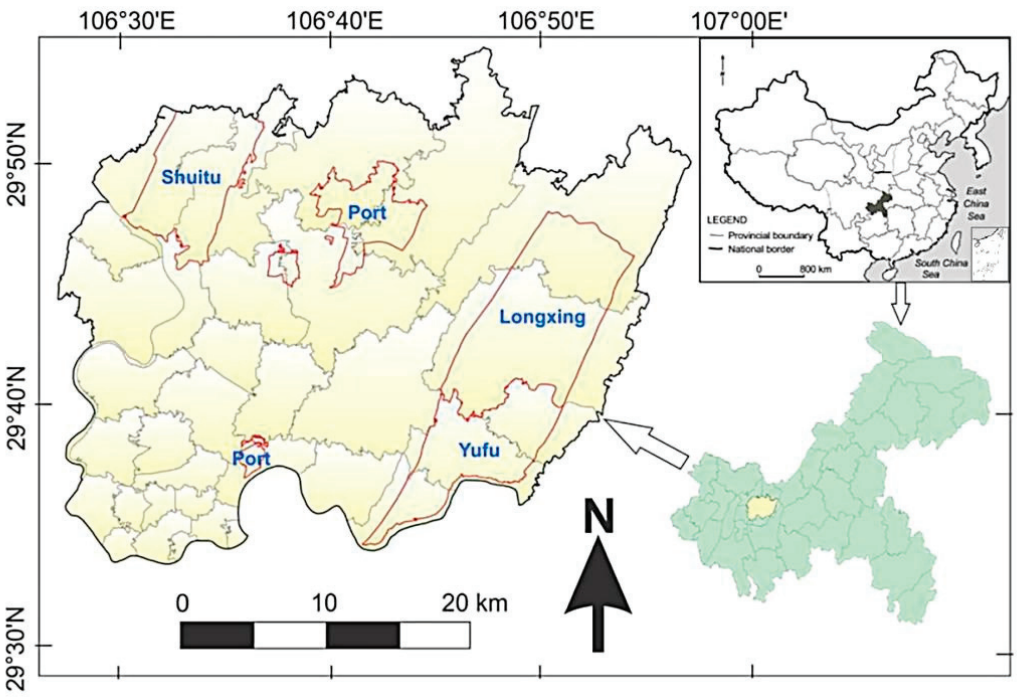


**Figure 1.** Study area: the Liangjiang New District, Chongqing, Southwest China. Red lines: boundaries of industrial zones and duty-free ports; grey lines: county boundaries.

**Table 1.** Variables considered in the modeling.

| Variable | Description |
|---|---|
| | Dynamic variables |
| Proxy: existing urban | Euclidean distance between existing urban cell and the target cell |
| Proxy: new road | Euclidean distance between the newly built roads (one year in advance) and the target cell |
| Land use | The proportion of all land use types within a Moore neighborhood (3 × 3 cells) |
| | Still variables |
| Digital Elevation Model (DEM) | Terrain factor, elevation value (height: meters) |
| Slope | Terrain factor, slope (in degrees) |
| Proxy: Motorway | Euclidean distance between the entrances or exits of motorway and the target cell |
| Proxy: Arterial Road | Euclidean distance between arterial roads and the target cell |
| Proxy: City major road | Euclidean distance between urban major roads and the target cell |
| Proxy: City medium road | Euclidean distance between urban medium roads and the target cell |
| Proxy: City minor road | Euclidean distance between urban minor roads and the target cell |
| Proxy: School | Euclidean distance between kindergarten, primary schools, and middle schools and the target cell |
| Proxy: Transports | Euclidean distance between bus stops, train stations, and ferry ports and the target cell |
| Proxy: Hospital | Euclidean distance between hospitals and the target cell |
| Proxy: Market | Euclidean distance between supermarkets and convenience stores and the target cell |

### *2.3. Methods*

#### 2.3.1. Artificial Neural Networks

ANN is one of the most popular modeling techniques used today, with self-learning, self-organizing, and self-adapting abilities [40,41,45]. In this study, two ANNs were integrated with CA–MC: MLP and LSTM. The MLP is considered the most frequently used and is constructed as the information feed-forward and error Back-Propagation Three-Layer Perceptron (BP-TLP) network architecture (Figure 2a). Due to its simple structure, ease of training, reasonable memory consumption, and fast as well as relatively accurate prediction results, this neural network was adopted to simulate urban expansion [46]. On the other

hand, the LSTM is explicitly designed to avoid the long-term dependency problem and has a strong focus on the temporal (sequential) scale; it can be combined with CA–MC to extract spatiotemporal information [47]. Instead of feed-forward, it is a recurrent neural network including a delayed input, also known as the feedback of the output, which creates a chain of repeating modules of the neural network (Figure 2b). For both ANNs, the most important aspect of their architecture is the number of hidden nodes in each hidden layer (also known as forgotten nodes and layers for LSTM), which significantly affects the ANN's performance [48]. Too few nodes will cause a significant prediction error, while too many will prolong the training process and lead to overfitting problems. Initially, the networks start training stepwise iteratively and will stop when the mean square error (MSE) meets the threshold value (0.01 in this study). The MSE is calculated from the difference between the network running output and the expected data value. However, insistence on meeting this supposed MSE threshold might lead to overfitting issues, which will decrease the model's accuracy. To avoid this problem, the two ANNs in this study applied an early stopping strategy by adjusting two training parameters: the number of training epochs and the maximum fail number. The time for a training epoch was set to 1000 and the maximum fail number was set to 50, which significantly reduced the possibility of overfitting in this study. In addition, the training batch size of LSTM also impacts the final result, so it is usually set as an integral time from the data.

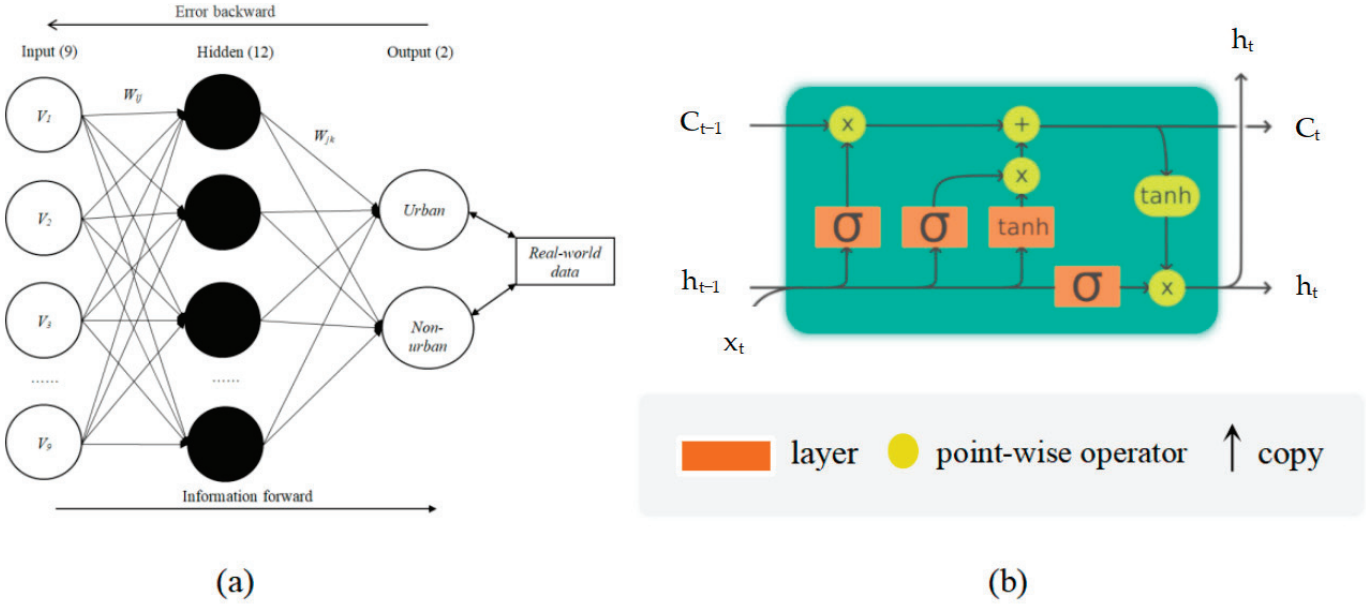


**Figure 2.** (**a**) The architecture of the BP-TLP ANN used in this study. *V* stands for the input variable, $W_{ij}$ is the connecting weights between the input layer and hidden layer, and $W_{jk}$ is the connecting weights between the hidden layer and output layer. (**b**) The architecture of LSTM. *X* is the vector (features) input; *h* is a hidden state vector, which is also known as the memory output vector of the LSTM unit; *c* is the cell state vector; σ and tanh are the activation functions. The green rectangle indicates the "forget" process for the LSTM.

#### 2.3.2. ANNs' Integration with Markov Chain—Cellular Automata

The Markov Chain model determines the expected amount of non-urban land transitioned to urban use in future urban expansions. It calculates the land use change process through the transitions of different land use types at a temporal interval of one year. Two results are generated from MC: a transition area matrix, which shows the absolute amount of change from different non-urban land uses to urban land, and a transition possibility matrix, which reveals the likelihood of the transition.

CA uses the present cell status and the cell's neighborhoods to forecast the future cell status, as expressed in Equation (1):

$$S^{t+1} = f\ (S^t, N, TR) \tag{1}$$

in which $S^{t+1}$ and $S^t$ represent the cell state at time $t$ and $t + 1$, respectively; $N$ is the effect neighborhood for one cell; $TR$ stands for the globe transition rule of the CA model; and $f$ represents the cell state transition function. For regular MC-CA, $R$ is the transition possibility matrix produced from MC, which shows only the numeric results from two land use datasets, without any information on the spatial distribution of the modeled changes. This problem is solved by using the *USI* map generated from *MLP* (Equation (2)) and *LSTM* (Equation (3)).

$$USI_MLP = f_{MLP}\ (V_1, V_2, \ldots, V_i) \prod C \tag{2}$$

where $f_{MLP}$ is the activation function of the ANN; $V_i$ serves as the $i$th input variable, and $C$ is a binary value of 0 or 1, indicating the constraint factors, such as water or ecological reserved zones.

$$USI_LSTM_t = f_t \times USI_LSTM_{t-1} + i_t \times S^t \tag{3}$$

where $f_t$ is the forget function of *LSTM*; it is the scaling down function for input variables and cell state $S^t$, and it is usually sigmoid or tanh.

Hence, the final state (urbanized or not) of $cell_{ij}$ in this ANN–CA–MC will be represented as Equation (4):

$$S^{t+1}{}_{ij} = f_{ca}\ (S^t{}_{ij}, A^{t+1}, USI_{ann}, N_{multiple}) \tag{4}$$

where $A^{t+1}$ is the projected amount of the future urban expansion by MC, $USI_{ann}$ is the *USI* generated from either the *MLP* or *LSTM* network, and $N_{multiple}$ represents different land use neighborhood effects at cell ($i$, $j$) ($i$-row, $j$-column). The CA transition rules are now the combination of *USI* and *N*.

### *2.4. Model Implementation*

Figure 3 illustrates the detailed steps in the integration of these two machine-learning-based ANNs with CA–MC to model urban expansion. Annual land use data and spatial data such as DEM, slope, road network, and facility locations (Table 1) were collected to create a geodatabase in the GIS environment, from which the urban expansion areas and related driving factor values were extracted. Afterwards, both changed and unchanged cell samples were selected using the maximum dissimilarity distance algorithm (MDA) or random sampling. The selected samples were used to train MLP and LSTM and to create the USI map. In addition, the annual land use data were delivered to the MC to calculate the planning amount for future urban expansion. The ANN–CA–MC simulated the urban expansion at a certain time from the expected amount of expansion and the USI map output from either MLP or LSTM, taking into account the multiple neighborhood land use effect. The output model results were validated against the actual land use data using kappa simulation. Only when the modeled results passed the validation process was the properly configured and trained model then used to predict future urban expansion, which could provide useful information for the modification of land use policies and plans.

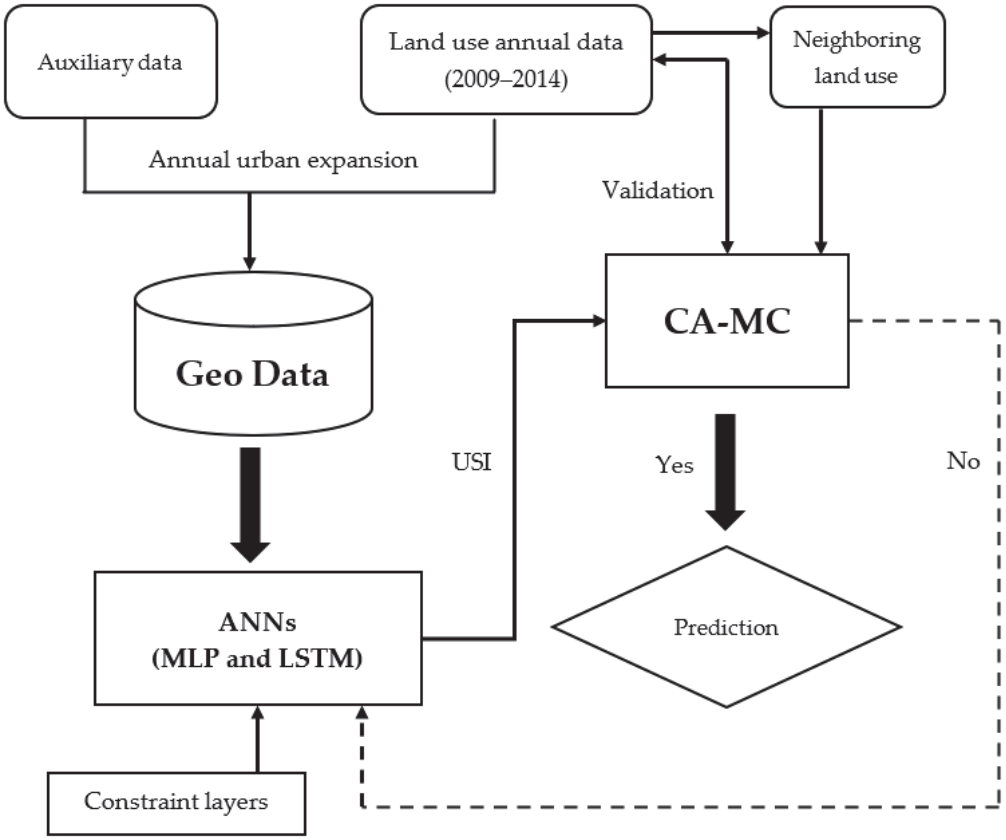


**Figure 3.** ANN–CA–MC framework for modeling urban expansion in the Liangjiang District of Chongqing, China.

## 3. Results and Discussion

### *3.1. Urban Suitability Index Map*

Three USI maps (Figure 4) have been created based on two ANNs. Cell values in the USI maps ranged from 0 to 1, indicating the suitability of non-urban cells for the future urban development (new urban areas) process. This range was grouped into five classes using an equal interval to present a more obvious spatial distribution of these cells' future urbanization possibilities, namely very high (0.8–1, red), high (0.6–0.8), moderate (0.4–0.6), low (0.2–0.4), and very low (0.0–0.2, green) (Table 2, with both areas and percentage values). Based on the results from MLP with two different sampling methods, known as random selection and the most dissimilarity algorithm (MDA) (Figure 4A,B), we can see that the vast majority of non-urban areas in the Liangjiang New District are not a suitable choice for future urban development, as, generally, over 75% of the non-urban land cells have a suitability index value of less than 0.2. From Table 2, rows one and two, cells having a suitability > 0.6 are relatively small in quantity (approximately over 8%). They are located either close to or inside mature, built-up urban zones, indicating a possible compact development (e.g., infilling and edge development) in this study area called the "organic urban growth mode"; all of these areas were accurately modeled by the MLP-based ANN. The most suitable focal areas for future urban development are distributed in the government-delineated industrial development zones (red line in Figure 2), as well as next to the developed counties. The medium suitability value indicates possible future urban expansion. Both maps show that the Longxing and Shichuan counties (top right), having this value, are the next most promising areas to be urbanized. However, both the quantity (Table 2, row 3) and spatial pattern (Figure 4C) of the USI from LSTM are different to those of the MLP network. Over 95% of these non-urban cells are predicted to have a very low likelihood of urbanization in the future, while only 2.6% of them have a USI > 0.6, much

lower than this value for the MLP. In addition, only a very small number of non-urban cells have a medium USI value (0.2–0.6), with less than 0.5% of this area predicted to be transitioned to urban uses based on the LSTM. The spatial patterns of high USI with the LSTM are still close to existing urban cells but are more dispersed, with a large amount of high USI cells only distributed in the three industrial zones, and very few outside their boundaries (Figure 4C). This zonal-based distribution shows that the LSTM has the ability to capture the land use planning information through the temporal learning process.

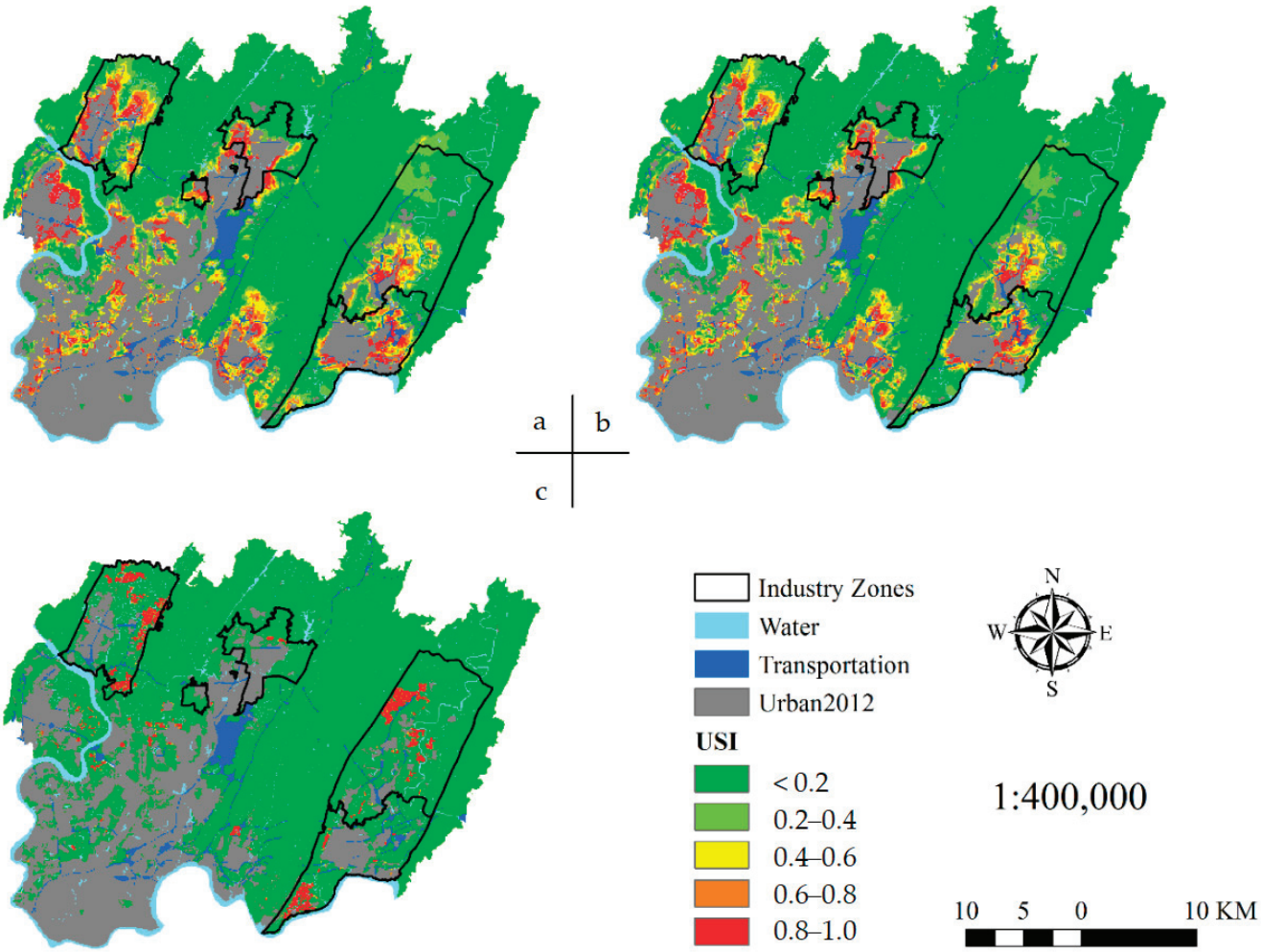


**Figure 4.** USI map of the study area from ANNs. (**a**) MLP with random sampling; (**b**) MLP with MDA sampling; and (**c**) LSTM.

**Table 2.** Proportions of areas for five groups of USI values predicted with three methods (unit: $km^2$/%).

| Range | <0.2 | 0.2–0.4 | 0.4–0.6 | 0.6–0.8 | ≥0.8 |
|---|---|---|---|---|---|
| MLP–Random | 596.38/75.3% | 79.38/10% | 47.94/6.0% | 38.11/4.8% | 31.27/3.9% |
| MLP–MDA | 612.23/77.2% | 73.30/9.2% | 44.98/5.7% | 33.92/4.3% | 28.65/3.6% |
| LSTM | 769.00/96.9% | 2.43/0.3% | 0.87/0.1% | 1.54/0.2% | 19.27/2.4% |

### *3.2. Model Validation*

To validate the model's accuracy, the simulated urban expansion result for 2014 (Figure 5) was obtained by feeding the annual land cover changes from 2009 to 2013 into the integrated ANN–CA–MC model. After this, the model results were compared to the ground truth urban land data for 2014, and the validated results are shown in Table 3. MC

analysis resulted in a projected future urban expansion value of 46.3 km$^2$ in 2014, compared to the actually expanded area of 48.78 km$^2$, leading to a maximum simulation accuracy of 95%. As we can see from the spatial urban expansion patterns in Figure 5, MLR-Random predicted fewer expansion areas than the other three models in the upper northern region of the study area. In addition, the infilling and edging expansions were more accurately simulated than the isolation expansion due to the model's capability. All the models showed a high degree of local agreement (kappa > 80%) between the model-simulated and the ground truth urban areas, which indicates that both MLP (regardless of the sampling method, either random or MDA) and LSTM could precisely simulate the urban area in 2014. Judged against (fuzzy) kappa simulation, which takes future possible land transitions into account, as well as modifying the agreement between two urban land use maps for the size of class changes and comparing the cell states' variations instead of the static status [49], LR has the lowest values, indicating that it has the weakest ability to model the nonlinear relationships among all the algorithms. LSTM has the highest validation values among the models, and thus the most accurately modeled results, because of its capability to learn within a short time interval, which is important in modeling fast-growing urban areas.

**Figure 5.** Simulation results of year 2014, Liangjiang New District.

**Table 3.** Validation results of (fuzzy) kappa simulation of four types of models.

| Method | Kappa | Kappa Simulation | Fuzzy Kappa Simulation |
|---|---|---|---|
| LR | 0.818 | 0.27 | 0.51 |
| MLP–Random | 0.829 | 0.36 | 0.64 |
| MLP–MDA | 0.827 | 0.32 | 0.53 |
| LSTM | 0.857 | 0.48 | 0.70 |

The significant differences between MLP and LSTM are due to differences in their treatment of temporal aspects. As Figure 6 illustrates, if the annual land use data (2009–2013 in this study) were used to simulate the most recent land usage (2014 in this study), the MLP would not consider the time differences of each factor but only use the data from the previous year as the entire training dataset to train the network, since it cannot

successfully reveal the temporal changes. However, on the other hand, the LSTM will consider every annual change and changes between different time gaps separately and add this time-scaled effect into the final result.

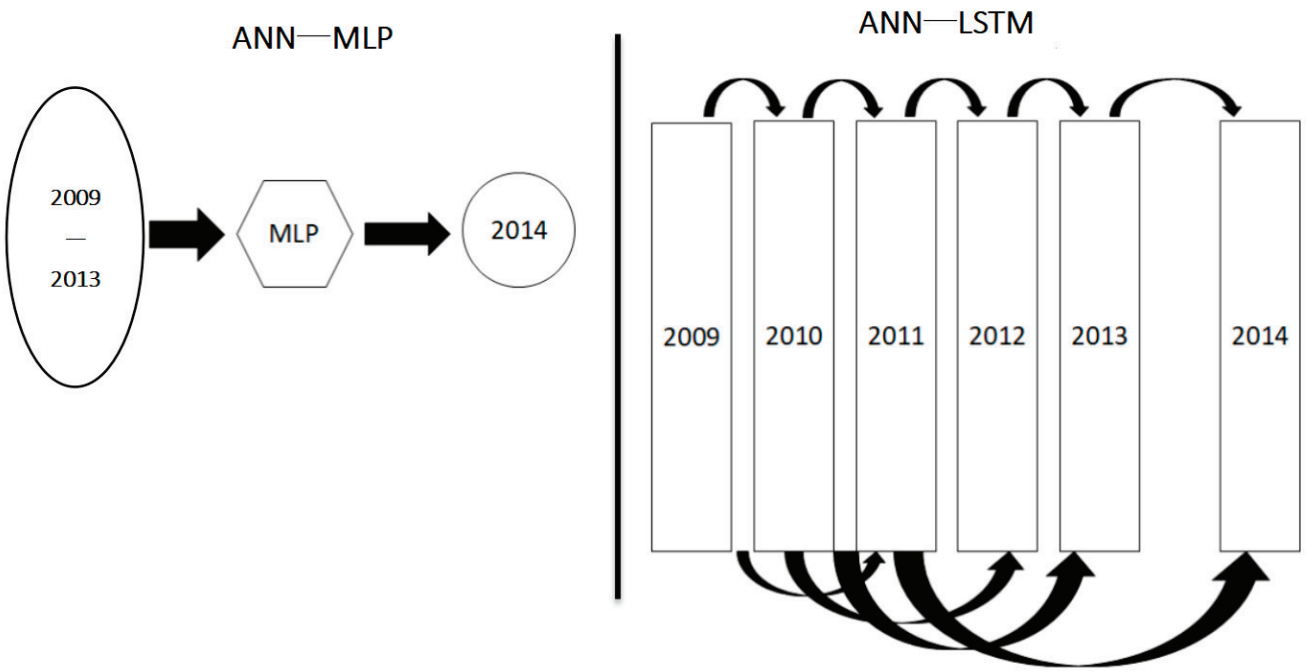


**Figure 6.** Differences between MLP and LSTM in dealing with annual land use data.

*3.3. Model Result Comparison between the Liangjiang New Distract and Southern Auckland*

We applied the same MLP-structured ANN–CA–MC model to southern Auckland, New Zealand, with a similar geodata set collected in 2018, to simulate urban expansion in this area. In this project, besides the ANN model, AHP-CA and logistic-CA were also applied to compare the simulation results and the ANN-based model that presented the best results as an intelligent urban model. More details for the Auckland-based research can be found in our earlier paper published in 2019 [42]; this former research provides us with the opportunity to perform a comparison. As a result, when comparing the results between Auckland (west) and Liangjiang New District (east), all the simulation model's validation results were higher in Auckland than in Liangjiang New District. The areas of simulated urban expansion in 2016 were validated by land cover change data from 1996 to 2006. Compared to Lianjiang New District, the simulation in Auckland showed a longer temporal discrepancy between the year of simulation and the year of the latest validation data (10 years for Auckland and 1 year for Liangjiang New District). However, all the model validation values were higher in Auckland than in Liangjiang New District (Table 4). With southern Auckland, the ANN–CA–MC could simulate urban expansion with a very high kappa (0.94) and acceptable kappa simulation (>0.50), demonstrating that both the urban pattern and urban expansion could be modeled at a high certainty level [42]. In Liangjiang New District, China, the model was less accurate. The validation results, though still considered acceptable, were less satisfactory compared to those for Auckland. The kappa was only slightly higher than 0.8, and the kappa simulation of MLP was below the medium level (0.4–0.6), while it was 0.48 for LSTM. These values suggest that we could still locate the major urban areas (kappa) within the study area, but the model is less accurate in simulating the changes in urban areas (kappa simulation).

**Table 4.** Model validation results between southern Auckland and Lianjiang New District.

| Area | Model with Best Performance | Kappa | Kappa Simulation |
|---|---|---|---|
| Southern Auckland | ANN | 0.941 | 0.547 |
| Liangjiang New District | LSTM | 0.857 | 0.48 |

The most significant reason for this discrepancy is the role of land use policies and planning in the simulation, which were not taken into account in the model, an issue that has also been identified by other researchers [50–52]. As is widely known, the governments in China act as the only legal landowners, and governments at different levels tend to have different perspectives on the prioritization of land utilization purposes [1,3,53]. The aforementioned Liangjiang New District plays a very important role in the national development strategy of China [54], where urbanization needs to be fast-paced and most of the new urban areas are pre-designated and planned by governments at both the local (Administration Committee of Liangjiang New District) and national levels (The State Council). Many policies and rules are used to restrict the location and distribution of future urban areas, such as the "Grain for Green", "Farmland Protection", and "Low Hilly Slope Zone" policies at the state level and "Destocking" and "Expropriation-Transfer Separation" at the local level. It is often found that the designated aims or outcomes of such multi-level policies conflict with their local or national counterparts [44]. Under this circumstance, the location of urban areas is more definitive, and their spatial distribution is more dispersed; these factors create difficulties in simulating and predicting their future patterns. Another possible reason for the less accurate modeled results is the quality of data supplied to the model. As a result, the urban expansion mode under government directions and guidance is much more complex than that in developed countries such as New Zealand. On the contrary, for cities such as Auckland, many have been experiencing slow development since the 1990s. However, the southern part of Auckland maintained significant growth, with an average annual urban development of almost 800.0 $km^2$. The simulated directional expansion of urban Auckland is in agreement with the government's desire and plan to build a compact city. Initially, the development in the south was mostly the continuation of the area's previous development, due to its low slope value (8.24 percent rise) compared to the other three directions. In 1996, the Metropolitan Urban Limit (MUL) was proposed and adopted to build a more compact city and to protect the coast and surrounding natural environment [55]. Therefore, the development in the first decade has moved from being primarily peripheral to infilling and intensification within the MUL. The land developers and new residents must obey the rules implemented by the government to match the land use, so the urban expansion over the last four decades in Auckland has been closely correlated to the government's 352 development strategies and policies [56]. The new urban areas are more regulated and clustered in distribution than those of fast-developing countries such as China.

Other factors affect the simulation accuracy, such as image spatial resolution: the urban information of Auckland was extracted from aerial photos with a very high spatial resolution (0.5 m), but it decreased to 30 m for Liangjiang New District. In addition, the precision of auxiliary data, such as DEM, had been degraded deliberately before they were released for public access from overseas. However, compared to policy factors, the impacts of these factors are relatively limited, especially in modeling urban development between western and eastern countries [57–60]. Furthermore, as many transportation components have been fed into the models, the relationship between transportation-related factors and future urban land expansion should also be analyzed. For example, does the urban area expand more quickly as more transportation facilities are created, or does the urban expansion follow the rules of transport plans? However, this paper classifies the urban area as one type rather than adopting transportation infrastructure as a single class. It does not calculate the different weights for all the impact factors, which reveals the ANN-based method cannot calculate the relative impacts as regression models [23]. Therefore, this is a

future study direction in that we will seek to clarify the impact weights for these significant factors in our future studies with ANN-based algorithms.

## 4. Conclusions

In this paper, we presented two ANN-based CA–MC models to simulate the urban expansion inside a very rapidly developing area—Liangjiang New District, Chongqing. The obtained results confirm the possibility of using machine learning methods, such as MLP and LSTM, to improve the capability of CA–MC simulation models for the urban expansion field. The ANN–CA–MC outperformed LR–CA–MC, obtaining higher kappa and kappa simulation values. In the simulation, the most important layer, the USI map, can be efficiently created by MLP or LSTM, and provides critical information on potential future urban areas. LSTM is more powerful at capturing temporal information, and hence is more stable as well as predictable than the other two MLP-based CA–MC models with different sampling methods in simulating the fast annual urban expansion process for the study area. The results could provide spatial and qualitative information on urban expansion. Researchers could compare it with existing plans to check the expansion trends, implement the correct modifications and plan out new directions. For Liangjiang New District, we can see from the results that a higher temporal resolution could lead to more accurate results, and only a model that captures the time characteristics could yield a reliable result. Therefore, the LSTM-based CA–MC can be a powerful tool to add value to the urban expansion modeling field. In addition, different urbanization policies may highly affect the model's accuracy since a developing country may yield a more dynamic and rapidly changing result, so any policy should be considered carefully, especially for China and India. In general, the designed urban expansion simulation approaches can be applied to yield valuable and insightful information for local government decision makers and urban planners.

However, the simulation results obtained for Liangjiang New District were not as successful as those in other urban areas, even with the same model and similar datasets. Unlike the urban class patterns, the changes could not be well simulated, possibly because of the important role of land use policies from different levels of governments in urban development, which were not considered in the modeling. The effects of the government-directed land use directives were randomly distributed land use patterns with an ambiguous expansion mode or trend that was very difficult to model and predict. Therefore, an integrated model is still needed to overcome the limitations in simulating human behavior/policies at different levels. Therefore, in future studies, multiple-scenario simulations and predictions should be considered to address the uncertainty in development problems relating to land use policies more appropriately [8,16,61]. Furthermore, socioeconomic factors that also affect the urban expansion process need to be included because human behaviors and their interactions with natural and social changes also play critical roles in this dynamic process. In the future, Gross Domestic Product (GDP), personal income, population density, human movements, religion, employment rates, and so on should all be considered to produce more reliable and reasonable modeling outcomes. Lastly, focal/local transition rules should be considered, including the the global transition rule for CA models, in which different areas may be subjected to different urban expansion policies and dynamics.

**Author Contributions:** Conceptualization, T.X.; methodology, T.X.; software, T.X. and D.Z.; validation, T.X., D.Z. and Y.L.; formal analysis, T.X.; investigation, D.Z. and Y.L.; resources, T.X. and Y.L.; data curation T.X.; writing—original draft preparation, T.X.; writing—review and editing, T.X., D.Z. and Y.L.; visualization, T.X.; supervision, T.X.; project administration, T.X.; funding acquisition, T.X. All authors have read and agreed to the published version of the manuscript.

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# Analysis of Land Use Optimization of Metro Station Areas Based on Two-Way Balanced Ridership in Xi'an

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**Abstract:** With the development of metro systems, the problem of unbalanced ridership into and out of the stations, caused by the singleness of station area development, has become increasingly prominent. Research on land use optimization in metro station areas based on a two-way balance of ridership is proposed. First, the stepwise regression analysis method was used to build a relationship model between ridership and the land use index under the guidance of the two-way balance of ridership. Second, the range was optimized by calculating the land use factors of the metro station area. Finally, the land use of the metro station area was optimized from the perspectives of development intensity and land usage. Taking metro stations in Xi'an as an example, the results show that the land use characteristics of metro station areas are quite different. Under the guidance of the two-way balance of ridership, the current land use values of Daminggongxi Station, Nanshaomen Station, and Tiyuchang Station exceed the optimal value range and can be reduced by more than 2.78%. The current land use values of Chaoyangmen Station, Longshouyuan Station, and Weiyijie Station are within the optimized range. The land use values of Kaiyuanmen Station, Banpo Station, and Fengchengwulu Station are below the optimized range and could be increased by more than 13.7%. In addition, optimizing the development intensity or adjusting the land type is further proposed to ensure that the land use factors of station areas are within the calculated optimal value range. The results provide a reference for the optimization of land use in the Xi'an metro station area.

**Keywords:** land use; two-way balance of ridership; metro station area; stepwise regression analysis

## 1. Introduction

The processes of urbanization and motorization in China have been accelerating in the 21st century, with mismatching problems between the carrying capacity of the city and traffic demand becoming increasingly prominent [1,2]. Due to their characteristics, public metro systems have become an important mode of transportation for people's daily travel. With the gradual development of metro networks, the proportion of metro trips to the total urban public transit trips is continuing to increase. However, the development of metros not only affects residents' travel but also affects the development and land use in metro station areas [3,4]. There is a two-way interactive relationship between station land use and station ridership which promote and restrict each other [5]. On the one hand, whether the land use of station areas is reasonable or not seriously affects the operational efficiency of the metro and affects the distribution of ridership in urban space. On the other hand, for metro stations with many outbound passengers and few inbound passengers, there will be problems with densely populated and overloaded land in the station area. Metro stations with many inbound passengers and few outbound passengers usually represent low land use rates and wasted space resources in station areas [6]. Therefore, optimizing the land

use in station areas under the balanced conditions of two-way ridership [7], developing both in harmony [8], and avoiding excessive two-way ridership unevenness [9] have arisen as problems in the development of metro systems.

In theoretical research, the exploration of the relationship between ridership and land use in station areas can clarify the modes of action and the mechanism principle between the two. Qualitative and quantitative research methods can be used to deeply explore the internal motivation mechanisms behind land generating inbound ridership and land attracting outbound ridership. In this way, the perspective of balance between inbound and outbound ridership guides the optimization of station area land reconstruction and enriches the theory and method systems of metro station area land optimization. In a realistic sense, because the Xi'an metro is in the development stage and is not yet a complete network, the impact of metro stations on surrounding land use is still changing. Therefore, on a practical level, research on the land use of metro station areas can provide a basis for the construction and development around the metro station area. The research can guide the optimization and transformation of land use in metro station areas, the imbalance of ridership into and out of the station can be improved, and a reliable basis for further construction around metro stations can be provided.

This research adopted the framework system of "data analysis-model building-threshold calculation-index optimization" to analyze the linear relationship between inbound and outbound ridership and the land use factors of station areas. Models were constructed for the independent variable land use factor and the dependent variable inbound and outbound ridership, so as to obtain the multiple regression equation between inbound ridership, outbound ridership, and land use factors. The aim was to find a balance between the generation and attraction of ridership, reduce environmental pollution, and ensure the social fairness of land development. The conceptual framework of the research is shown in Figure 1. The main contributions of this research are as follows:

- The expansion of theoretical research. Focusing on the basic theory of inbound and outbound ridership and station area land use, we deeply studied the internal mechanism between ridership and land use and enriched the theoretical system of station area land use optimization research.
- Innovation of technical means. Combined with multi-source data (cell phone signaling, built-up area GIS data) for analysis, a data processing model for analyzing ridership distribution was developed. The model focused more on the distribution characteristics of land-generated inbound ridership and attracted outbound ridership.
- Innovation in research methods. Through the study of relevant literature and data analysis, the influence mechanism and relationship model of inbound and outbound ridership and land use factors were established. On this basis, optimization research was carried out, a land use index optimization system under the guidance of the two-way balance of ridership was established, and specific optimization measures for land use in each station area are proposed.

In the remainder of this paper, Section 2 reviews the relevant literature. Section 3 presents the scope of the study and the sources of data collection. Section 4 introduces the model used in this paper, the calculation method of variables, and the calculation method of the suitable value of metro ridership. The findings and discussion are presented in Section 5, and finally, the conclusions of this study are summarized.

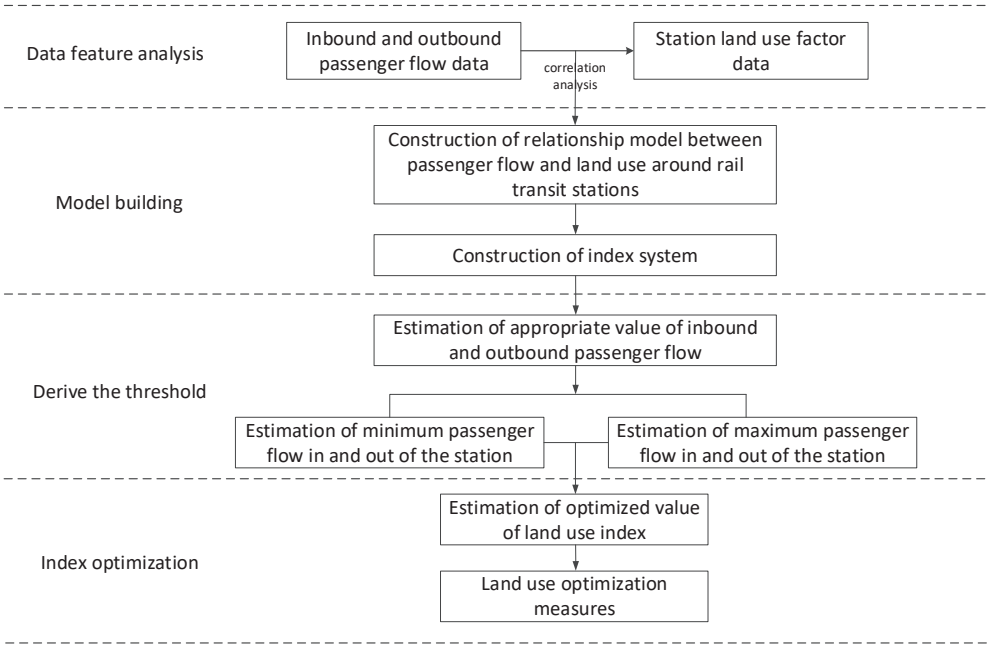



**Figure 1.** Research conceptual framework.

## 2. Literature Review

Scholars have achieved some results in related research on station ridership and station area land use. The interactive relationship between station land use and ridership has been confirmed by many studies [10–14]. Land use is the dominant factor in metro ridership [11]; optimizing station land use can improve this. Some existing studies have identified important contributions of land use attributes to metro ridership, including density [15,16], land use mix diversity [10], and other related factors. For example, the study by Chan et al. found that during the morning rush hour, for every 10% increase in commercial and administrative office space, the outbound ridership increased by 6% [17]. Cervero et al. found that improving the levels of intensity, diversity, and connection with public transport was an effective means to increase ridership [10]. Combining the actual historical ridership data of Beijing's metro operations, Guang [18] selected discrete indicators such as land use nature, development intensity, and station accessibility as fuzzy indicators for the basis of an in-depth analysis of land use around the station and ridership at the station. Additionally, the relationship between the inbound and outbound ridership of metro stations and land use under the condition of new line access was established. Cai [19], Cheng [20], Tan [21], and others have conducted research from the perspective of a relationship between ridership and land use, established a ridership prediction model for metros, and analyzed land-influencing factors. However, the above studies are based on analyses of the impacts of land use on metro ridership, and less attention has been paid to the impact of metro ridership on station land use.

Research on the impact of metro systems on land use in station areas has mainly focused on land use value [22,23] and land use structure and intensity [24]. From the perspective of metro station ridership, research on the impact of metro stations on land use is still limited. Liu et al. proposed a comprehensive development model of metro station areas based on the two-way balance of ridership in view of the imbalance of station ridership caused by contemporary developments of metro station areas and built an optimization model [25]. Zhang studied the relationship between the two-way balance of public traffic flow and land use in urban public transport corridors, proposed a method of classifying urban public transport corridors according to different development intensities and development methods, and built a two-way traffic flow calculation model and land use adjustment model [26]. Qiao et al. analyzed microscopic pedestrian characteristics and proposed a computing system to analyze the best two-way pedestrian flow [27]. However,

quantitative relationships on the impact of metro ridership on station land use are still unclear, such as the impact of ridership on land use mix diversity and land use intensity.

Regarding the modeling relationship between ridership and station area land use, many scholars have constructed different method systems for different land use factors. In recent years, scholars have mostly chosen to use empirical analysis and regression models to explain the relationship between station ridership and land use factors and present optimization suggestions. Scholars have also established direct estimation models based on ordinary least squares (OLS) and partial least squares to reflect the impact of factors in land use types on ridership [17,28]. These multiple regression methods assume that the global parameters are consistent, and consider that each influencing factor has nothing to do with the spatial location and do not consider the difference in its spatial location. Scholars who used empirical analysis, such as Guo [29] and Cui [30], have proposed random equilibrium distribution methods for predicting ridership. Those who utilized regression models, such as Zhang [31] and Sung [32], incorporated land elements as independent variables and ridership as dependent variables to establish multiple regression models, adjusting land elements for different optimization objectives.

In summary, most of the previous studies have focused on the analysis of the total ridership of the station with models that lacked the fine classification of land use and could not accurately reflect the impact of metro ridership on land use. There are few studies on the two-way balance of ridership in the existing literature, and it is difficult to reveal the law of land use under the two-way balance of ridership. Therefore, how to effectively analyze the characteristics of two-way ridership and guide the rational optimization of station area land are some of the current problems. Based on this, in this study, a stepwise regression model was developed from the perspective of the two-way balance of ridership, and an optimization strategy of land use in the station area was explored.

## 3. Study Area and Data Source

### *3.1. Study Area*

The capital city of Shaanxi Province, Xi'an is an urban area with a high population density in northwestern China. In recent years, considerable progress has been made here in the construction of a metro system. As of December 2021, there are eight metro lines in operation in Xi'an (Lines 1–6, Line 9, and Line 14), with a total operating mileage of 258 km and a total of 154 stations. The metro accounts for more than 50% of urban public transportation. With the expansion of urban scale and the increasing traffic demand, the metro station area, which is the main center of activity for metro ridership, has huge growth potential and needs to be continuously updated and optimized. In addition, the land use of the metro station area is difficult to coordinate with the construction and operation of the metro. The inbound ridership generated by the land and the attracted outbound ridership is unbalanced, resulting in different forms and degrees of influence of ridership on the station area. Lines 1 and 2, the earliest built lines in Xi'an, running through the city from east to west and north to south, are also the backbone lines for the development of Xi'an's metro network. The development of land characteristics along the lines is more stable than on other metro lines. Therefore, this study took the stations of Xi'an metro Line 1 and 2 as candidate research objects. In addition, we further excluded some stations according to the following principles:

- Stations outside the Third Ring Road in Xi'an. The metro station areas outside the Third Ring Road are still in the development and construction stages.
- Metro transfer stations. Transfer stations are affected by the flow of passengers, the different distribution characteristics of ridership at the station, and the complex characteristics of the ridership; the land use of the metro station area is affected by various factors as well, showing different characteristics.
- Stations with abnormal ridership. Similar to Zhonglou Station, Xiaozhai Station, Yongningmen Station, etc., are affected by holidays or flow restriction control measures.

- The selection was according to the administrative region where the site was located. The stations are distributed in different positions in the east, south, west, north, and center of the built-up urban area.

According to the analysis of the land characteristics of the metro station area, it was found that residential, commercial, and public service land are the main land types for the generation and attraction of ridership in the metro station. Therefore, the land use of the selected metro station area should include the most basic functions of work and housing, and the proportions of these three types of land area are relatively large, though there are clear differences between stations. According to the above principles, this study analyzed a total of nine stations: Fengchengwulu Station, Daminggongxi Station, Longshouyuan Station, Nanshaomen Station, Tiyuchang Station, Weiyijie Station, Chaoyangmen Station, Banpo Station, and Kaiyuanmen Station. These sites were the final research objects of this paper, as shown in Figure 2.

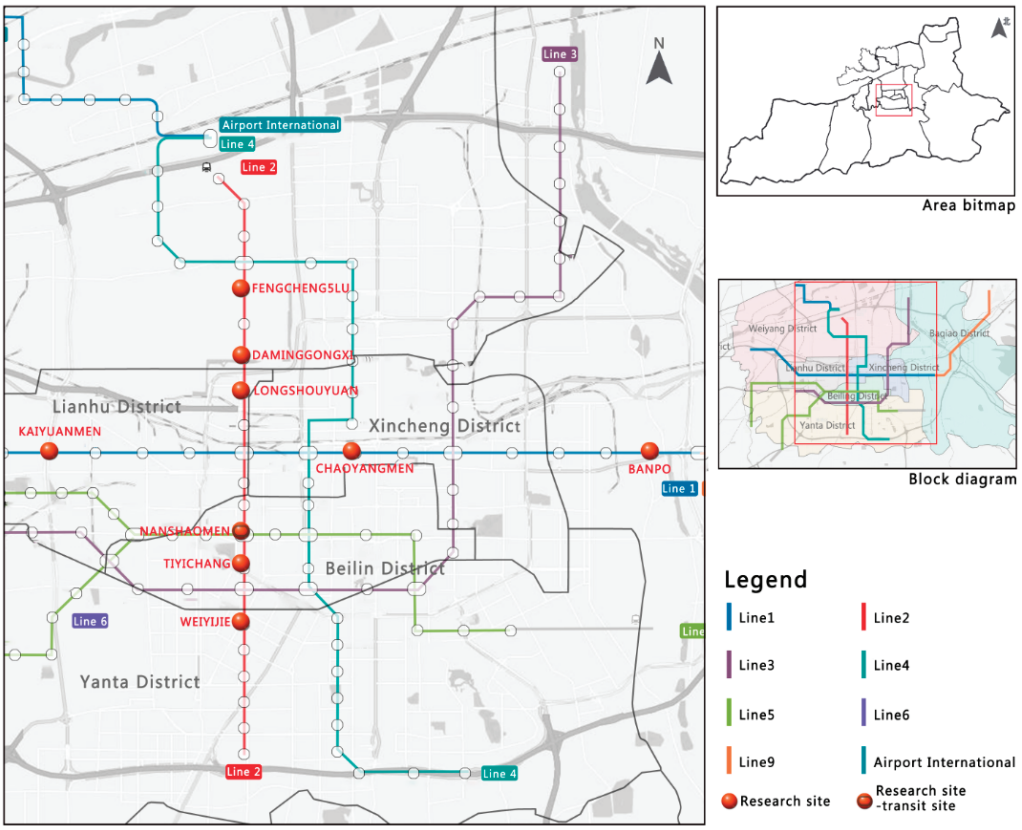



**Figure 2.** Study area.

Most of the literature research results show that the service range of metro stations is mainly between 400 m and 800 m [32–34]. China's "Guidelines for Planning and Design of Areas Along Urban Rail Lines" defines a metro station area as "an area that is about 500–800 m away from the station and can reach the station entrance within about 15 min' walk, and is closely related to the rail function". Therefore, considering that the metro network in Xi'an is not yet perfect, the density of the network is low, and there is high popularity of shared bicycles, the metro station domain referred to in this study was defined as the built-up urban area with the station at the center and a radius of 800 m, in concentric circles, which is influenced by the station's ridership.

### *3.2. Data Source*

The main data of this study included metro station area land use, cell phone signaling data, and long-term station ridership forecasts. Among them, the land use data were based

on high-definition satellite images (Baidu map (5 November 2019 baidu.com)), on-site field surveys and measurements, and statistics from a GIS database of built-up areas within the Third Ring Road of Xi'an in 2017. Land use data are mainly used to calculate a series of characteristic indicators of the built environment, such as the land use nature and building area of the metro station area. Cell phone signaling data came from 2G, 3G, and 4G user data of Xi'an Unicom users, which are records generated by active and passive interactions between cell phones and base stations. The time period selected for cell phone signaling data followed two principles: one was to avoid special periods such as holidays; the second ensured that the daily collection period covered the complete operation time, which was one continuous week. Therefore, this study collected the cell phone signaling data of passengers at metro stations for one continuous week (5 to 12 November 2019) to calculate the number of inbound and outbound passengers at metro stations. The long-term station ridership forecast data comes from Xi'an Rail Transit Group Company Limited and is used to estimate the appropriate value of ridership at metro stations.

## 4. Methodology

According to the characteristics of the obtained data and the research purpose, the methods used in this paper included three aspects: a regression analysis model, the construction of a variable set, and the estimation of suitable values.

### *4.1. Regression Analysis*

Regression analysis models are some of the most effective and intuitive models used by scholars to study the relationship between multiple land use factors and the ridership of metro stations. Based on previous research experience, this study used a stepwise multiple linear regression model to construct a relationship between land use factors and ridership. Using stepwise multiple linear regression models is an optimal approach; every time a new variable is introduced into the model, it is necessary to check whether the independent variables in the original model still have statistical significance. Independent variables with insignificant partial regression sums of squares are excluded. In this way, variables are introduced and eliminated until no new variables are introduced, and old variables are not deleted. Therefore, the model retains the most significant important variables and the prediction accuracy is high. Moreover, the stepwise multiple linear regression can correct for multicollinearity to a certain extent, resulting in a relatively simple model with fewer variables.

Stepwise multiple linear regression is often used to describe random linear relationships between the dependent variable, $y$, and multiple independent variables, $x$. The model equation is shown in (1):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \delta \quad (1)$$

where $x_1, \ldots, x_k$ is a set of independent variables, $y$ is the dependent variable, $\beta_0, \ldots, \beta_k$ is the regression coefficient, and $\delta$ is the error term.

### *4.2. Building a Variable Set*

The interaction relationship between land use and ridership in the metro station area has been clarified. However, different scholars have constructed different sets of independent variables for land factors. The total land area can be used as a quantitative index to describe the scale of land use. The traffic volume per unit area of buildings of different natures is different. When the land area is fixed, the larger the plot ratio, the larger the building area, and the greater the inbound ridership. Thus, the plot ratio affects the size of the building, and the size of the building directly determines the basic degree of inbound and outbound ridership.

For the mixed diversity of buildings and land use, the higher the degree of mixing, the more complex and richer the functions of the station area, and the more it can meet the needs of people's daily life. Under the premise of satisfying people's travel purposes,

people are more inclined to choose a shorter commuting distance to avoid long-distance travel by metro, thereby reducing the inbound ridership in station areas. Although with a greater diversity of buildings and land use, more people's desire to travel can be stimulated, the motivation of people to take the metro in station areas is reduced. Therefore, the degree of mixing is an external constraint that generates inbound ridership and is a direct influencing factor.

Therefore, this study drew on the extant literature and combined actual data to construct land use factors, including the total land area, total building area, average building density, average plot ratio, building mix diversity, and land mix diversity. Among them, the total land area is the land within a radius of 800 m from the metro station. The total construction area is the area of the plots within an 800 m radius from the metro station. The average building density describes the vacant land ratio and building density of the station area and is the area of the building footprint/total area of the station area. The average plot ratio describes the land development intensity of the same type of land in the affected area of the site, and the value is the total construction area of the same type of land/the area of the same type of land. The variables and statistics of the nine stations are presented in Table 1.

**Table 1.** The variables and statistics of the nine stations.

| | Variables | Min | Max | Mean | SD |
|---|---|---|---|---|---|
| Land characteristics | Total land area (X1) (ten thousand $m^2$) | 170.01 | 247.89 | 216.76 | 25.88 |
| | Total building area (X2) (ten thousand $m^2$) | 215.61 | 618.16 | 429.85 | 126.22 |
| | Average building density (X3) | 0.26 | 0.42 | 0.32 | 0.565 |
| | Average plot ratio (X4) | 1.05 | 2.95 | 1.99 | 0.563 |
| | Building mix diversity (X5) | 1.12 | 1.52 | 1.28 | 0.133 |
| | Land use mix diversity (X6) | 1.46 | 1.95 | 1.71 | 0.165 |
| Traffic characteristics | Outbound ridership (y1) | 475 | 2900 | 1822 | 1143.8 |
| | Inbound ridership (y2) | 482 | 4164 | 1622 | 779.1 |
| | Metro sharing rate (X7) | 20.61% | 24.57% | 22.16% | 1.31% |

Building mix diversity describes the richness and complexity of buildings in the station area, The model equation is shown in (2):

$$B = -\sum_{i=1}^{n} K_i ln K_i \quad (2)$$

Land use mix diversity describes the richness and complexity of land use within a station area, The model equation is shown in (3):

$$L = -\sum_{i=1}^{m} P_i ln P_i \quad (3)$$

where $L$ is the mixed diversity of land use, $m$ is the variety in land use types, and $P_i$ is the proportion of the $i$th land use type. $B$ is the mixed diversity of the buildings, $n$ is the number of building types, and $K_i$ is the proportion of the $i$th building type.

The ridership characteristics survey of the research object refers to the distribution of ridership within the station area, i.e., the inbound and outbound ridership, excluding the inbound and outbound ridership and the transit ridership outside the station area. When filtering the raster data of cell phone signaling, we performed the following operations to exclude out-of-range ridership and other transit ridership.

Screening of inbound ridership: cell phone signaling with a starting point within the station area and an end point at the station was selected as site ridership generated by the land, i.e., the inbound ridership.

Screening of outbound ridership: cell phone signaling with a starting point at the station and an end point within the station area was selected as site ridership attracted by the land, i.e., the outbound ridership.

Through the cell phone signaling database of traffic travel modes in Xi'an within the Third Ring Road, the grid data of the starting point O of the traffic occurrence within the station area were taken as the place of traffic occurrence, and the grid data of the end point D of the traffic occurrence within the station area were used as the grid data. The grid data were used as the traffic termination point to filter out the total traffic trips in the station domain grid, combined with the metro trips within each station domain. The rail traffic sharing rate of each station could then be calculated; the sharing rate directly reflects the relationship between the station area rail traffic volume and the total travel volume, The model equation is shown in (4):

$$t = Q_{train}/Q_{all} \tag{4}$$

where t is the sharing rate and $Q_{train}$ is the actual number of metro trips. Additionally, $Q_{all}$ is the number of trips made by all modes of transportation.

*4.3. Estimation of a Suitable Value of Metro Ridership*

The suitable value of metro ridership refers to the design of inbound or outbound ridership for a metro station under ideal conditions. The two-way balance of ridership means that, in an ideal state, the inbound ridership is equal to the outbound ridership. Based on this premise, this study took the metro demand generated by existing land as the lower limit of the suitable value of the constraint ridership and took the long-term maximum supply of metro stations as the upper limit of the suitable value for the constraint ridership to determine the two thresholds to solve the metro problem. The contradiction between demand and supply thus guides the optimization of land use.

The current state of land use determines the most basic traffic demand; thus, the metro demand generated by the current land was used as the minimum value for estimating the appropriate value for metro ridership. Secondly, the maximum supply of the long-term development of the metro determined the maximum suitable value of metro ridership. The specific equation is shown in (5):

$$y_{S\ min} \leq y_1 = y_2 \leq y_{S\ max} \tag{5}$$

where $y_{S\ min}$ is the metro demand generated by the current land use, $y_{S\ max}$ is the maximum supply for the long-term development of the metro, $y_1$ is the outbound ridership, and $y_2$ is the inbound ridership.

**Estimation of the long-term inbound (outbound) ridership of the metro, $y_{S\ max}$**

This study explored the relationships between inbound ridership, outbound ridership, and land use; thus, the weighted values of inbound and outbound ridership in long-term peak hours were used as the inbound and outbound ridership in peak hours. Then, the daily average of inbound and outbound ridership, using the inbound and outbound ridership during peak hours, was calculated. Under the guidance of the two-way balance of ridership, the inbound and outbound ridership were considered to be equal, and the directional unbalance coefficient should have tended to 1. Under the guidance of the two-way balance of ridership, the inbound and outbound ridership were considered to be equal. Therefore, the daily average ridership into and out of the station was multiplied by a factor of 0.5 to determine the maximum supply for long-term development, $y_{S\ max}$.

Average daily inbound and outbound ridership, The model equation is shown in (6):

$$D = \frac{F_1 + F_2}{PHR} \tag{6}$$

The largest supply for the long-term development of the metro, The model equation is shown in (7):

$$y_{S\ max} = D \times 0.5 \tag{7}$$

where $D$ is the average daily inbound and outbound ridership, $F_1$ is the outbound ridership during long-term peak hours, $F_2$ is the inbound ridership during long-term peak hours, and $PHR$ is the peak hour traffic ratio.

**Estimation of the current inbound (outbound) ridership of the metro, $y_{S\ min}$**

Using the classic original unit method in the field of transportation, ridership forecasting of the current metro station ridership was performed. For each land use or building type, the ridership generated and attracted per unit area was different. Therefore, the occurrence rate and attraction rate of the unit land area or unit building area of different uses were used to calculate the current ridership of the metro station.

Current metro inbound ridership, The model equation is shown in (8):

$$\sum P_i = S_i \times p_i \times t \tag{8}$$

Current metro outbound ridership, The model equation is shown in (9):

$$\sum A_i = S_i \times a_i \times t \tag{9}$$

where $P_i$ is the amount of ridership generated by the land area or building area of class $i$, $A_i$ is the amount of ridership attracted by land area or building area of class $i$, $S_i$ is the land or building area of class $i$, $p_i$ is the land or building of class $i$ traffic generation rate, $t$ is the metro sharing rate, $a_i$ is the traffic attraction rate of $i$-type land or building, and $P_i$ and $A_i$ are values from the reference table of traffic travel rates for different construction projects in Xi'an.

Under the guidance of the two-way balance of ridership, it is considered that the inbound ridership is equal to the outbound ridership, the model equation is shown in (10) and the metro demand generated by the existing land is obtained as $y_{S\ min}$:

$$y_{S\ min} = \frac{\sum P_i + \sum A_i}{2} \tag{10}$$

where $\sum P_i$ is the current inbound ridership and $\sum A_i$ is the outbound ridership.

## 5. Results and Discussion

### *5.1. Relationship Model between Ridership and Land Use Factors*

Before building the regression model, the correlations between average daily station ridership, attracted station ridership, and the land use factors in the station area were analyzed. By screening out the relevant land use indicators that influence ridership, the interaction mechanisms of each station area generating and attracting station ridership and land use were explored. At the same time, there may be multicollinearity among the independent variables; therefore, the multicollinearity test was carried out among the independent variables. Through the analysis of indicators, the correlation of each indicator was determined to be poor. In order to better discuss the relationship between land use and ridership, the study did not exclude independent variables.

In this study, IBM SPSS Statistics Version 28 software was used to solve the stepwise regression model, X1 to X7 were imputed step by step, and the coefficients after linear regression of the respective variables were obtained. According to the results of the model, the average building density of X3 and the sharing rate of X7 were not found to be significant independent variables; thus, they were not included in the final model results. The final model results are presented in Table 2 which shows the fit of the multiple regression model.

**Table 2.** Stepwise multiple linear regression of station inbound and outbound ridership.

| Land Use Factors | Estimated Coefficient | Standard Error | Standardized Coefficient | T-Value | *p*-Values |
|---|---|---|---|---|---|
| Intercept | −37.38 (−31.51) | 0.50 (0.30) | | −74.10 (−106.22) | 0.009 (0.006) |
| Total land area (lnx1) | 1.57 (1.51) | 0.12 (0.07) | 0.20 (0.20) | 12.88 (21.00) | 0.049 (0.030) |
| Total building area (lnx2) | 1.40 (1.03) | 0.11 (0.06) | 0.46 (0.35) | 13.15 (16.27) | 0.048 (0.039) |
| Average plot ratio (x4) | 0.81 (0.95) | 0.06 (0.04) | 0.47 (0.57) | 12.88 (25.84) | 0.049 (0.025) |
| Building mix diversity (x5) | 0.76 (0.83) | 0.06 (0.03) | 0.11 (0.12) | 13.55 (25.04) | 0.047 (0.025) |
| Land use mix diversity (x6) | 0.57 (0.84) | 0.04 (0.02) | 0.10 (0.15) | 15.38 (38.34) | 0.041 (0.017) |
| $R^2$ | | | 0.988 (0.979) | | |
| Adjusted $R^2$ | | | 0.994 (0.979) | | |
| Sum of Squares | | | 7.582 (7.027) | | |
| df | | | 7 (7) | | |
| Mean Square | | | 1.090 (1.015) | | |
| F | | | 19,095.882 (51,432.081) | | |
| P | | | 0.006 (0.003) | | |

### *5.2. Estimation of Optimal Values of Land Use Factors in Station Areas*

Through the analysis, it can be seen that the total land area X1, total building area X2, average plot ratio X4, building mix diversity X5, and land use mix diversity X6 are the key factors affecting ridership into and out of the station. The total station land area was taken as a given condition and no optimization study was performed for the total land area. Under the premise of X1, X2 was affected by X4; therefore, X4 was optimized first, then X2 was optimized for the nature of the land.

Through the constraints of the appropriate value of ridership into and out of the station, the minimum and maximum values of the metro ridership were obtained. Land-use-related factors were calculated using relational models. The calculation results for the average plot ratio, building mix diversity, total building area, and land use mix diversity are shown in Table 3.

(1) Average plot ratio

From the analysis of the relational model, it can be seen that the average plot ratio had an obvious positive correlation with the inbound and outbound ridership. Table 3 shows that the development intensity of Daminggongxi Station, Nanshaomen Station, and Tiyuchang Station exceeded the optimized upper limit. Fengchengwulu Station, Kaiyuanmen Station, and Banpo Station did not reach the optimal lower limit, whereas Longshouyuan Station, Weiyijie Station, and Chaoyangmen Station were all within the optimal value range. The level of the average plot ratio of the station area represents the level of development intensity: the higher the development intensity, the higher the land development benefit. Therefore, when the average plot ratio of the station area exceeded the appropriate value, the upper limit of the appropriate value was taken as the lower limit of optimization, and the current plot ratio was used as the upper limit of the guide average plot ratio. When the average plot ratio was lower than the appropriate value, the appropriate value was adopted as the standard to guide the average plot ratio. When the average plot ratio of the station area conformed to the appropriate value, the current plot ratio was taken as the lower limit of optimization and the upper limit of the appropriate value as the upper limit of the guide average plot ratio. Except for Daminggongxi Station, Nanshaomen Station, and Tiyuchang Station, the average plot ratios of other stations can be increased.

**Table 3.** Optimum value ranges of the average plot ratio, total building area, building mix diversity, and land use mix diversity.

| Stations | | Fengchengwulu | Daminggongxi | Longshouyuan | Nanshaomen | Tiyuchang | Weiyijie | Kaiyuanmen | Chaoyangmen | Banpo |
|---|---|---|---|---|---|---|---|---|---|---|
| Current value | $X_4$ | 1.79 | 2.59 | 2.06 | 2.95 | 2.31 | 1.69 | 1.7 | 1.75 | 1.05 |
| | $X_2$ | 339.91 | 618.15 | 481.53 | 501.71 | 573.61 | 392.65 | 344.43 | 401.04 | 215.61 |
| | $X_5$ | 1.14 | 1.13 | 1.23 | 1.28 | 1.45 | 1.32 | 1.3 | 1.52 | 1.18 |
| | $X_6$ | 1.5 | 1.75 | 1.74 | 1.77 | 1.82 | 1.57 | 1.46 | 1.95 | 1.84 |
| Y1 Outbound ridership optimization value range | $X_4$ | 2.19–3.48 | 0.98–2.27 | 1.19–2.48 | 1.58–2.87 | 0.66–1.95 | 1.5–2.79 | 1.97–3.26 | 0.99–2.28 | 2.22–3.51 |
| | $X_2$ | 493.65–1642.03 | 138.24–459.83 | 215.38–716.42 | 139.96–465.55 | 122.37–407.06 | 328.62–1093.07 | 442.05–1470.38 | 197.58–657.21 | 644.38–2143.37 |
| | $X_5$ | 1.6–3.08 | 0.71–0.77 | 0.24–1.72 | 0.29–1.19 | 0.45–1.03 | 1.11–2.58 | 1.61–3.09 | 0.65–2.13 | 2.53–4.01 |
| | $X_6$ | 1.96–3.41 | 0.07–1.39 | 0.77–2.22 | 0.22–1.68 | 0.06–1.4 | 1.35–2.81 | 1.76–3.22 | 1.09–2.55 | 3.17–4.62 |
| Y2 Inbound ridership optimization value range | $X_4$ | 2.11–3.63 | 0.46–1.99 | 0.83–2.36 | 1.31–2.83 | 0.15–1.67 | 1.24–2.77 | 1.84–3.36 | 0.77–2.29 | 2.47–3.99 |
| | $X_2$ | 407.94–978.14 | 182.20–436.88 | 238.60–5721.17 | 194.96–467.46 | 165.49–396.79 | 303.06–726.68 | 372.46–893.06 | 229.16–549.47 | 488.34–1170.92 |
| | $X_5$ | 1.48–3.08 | 0.12–0.49 | 0.06–1.55 | 0.45–1.15 | 0.35–0.77 | 0.85–2.46 | 1.45–3.05 | 0.49–2.1 | 2.68–4.29 |
| | $X_6$ | 1.95–4.09 | 0.24–0.9 | 0.03–2.16 | 0.54–1.6 | 0.22–0.92 | 0.93–3.07 | 1.65–3.79 | 0.58–2.72 | 3.84–5.97 |

(2) Building mix diversity and land use mix diversity

From the regression equation analysis, it can be seen that there was a positive correlation between the building mix diversity, land use mix diversity, and ridership into and out of the station. For the development of station land, a higher mix diversity can also bring greater land use benefits and improve urban vitality. Therefore, according to the appropriate mix diversity, the station area building mix diversity and land use mix diversity were further determined. When land use mix diversity was higher than the suitable value, the upper limit of the suitable value was used as the lower limit of optimization, and the current mix diversity was used as the upper limit of optimization. When the mix diversity was lower than the suitable value, the upper and lower limits of the suitable value were adopted as the guiding standards. When the station area mix diversity conformed to the appropriate value, the current mix diversity was used as the lower limit of optimization, and the upper limit of the appropriate value was used as the upper limit of the guiding mix diversity.

It can be seen from Table 3 that the building mix diversity and land use mix diversity of Daminggongxi Station, Nanshaomen Station, and Tiyuchang Station exceeded the optimized upper limit. Fengchengwulu Station, Kaiyuanmen Station, and Banpo Station did not reach the optimal lower limit, whereas Longshouyuan Station, Weiyijie Station, and Chaoyangmen Station were all within the optimal value range. Notably, except for Daminggongxi Station, Nanshaomen Station, and Tiyuchang Station, the mix diversity of the rest stations needs to be improved. Therefore, according to the current situation of each station, increasing the number and scale of functional types of land and buildings could effectively increase the functional diversity of urban land, stimulate vitality, and promote use efficiency. However, due to the different actual land use and construction statuses of each station area, some station areas can increase their mix diversity, though some station areas are not suitable for increasing their mix diversity.

According to the regression model, the optimal threshold ranges of average plot ratio, building mix diversity, and land use mix diversity were analyzed. Therefore, the next step was to optimize the land use of the station area from the perspectives of development intensity and the adjustment of land use properties.

### *5.3. Optimizing Measures for Land Use in Station Areas*

Two threshold ranges are closely associated with the measures for optimal land use: objective theoretical calculations and land use optimization measures. The current development intensity (plot ratio) of each station area was compared with the optimization range, and, according to the difference between the average plot ratio of each station area and the value of the optimization range, the plot could be divided into areas with a low development intensity, areas with a suitable development intensity, and areas with a high development intensity (the intensity division of each station is shown in Figure 3). The formulation of optimization measures in this study followed the principle of stock planning. On the basis of the current stock, local update optimization is proposed for different plots.

(1) Development intensity optimization

When the land use layout of the station area was carried out, the land development intensity of the core area of the station area could be improved; the schematic diagram is shown in Figure 4. This advocates for the construction of comprehensive service facilities with a high plot ratio and the implementation of joint development. In adjusting the land use structure, it is recommended that the station area should be arranged from the inside to the outside, such as commercial, catering and entertainment, office, residential, and other functions, focusing on the compounding of functions, and integrating and improving the comprehensive service function of the station area. By properly controlling the development volume of peripheral areas and balancing the total development volume of the whole area, the land use of the whole station area presents a circle-level decreasing mode centered on the station.

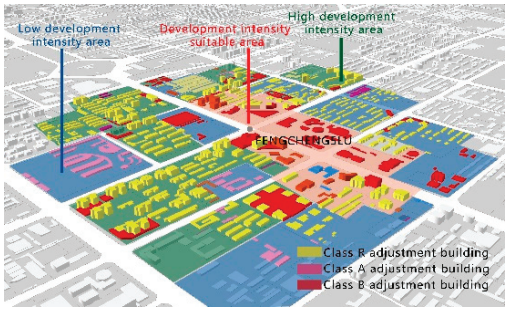
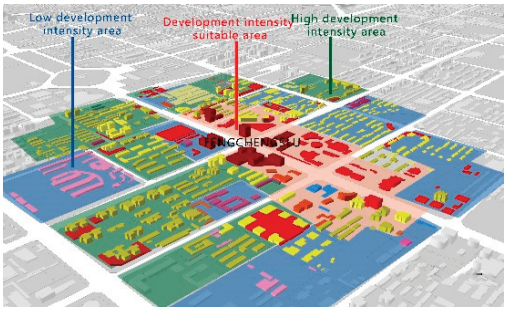
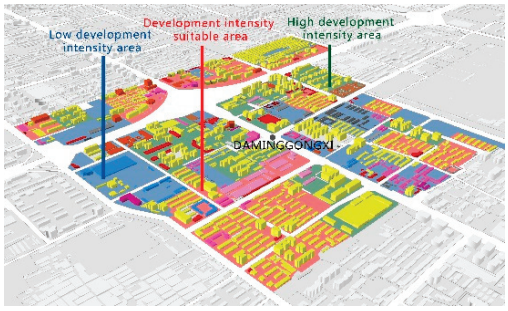
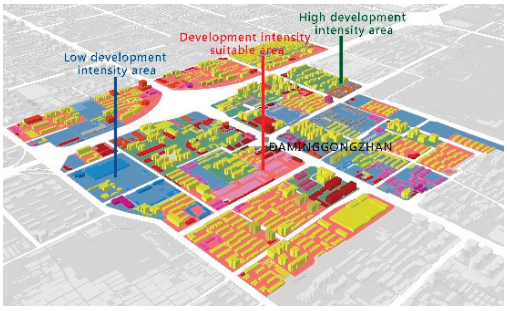
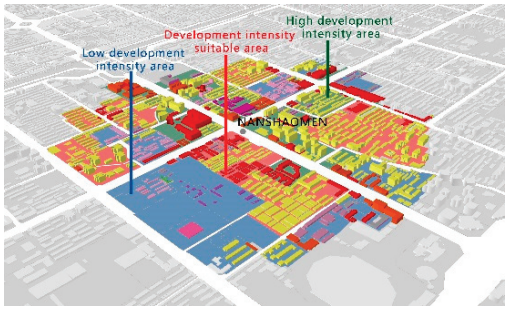
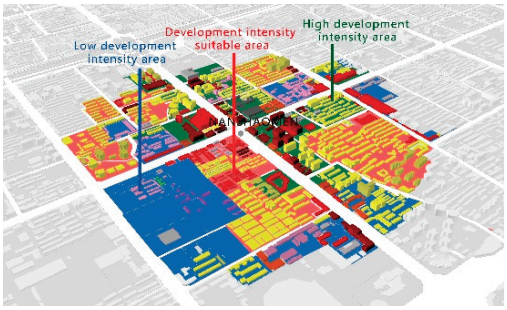
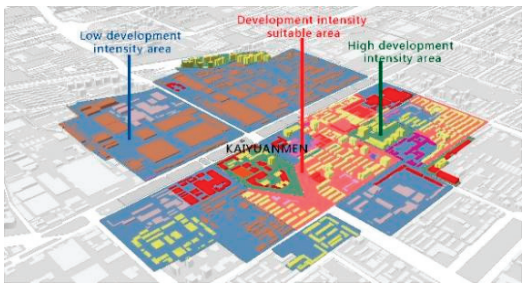
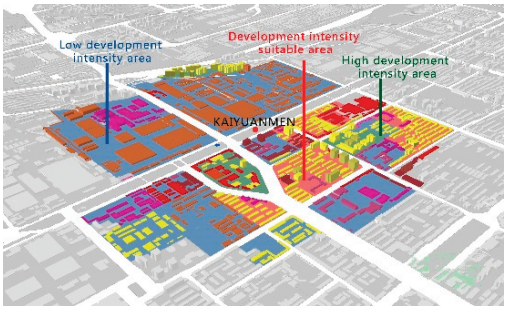
| Stations | Current situation | Optimized |
| --- | --- | --- |
| Feng-chengwulu |  |  |
| Daming-gongxi |  |  |
| Nansha-omen |  |  |
| Kaiyanmen |  |  |



**Figure 3.** *Cont.*

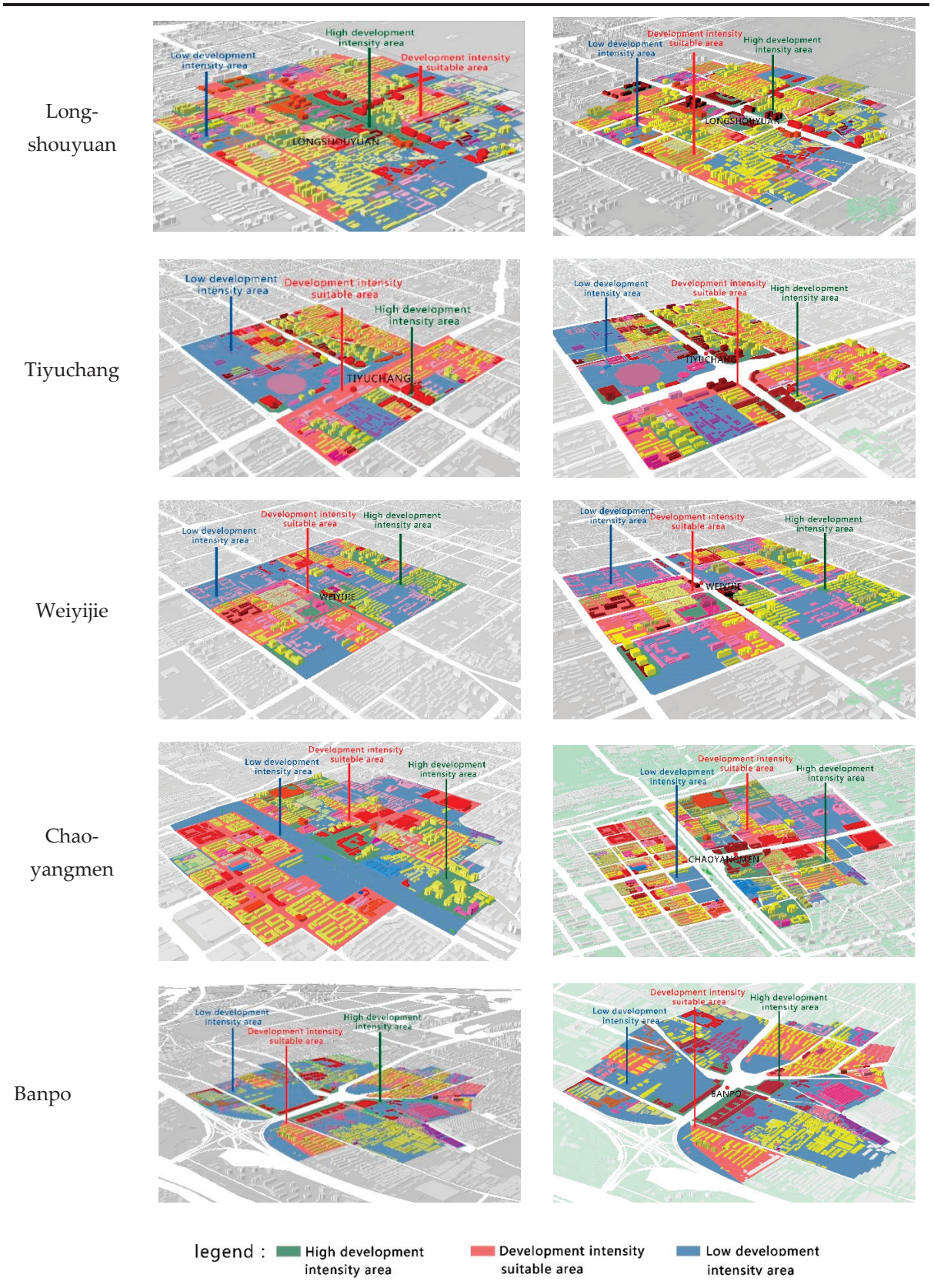



**Figure 3.** The development intensity zoning of each station and the spatial intention before and after optimization.

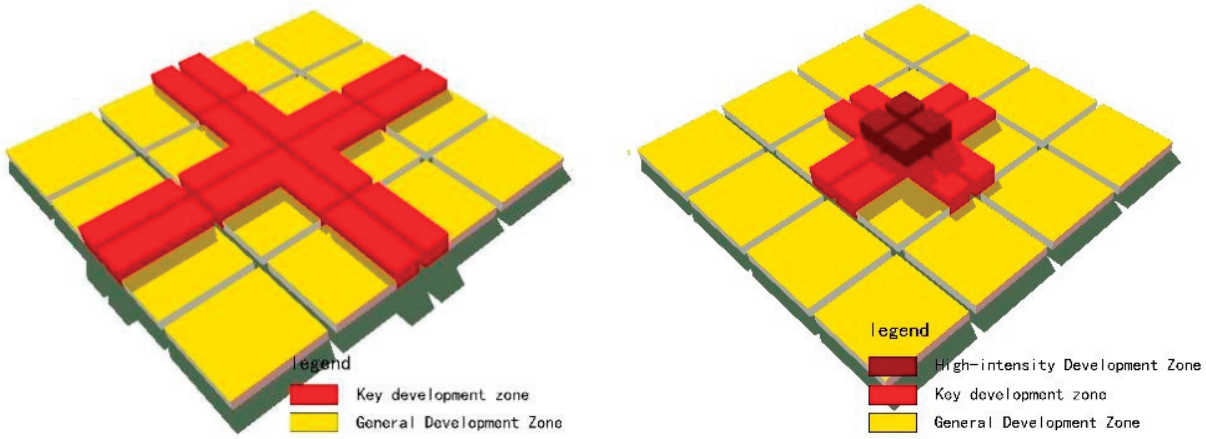



**Figure 4.** Schematic diagram of development intensity optimization.

For areas with low development intensity, the main types of land use are old residential areas (or low-intensity residential areas), urban villages, industrial land, schools, squares, green spaces, and land to be developed. Due to the special functions of school land and industrial land, the development intensity should not be too high. Squares and green space provide ample open space for a city. Therefore, the recommendations herein are mainly aimed at the renovation of old residential areas and urban villages. On the one hand, the plot ratio is increased, and on the other hand, the living environment is improved to enhance the image of the city, optimization plans is shown in Table 4. According to the optimization value of development intensity, it is suggested that Fengchengwulu Station should increase the plot ratio of such land to above 2.11, Daminggongxi Station should at least be kept above 2.27, Nanshaomen Station should be increased to above 1.31, Kaiyuanmen Station should be increased to above 1.97, Weiyijie Station should be increased to above 1.69, Chaoyangmen Station should be increased to 1.75 or above, and Banpo Station should be increased to 2.22 or above, optimization plan for the development intensity of each station is shown in Figure 5.

**Table 4.** Areas with low development intensity and optimization plans for the development intensity at each station.

| Land classification | Fengchengwulu | Daminggongxi | Nanshaomen | Kaiyuanmen | Longshouyuan | Tiyuchang | Weiyijie | Chaoyangmen | Banpo |
|---|---|---|---|---|---|---|---|---|---|
| A | Remain | Remain | Remain | Increase | Increase | Remain | Increase | Remain | Remain |
| B | Increase | Increase | Remain | Increase | Increase | Increase | Increase | Increase | Increase |
| G | | Remain | Remain | | | Increase | | | Remain |
| M | Remain | Remain | | Remain | Remain | | | | |
| R | Increase | Increase | Increase | Increase | Increase | | Increase | Increase | Increase |
| S | | Remain | Remain | | | | | | |
| U | Remain | Remain | Remain | Remain | | | | | |

A, land for public administration and public service facilities; B, land for commercial service facilities; G, land for green space and squares; M, industrial land; R, residential land; S, land for roads and transportation facilities; U, land for utilities.

For areas with suitable development intensity, the main land types were newly constructed residential quarters, some commercial land, and public service land. This kind of land has good environmental and building qualities and it is recommended to maintain the original state and not transform it.

For areas with high development intensity, the main types of land use are commercial land distributed along both sides of main roads. Although this type of land has a high development intensity, it is in line with its own business format and urban construction standards and the original development intensity value should be maintained. The other type is mostly new construction projects with good construction quality and complete corresponding equipment and facilities; in this case, the original development intensity value should also be maintained. However, to strengthen the aggregation effect of the site,

it is recommended that individual commercial land should be subjected to increased construction intensity, although the value of the plot ratio should not exceed 3.99, optimization plan for the development intensity of each station is shown in Figure 6.

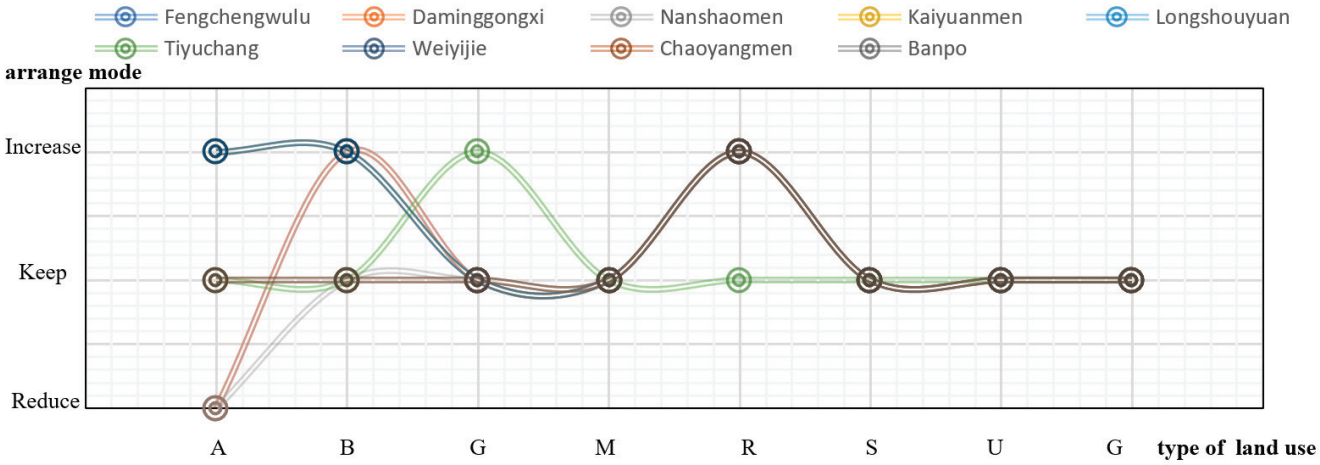



**Figure 5.** Areas with low development intensity; diagram of the optimization plan for the development intensity of each station.

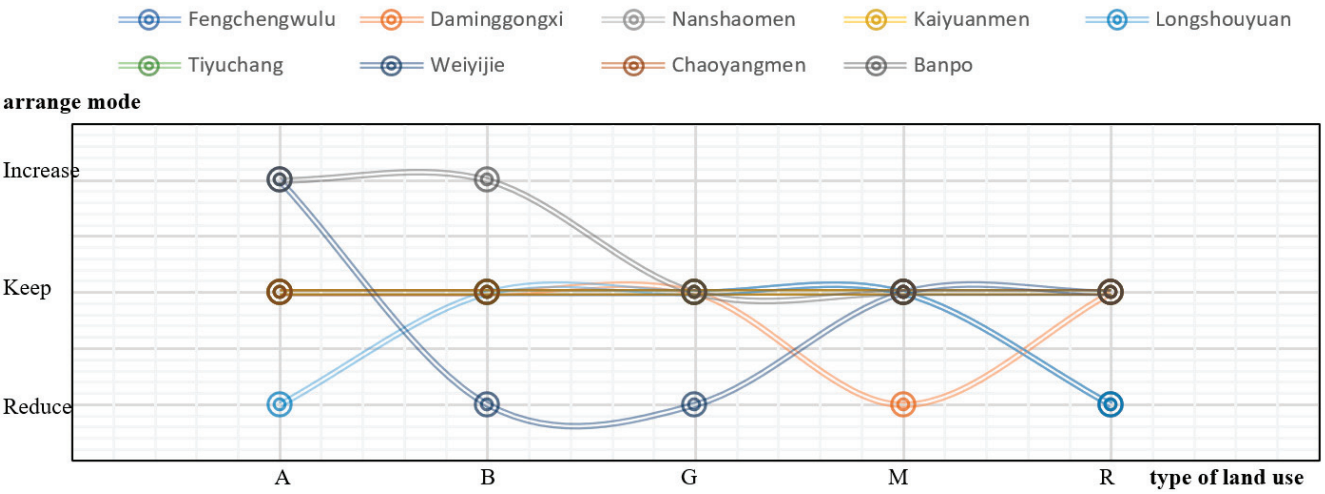



**Figure 6.** Areas with high development intensity; diagram of the optimization plan for the development intensity of each station.

(2) Optimization of land use properties

By comparing the status quo with the optimized development intensity, the land types that can be replaced by that of station land are proposed.

Third-class residential land dominated by urban villages or old residential areas is characterized by a high building density and incomplete basic service facilities. The environment is good, mainly low-rise residential land, and commercial facilities are arranged along the street. Each site covers such land and needs to be replaced optimally.

For commercial land in areas with low development intensity, such as old commercial areas with low building density, it is recommended to transform them into high-intensity commercial land by adjusting various indicators of land use in the station area until they meet the above optimized value range. Stations including Daminggongxi Station and Kaiyuanmen Station need to be optimized.

For mixed commercial and residential plots with high construction and development intensity, it is recommended to reduce the construction intensity and convert them into

second-class residential land with higher environmental quality, reduce the amount of commercial land, and add a small amount of green land.

The results of the adjustment and optimization of the land use properties of each station area in this study are shown in Figure 7.

**Figure 7.** *Cont.*

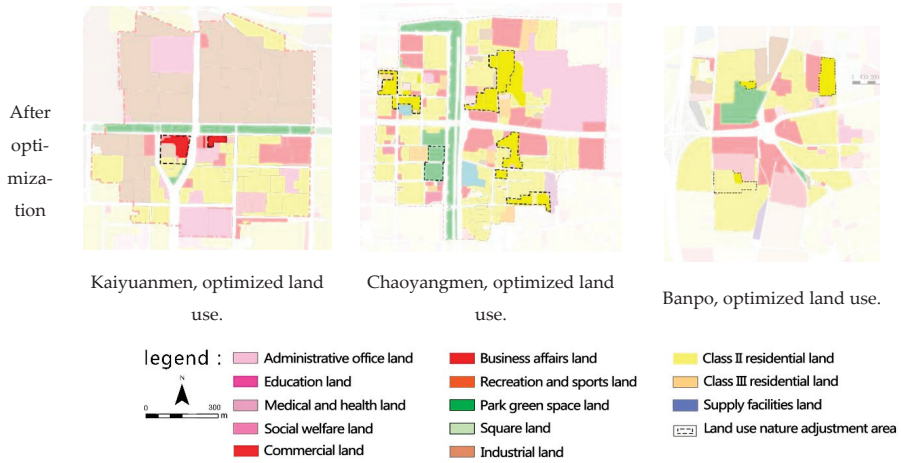



**Figure 7.** Optimization map of the land use for each station.

## 6. Conclusions

This study aimed to further understanding of the problem of unbalanced ridership into and out of metro stations caused by the single development of the station area. From the perspective of the two-way balance of ridership, thorough research of the relevant literature, and multi-source data analysis, the relationship model between land use and ridership into and out of the Xi'an metro station area is established. On this basis, optimization research was carried out, a land use optimization system under the guidance of a two-way balance of ridership was established, and specific optimization measures for land use in each station area are proposed. A scientific and effective station area land use optimization method system has been developed to provide a reliable reference for the optimization of urban metro station area land use. The main conclusions of "one model, two thresholds, and two schemes" are as follows.

A stepwise regression model between ridership and land use in Xi'an was constructed. Using IBM SPSS Statistics Version 28, a stepwise multiple linear regression model of inbound ridership, outbound ridership, and land use factors is established. The land use factors are summarized as the total land area, total building area, average plot ratio, average building density, building mix diversity, land use mix diversity, and a relationship between inbound and outbound ridership.

The optimal range of each factor of land use in the station area under the balance of inbound and outbound ridership was obtained by calculation. Based on the two-way balance orientation of ridership, the current ridership and the maximum ridership of the metro in the future were calculated to estimate the appropriate value of ridership into and out of the station. At the same time, a relational model was used to calculate the land use factors, and the optimal range of the intensity and mix diversity was obtained.

A land use optimization scheme has been proposed from the perspective of adjusting the development intensity and the nature of land use. On the one hand, from the perspective of development intensity optimization, by dividing the station area into areas with higher development intensity areas, suitable areas, and lower development intensity areas, the optimal value range of land use factors was obtained, and the optimization direction of the development intensity of various types of land is proposed. The optimized spatial morphology of the station domain has also been graphically expressed. On the other hand, from the perspective of land use property optimization, the land use property categories and adjustment schemes that need to be optimized are proposed.

It is a tedious and complicated task to explore the relationships between the ridership of metro stations and the factors of land use in station areas and so there are still some limitations in this research. For example, when analyzing the characteristics of ridership, the proportional expansion of some cellphone signaling data was used to reflect the proportional relationship of the relevant data for the whole population in Xi'an. Certain errors

in this process need to be further investigated and corrected. In addition, this study did not consider station classification; the relationship between ridership and land function should be different for different types of stations. The next step is to study the land use optimization scheme for different types of stations, further expanding the content of the research object. In addition to the macro indicators discussed in this study, the built environment characteristics in the station area can be further analyzed and discussed, considering some micro-level indicators (connection facilities, street facilities, and environmental elements) as well. Secondly, the specific optimization measures proposed in this study for each station may have some personal subjectivity. In the future, various conditions, such as construction status, scientific research, daily operation management, and residents' demands could be more comprehensively analyzed and additional objective and effective optimization measures could be proposed.

**Author Contributions:** M.Z.: Conceptualization, Writing—original draft. H.T. and B.L.: Methodology, Formal analysis. Y.D.: Data curation, Visualization. Y.L.: Supervision, Project administration. J.W. and K.L.: Formal analysis, Data curation. All authors have read and agreed to the published version of the manuscript.

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# Exploring the Relationship between the Clustering Degree of Children's Business Formats and the Attractiveness of Commercial Centers in Wuhan by Modifying the Classic Retail Model

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**Abstract:** In recent years, the continued popularity of children's consumption has made it a new factor that affects the attractiveness of Wuhan's commercial centers. This study analyzes the characteristics of children's business format agglomeration in Wuhan commercial centers based on the results of an on-the-spot investigation and estimates the passenger attraction of 66 commercial centers in the main urban area with the support of LBS data. In addition, we set up a control experiment group of commercial centers of various levels and explore the influence mechanism of the density of various types of children's stores on the attraction of commercial centers by improving the classic retail model. The results indicate the following. (1) Children's business formats in Wuhan's commercial centers are active as a whole, and different types of children's businesses have an unbalanced layout at the different levels of business centers. (2) There are both level ladder and internal level differences in the attractiveness of Wuhan commercial centers. (3) The direction and intensity of the influence of children's business types on commercial centers of different levels differ. In city-level commercial centers, children's education and entertainment formats play a role in promotion. In county-level commercial centers, the children's education format is the most important, and overinvestment in the children's department store format may not meet expectations. In community-level commercial centers, investment in children's department stores yielded the best results. (4) Traffic impedance has a stable inhibitory effect at all levels of Wuhan commercial centers, which is in line with the classic retail gravity theory. Further, based on the above results, this paper puts forward suggestions on several types of adaptations that can be applied to children's consumption stores at different levels of commercial centers to provide support for rationally utilizing the potential of the children's consumption market.

**Keywords:** children's business formats; commercial center; attractiveness; influence mechanism; retail model

## 1. Introduction

The attractiveness of commercial centers refers to their ability to attract customers from areas with concentrated commercial activities within a certain range, which is of great value to urban economic recovery in the post-epidemic era. Under the guidance of the common goal of promoting economic growth and social prosperity, the attractiveness of commercial centers has also become a focus of attention in the field of urban economy and planning of major cities worldwide [1–4]. In research on the factors influencing the attractiveness of commercial centers, numerous scholars find that commercial scale (usually expressed by the floor area of commercial centers) and traffic resistance have a steady impact on

the attractiveness of commercial centers [5–8], and the relevant planning practices of commercial centers have mature optimization technologies in these two aspects.

The clustering degree of children's business formats refers to the concentration of children's business formats within a certain area, which has become an important starting point for commercial operations in the period of expanding the children's consumer market. Growth in the number of consumers and improvement in consumption levels are key manifestations of the expansion of the consumer scale. Children play an increasingly active role in consumer groups [9], and the commercialization of children's space has also become a new development trend on a global scale [10]. Dotson et al. believed that the rapid growth of children's commercial space in the United States is an important factor in promoting the socialization of children's consumption [11]. Broberg et al. pointed out in their research on the structure of Finnish child-friendly cities that commercial spaces, such as shops, restaurants, and playgrounds, offer important environmental support for the construction of child-friendly cities [12]. Crewe et al. found that extensive children's retail commercial space is key to the success of the British children's fashion market [13]. According to Vinken's survey, the Japanese consumer market is generally connected to maternal and child services and children's education [14]. With the upgrading of consumer markets and the improvement of maternity security policies worldwide, it is evident that the "children's economy" is heating up. The children's market is characterized by the expansion of consumer scale and higher consumption levels. China is one of the most representative countries in the world. As of the end of 2020, children aged 0–14 accounted for 17.95% of the total population in China, an increase of 1.35% from A decade ago [15]. According to the "2018 China Children's Family Survey White Paper", the scale of China's children's consumption market has approached RMB 4.5 trillion, and the average annual expenditure per child can reach RMB 20,000. At the same time, marketers have become aware of children's influence on consumption, leading to a significant increase in the proportion of children's business formats in commercial centers. Among the top 100 newly opened shopping centers in China in terms of comprehensive strength, parent–child business accounts for 9.54%, making it the second-largest experience business after the catering business.

At present, both commercial consumption demand and the children's consumption market in Wuhan are expanding rapidly. Wuhan is an important commercial town that has "prospered by business" [16]. In the past ten years, the area of Wuhan's commercial center has increased significantly. In 2020, the area of Wuhan's commercial center will reach 9.45 million square meters, and the per capita commercial center area will reach 0.766 square meters, second only to Shanghai and Hangzhou. Moreover, the number of children with household registrations in Wuhan reached 1.478 million in 2020, accounting for 16.7% of the city's population. The overall population of children is growing and the demand for children's consumption is expected to further increase in the future.

Although commercial centers oriented to children's consumption have been proven to be a highly profitable business model in extensive commercial practice, it is common to see that the "high area" of children's business formats has not brought "high popularity" and "high income" in recent years. Such centers are not a band-aid for alleviating the impact of COVID-19 nor a panacea for offline consumption transformation due to their low rental capacity, large footprints, and low efficiency. Specifically, "how to play a positive role in children's formats while promoting the appeal of commercial centers" and "what are the differences in the influences of different types of children's formats on different levels of commercial centers" are urgent questions to answer.

In this paper, we first review the related research progress on children's business formats and the attractiveness of commercial centers. Second, we expound on the data and methods used for analyzing clustering degree and attractiveness before describing the features of children's business format agglomeration and commercial center attraction in Wuhan. Third, we revealed the influence mechanism of different types of children's business formats on the attractiveness of different levels of commercial centers. Finally, we

put forward suggestions on the adaptation, transformation, and developmental direction of children's business formats at various levels of commercial centers.

## 2. Literature Review

### *2.1. Research Progress on Children's Business in Commercial Centers*

Children constitute a special group of consumers. Importantly, children's consumption behavior in commercial centers cannot simply be understood as parental subrogation consumption. Ironico asserted that children are not consumers in the full sense, but rather "progressing consumers" who constantly collect information and improve their skills in their consumption behavior. He also highlighted that children have a positive role in redefining commodities, stimulating commercial vitality, and encouraging the reuse of commercial spaces through play [17]. Berti et al. believed that children are not fully aware of the commercial nature of commodities, and preschool children usually use their intuition to explain purchase behavior and deepen their understanding through further learning in the consumption process [18]. McNeal argued that children can learn consumer behavior and meet creative activity needs by interacting with commercial products and spaces, even without the involvement of other social actors [19]. The influence of children's groups on family shopping decisions is significant and dynamic [11,20]. Miller et al. found that parents are not as rational in their consumption process as they think they are [21]. Hamilton et al. thought that parents would increase spending out of love and protect their children [22]. Several studies have shown that the influence of children on the family consumption process is difficult to assess [23–25].

As the influence of children's consumption gradually expands, education, entertainment, retail, and other types of children's business formats have increasingly become the mainstream configuration of commercial centers. Marketers have conducted extensive business practices centered on children's business formats [25]. This is especially true since children today spend more time in commercial settings, e.g., shopping centers, than ever before and are surrounded by commercial messages in a variety of forms [26]. On the one hand, diverse business models for children have emerged. Feenstra et al. pointed out that to build family traffic and develop consumption in the store, the business model of educational seminars and events for children is widely used, such as workshops, birthday services, and commercial events with national brands [27]. Wiener found that retailers adopt the "playtail" business model and organize activities to attract children to play with products, which can effectively enhance a store's attractiveness [28]. Guichard and Damay suggested that commercial events and workshops may fulfill some children's emotional and social expectations of an ideal store [29]. On the other hand, various children's business formats have gradually become an important part of urban commercial centers. The China Children's Business Formats Management Center divides children's business formats into four categories: children's education, retail, services, and entertainment. A research report on China's children's business format reveals that the top three brands reflect children's retail, education, and entertainment in terms of the number of business formats. Many scholars have provided insights into the role of various types of children's business formats in commercial centers. Zhang proposed that children's entertainment format is an essential resource for high-level commercial centers in Chinese cities [30]. Shen et al. argued that children's entertainment format is an indispensable part of today's commercial complexes in large cities in China [31]. Zhang et al. [32], Cai et al. [33], and Liu et al. [34] proposed increasing the proportion of children's education and entertainment formats to form essential differentiated competitive advantages with online e-commerce and to stimulate the vitality of physical business centers. Chan identified that the children's retail format is popular with urban children in China [35].

### *2.2. Related Research on the Attractiveness of Commercial Centers*

Measurement methods and factors influencing the appeal of commercial centers have attracted the attention of many scholars for a long time. In terms of attracting customers, the

famous models include J. Reilly's "law of retail attraction", P.D. Converse's breaking point formula, A.G. Wilson's "entropy maximization model", D.L. Huff's probability model, G. Rushton's gravitational model, and R.M. Downs' shopping mall cognitive structure. The wide application of urban big data, such as GPS floating vehicle trajectory data and LBS location information service data, has progressively perfected the method to measure passenger attraction [36–38]. In terms of influencing factors, it has become a common understanding that the relationship between business center attraction and commercial scale is positively correlated, and the negative correlation with traffic impedance has been repeatedly tested by many scholars [5–8]. In recent years, research has extensively analyzed the influence of business formats, levels, consumer characteristics, development strategies, and the surrounding environment of commercial centers on customer attraction. Wang et al. separated the attractiveness intensity of commercial centers from the attractiveness range and proposed that commercial centers of all levels will have a trend of either "improvement" or "recession" under certain conditions [39]. Hao et al. revealed that different commercial centers show different levels and scales, and the scales and patterns of the spatial agglomeration of different formats also differ [40]. Wang et al. conducted an empirical study on customer attraction to community-level commercial centers in Xi'an and stated that it was related to the density of the street network and the number of schools [41]. Zhou et al. confirmed that the traditional geospatial attenuation law is disturbed locally owing to the influence of market rules, consumer preferences, and other factors. To a certain extent, the complementarity of business formats promotes interdependence among commercial centers [42]. Qin et al. observed that the spatial distribution of the catering format in Nanjing follows the central place theory, and the overall popularity is low [43]. Chen et al. found that the entertainment format is an essential factor in improving the attraction of commercial center passenger flows [44]. Lin et al. also believed that leisure and entertainment were the main purposes of physical consumption [45].

### *2.3. Construction and Optimization of the Retail Model*

The retail model, favored by researchers for nearly half a century, is based on Newton's law of gravitation and applicable to the retail field. With ongoing improvements in research, it has matured and is now widely used in studies on the passenger attraction mechanism of urban commercial centers. In the 1930s, Reilly first introduced Newton's gravitational model to the study of urban economic geography when analyzing the retail relationship in Texas, demonstrating that the commercial attraction of a city is directly proportional to the size of the urban population and inversely proportional to the square of the distance [46]. Hotelling further pointed out that consumer payment of transportation costs is key to price competition in commercial centers [47]. Subsequently, other consumer behavior research revealed that consumers exhibit a wide range of "irrational" economic and spatial behaviors [48], thus challenging the single commercial center minimum effort rule in traditional models [49]. Huff confirmed that consumers' purchasing behavior exhibits spatial randomness and proposed a Huff model to measure the interaction probability between consumers and retail stores in a specific location [50]. Lashmanan and Hansen constructed a shopping model closely related to the transportation model, based on network tracking and the gravity model trip distribution theory [51]. Wilson introduced the concept of "entropy" to the study of social geography and described the dynamic equilibrium system constructed by the retail gravity model with the process of entropy maximization [52]. The model was later applied on a smaller scale and extended by Fotheringham and Knudsen to study location rents, external economies of scale, and retail agglomeration [53]. Dearden and Wilson further refined the model, identifying discontinuities in the Greater London retail system and arguing that understanding the underlying discontinuities of a retail system can provide effective advice to policymakers and retail businesses [54]. In 2018, Wilson further optimized the dynamic retail model and introduced a system of stochastic differential equations (SDEs) to solve fluctuations that the system may cause due to force majeure factors. The construction of this model has remained relatively stable for decades [55].

Since then, researchers have improved the retail gravity model with multiple disciplines and proposed numerous application methods. For example, Piovani et al. combined the gravity model with percolation theory to explain the impact of transportation networks on the attractiveness of commercial centers [56]; Schlaich et al. used a retail gravity model to simulate consumer shopping interactions related to the retail food environment, nutrition, and public health [57]; Ellam et al. simulated and explored the dynamic characteristics of the spatial interaction of the UK retail system by constructing a stochastic differential equation [58]. Shan et al. explored the influence mechanism of the consumer age, industry type, and development time on the attractiveness of the Wuhan commercial center by improving the classic retail attraction model [36].

### *2.4. Insufficient Existing Research*

The existing studies have three shortcomings: (1) less attention has been paid to the agglomeration characteristics of children's business formats, and more empirical research is needed to support them; (2) although the promotion of children's business formats on attractiveness has been widely recognized, how different types of children's business formats contribute to the attractiveness of commercial centers at different levels remains unclear; and (3) the classic retail gravity model does not include the children's business format factor; thus, it needs to be improved and reconstructed to meet the current development needs. To address these shortcomings, this study used modeling ideas from social physics and statistical mechanics to improve the classic retail gravity model. To that end, it includes variables of the clustering degree of children's business formats (i.e., children's retail, entertainment, education, and other formats). Furthermore, a commercial center-level control group experiment was conducted to test the variation in the attractiveness mechanism (Figure 1).

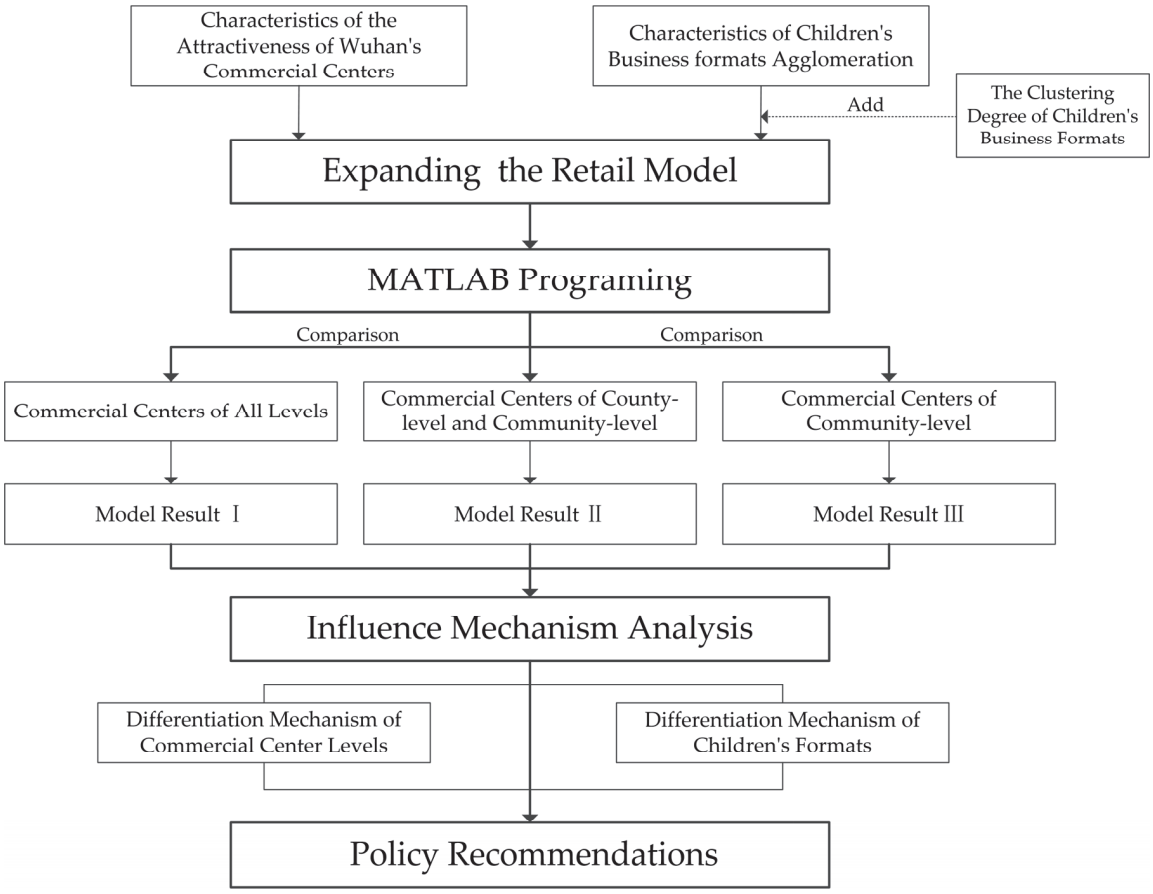


**Figure 1.** Analysis framework.

## 3. Materials and Methods

### *3.1. Research Material*

#### 3.1.1. Built Environment Data for any Commercial Center

The data mainly include the name, grade, building outline, and geographical location of each commercial center. Among them, the name and level of commercial centers are mainly derived from the relevant content in the Wuhan Commercial Network Layout Plan (2016–2020), the Wuhan City Master Plan (2010–2020), and Shan et al.'s classification of Wuhan's commercial centers [36]. The building outline and geographic location were obtained from the AutoNavi Map API (2021). Based on these data, we defined 66 commercial centers in the main urban area of Wuhan, including six municipal-level commercial centers, 20 county-level commercial centers, and 40 community-level commercial centers.

#### 3.1.2. Children's Stores Data in Any Commercial Center

The research mainly collected two types of data: (1) data on the categories of children's stores and (2) data on the number of children's stores in commercial centers. The children's stores mentioned in this article refer to commercial operation sites that primarily target children, including children's retail stores, education stores, entertainment stores, and other stores. Children's entertainment stores include not only outdoor and indoor children's entertainment stores with fixed storefronts but also semi-mobile operating facilities for children's games that use public space in commercial centers to operate for an extensive period of time. Children's stores, as defined by the research, do not include non-profit public service facilities for children (e.g., mother and baby rooms, children's rest areas, etc.); comprehensive stores that do not have child-specific goals; stores that do not operate normally for one month or more or operate normally for less than one month without follow-up business intentions; small, fully self-service vending machines; temporary mobile stores; etc.

We conducted a three-month field survey of 66 commercial centers in the main urban area of Wuhan in 2021. According to non-participatory observations of the attributes and behaviors of visiting customers and store operators, 3000 children's consumer stores that met the research needs were selected, with the number of children's stores in each commercial center and each format counted separately. To minimize the deviation of results caused by individual differences between children's stores (e.g., differences in store area), we will increase or decrease the number of stores as appropriate in the counting process according to the actual situation of each store.

#### 3.1.3. Geographic Information Data of Wuhan

We collected administrative division data and traffic time consumption data for Wuhan from AutoNavi Map API (2021). The administrative division data included the main urban area of Wuhan and the administrative boundaries of each street. The traffic time data are the average minimum traffic time during the data collection period (31 August 2021 to 13 September 2021, working days 1700 to 2200, and rest days 1000 to 2200) for the four modes of transportation: walking, driving, cycling, and public transportation (including transfer time). After obtaining the minimum traffic time from any street to any commercial center, the average time was taken as the traffic time of any commercial center.

#### 3.1.4. LBS Location Service Data

The LBS location service dataset used in this study is user anonymous geographic location data obtained from when users use multiple apps (WeChat, Dianping, Meituan, etc.) in which they authorize the use of their location. The data include the anonymous ID of the user, the latitude and longitude of the user's residence, and the code for and time when the user visits the business center. The LBS data were collected from 66 commercial centers from 31 August 2021 to 13 September 2021 (holidays and periods of rain and snow were avoided), from 1700 to 2200 on weekdays and from 1000 to 2200 on weekends. After denoising, the invalid collection points for those passing by the commercial center, staying

on the water or on the road, and living and working in the commercial center, 7128 pieces of valid data were finally used.

### *3.2. Research Methods*

#### 3.2.1. Calculating the Clustering Degree of Children's Business Formats

The business point density index is widely used in the empirical analysis of business agglomeration. This study uses the density of children's stores (including the density of children's retail entertainment stores, education stores, other stores, and the overall density of children's stores) as an indicator of the children's format clustering degree. The density of children's stores is defined as the number of children's consumer stores in any commercial center or base area of the building outline. Ultimately, 264 pieces of valid data on the density of children's stores were obtained.

#### 3.2.2. Measuring the Attractiveness of Commercial Centers

In an empirical analysis, the concept of customer attraction in commercial centers is often based on the interaction between customers and commercial spaces. In the case that a customer visits the same commercial center multiple times in a single day, only one spatial interaction was counted. We captured mobile communication devices within the range of 66 commercial centers using LBS data and used device IDs to identify the coordinates data of each consumer's residence. We used 108 sample blocks as the statistical unit, sequentially aggregated all street IDs to 66 commercial centers and the number of people interacting with each commercial center, and established a data matrix for the number of interactions between the sample blocks and commercial center spaces. Furthermore, we measure the attraction of any commercial center to any street based on Equation (2) and add the value of its attraction to all streets to obtain the attractiveness of any commercial center (Table 1).

**Table 1.** Matrix of spatial interaction among streets and commercial centers.

| Street | NO.4 | NO.1 | NO.30 | NO.39 | NO.35 | ..... |
|---|---|---|---|---|---|---|
| Baishazhou Street | 0.0057592 | 0.00280938 | 0.07978649 | 0.011658941 | 0.045933418 | |
| Baibuting Street | 0.0022283 | 0.00119986 | 0.00308536 | 0.016112444 | 0.014226945 | |
| Baofeng Street | 0.0028648 | 0.0026738 | 0.00305577 | 0.026355997 | 0.018716578 | |
| Beihu Street | 0.0040866 | 0.00122599 | 0.00367797 | 0.025337148 | 0.018798529 | |
| Caidian Street | 0.0051118 | 0.00340788 | 0.01299255 | 0.032800852 | 0.027050053 | |
| ..... | | | | | | |
| The value of Attractiveness | 1.1673702 | 1.04127612 | 1.66115807 | 3.826869759 | 3.594317598 | ..... |

Derived from LBS data.

#### 3.2.3. Expanding and Solving the Retail Model Using MATLAB

With comprehensive consideration given to the research needs and data collection types, we finally selected the retail gravity model of physical and statistical mechanics for adjustment. The mathematical model is as follows:

$$T_{ij} = \frac{e_i p_i W_j^{\alpha} exp(-\beta C_{ij})}{\sum_k W_k^{\alpha} exp(-\beta C_{ik})} \quad (1)$$

where $T_{ij}$ represents the attractiveness of commercial center $j$ to residence $i$ (usually expressed by the number of customers and the probability that a customer at $i$ will choose business center $j$). $e_i$ is the per capita shopping demand, $p_i$ is the size of the population in residence $i$, $W$ is the construction area of any commercial center, $C$ is the comprehensive cost from the residence to the commercial center (expressed by distance or time consumption), and $k$ is the total number of competing commercial centers. $\alpha$ and $\beta$ are the adjustment coefficients for $W$ and $C$, respectively. In addition, we considered the overall shopping demand of residence $i$ as $Y_i = e_i p_i$, which is usually defined as $\sum_j T_{ij} = Y_i$.

Equation (1) can be regarded as a fast dynamic model based on the entropy maximization process to describe the flow of commercial centers [56]. In the process of competing for limited resources, various commercial centers achieve a dynamic balance of commercial scale and traffic resistance, forming a relatively stable retail distribution space pattern. The number and spatial distribution of commercial centers in this equilibrium state strongly depend on commercial scale parameter $\alpha$, distance cost parameter $\beta$, and the value of the input data. Any small change in the input data would yield a rapid reconfiguration to a new attractor state. In the process of expanding the classic model, scholars have proved that $\alpha$ is greater than 0, the value converges toward 1, and the value of $\beta$ is discrete but always greater than 0.

We made the following adjustments to the classic retail model.

(i) We used the number of visitors to define $T_{ij}$ and $Y_i$, so it can more accurately reflect the multi-frequency and multi-destination characteristics of modern consumer behavior. Therefore, we redefined $T_{ij}$ as the number of visitors from residence (street) $i$ to business center $j$ and $Y_i$ as the total number of visitors from residence (street) $i$ to all commercial centers. Finally, based on the definition of the spatial interaction matrix, we redefined the attractiveness of commercial center $j$ to residence (street) $i$ as

$$A_{ij} = \frac{T_{ij}}{Y_i} \tag{2}$$

(ii) In recent years, more and more studies have confirmed that the clustering degree of children's business formats has a potential impact on customer attraction, but this is rarely covered in the study of classic retail models. Therefore, we added the clustering degree of children's formats $Z_j$ to meet the research needs, and expanded the term $exp(-\beta C_{ij})$ to $exp(aC_{ij} + bZ_j)$.

$$Z_j = \sum_n F_n \ (n = 1, 2, 3, 4) \tag{3}$$

(iii) The traffic cost has a stable negative impact on the attractiveness of commercial centers, while the impact of the clustering degree of children's business formats is relatively positive, so we assume $\alpha < 0$, $\beta > 0$. Besides, Since the value of $\alpha$ always converges to 1, we defined $\alpha = 1$.

The improved model expression is as follows:

$$A_{ij} = \frac{W_j exp(aC_{ij} + b\sum_n F_n)}{\sum_k W_k exp(aC_{ik} + b\sum_n F_n)} \tag{4}$$

In Equation (4), we defined residence (street) $i$ as 108 sample blocks and $j$ as 66 commercial centers. $\sum_n F_n$ was used to express the total clustering degree of the children's business formats, and $C$ was used to express the traffic cost.

To solve the influence mechanism of the density of various children's consumer service stores on commercial centers at various levels, we used MATLAB to compile the calculation program. First, three groups of controlled trials were established according to the classification of commercial centers: full-level commercial centers (66), county-level and community-level commercial centers (60), and community-level commercial centers (40). Next, the sample street code (108 rows × 2 columns) and the total number of visitors to the sample street (108 rows × 1 column) were determined. Thereafter, three control group datasets were input: the spatial interaction probability matrix (108 rows × 66 columns/108 rows × 60 columns/108 rows × 40 columns), the spatial interaction matrix (108 rows × 66 columns/108 rows × 60 columns)/108 rows × 40 columns), the business center-street traffic time-consuming matrix (108 rows × 66 columns/ 108 rows × 60 columns/108 rows × 40 columns), and the business center attributes (66 rows × 7 columns/60 rows × 7 columns/40 rows × 7 columns). By changing the independent variables, we could compare the model output results to determine the optimal model, which was selected based on reliability, T-stat significance, the principle of

maximum $R^2$, and minimum error. Finally, the correlation coefficients of each influencing factor were derived.

## 4. Results and Analysis

### *4.1. Characteristics of Children's Business Agglomeration in Wuhan's Commercial Centers*

#### 4.1.1. Active Children's Business Formats

First, among the 66 sample commercial centers we surveyed, there were more than 3000 children's stores in total. Additionally, more than 90% of the commercial centers in the main urban area had functions associated with children's consumption and related services (Figure 2). Second, among the 66 sample business centers, approximately one-third of the business formats were children's formats (33.8%), which is nearly three times the average level in China in 2020 (12.5%, according to the "2021 China Winning Business Big Data Report"). Third, the density of children's stores was clustered at 0–0.5 per hectare (Figure 3), with an average clustering degree of 0.65 per hectare and a maximum degree of 2.98 per hectare (Figure 4). Therefore, it can be seen that children's businesses in Wuhan's commercial center are generally active.

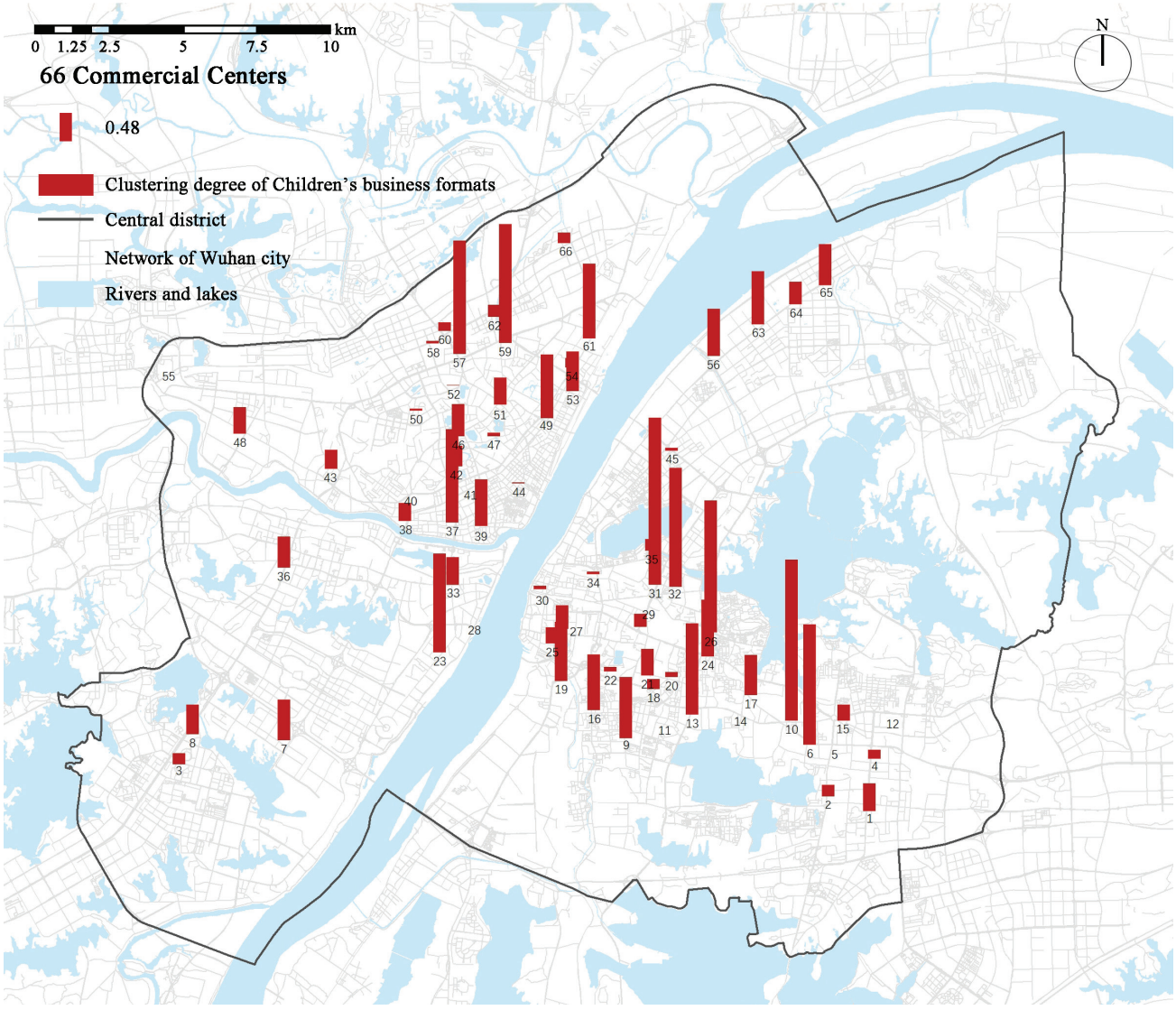


**Figure 2.** Ninety percent of the sample commercial centers have different degrees of children's business distribution. Data sources: the field investigation data.

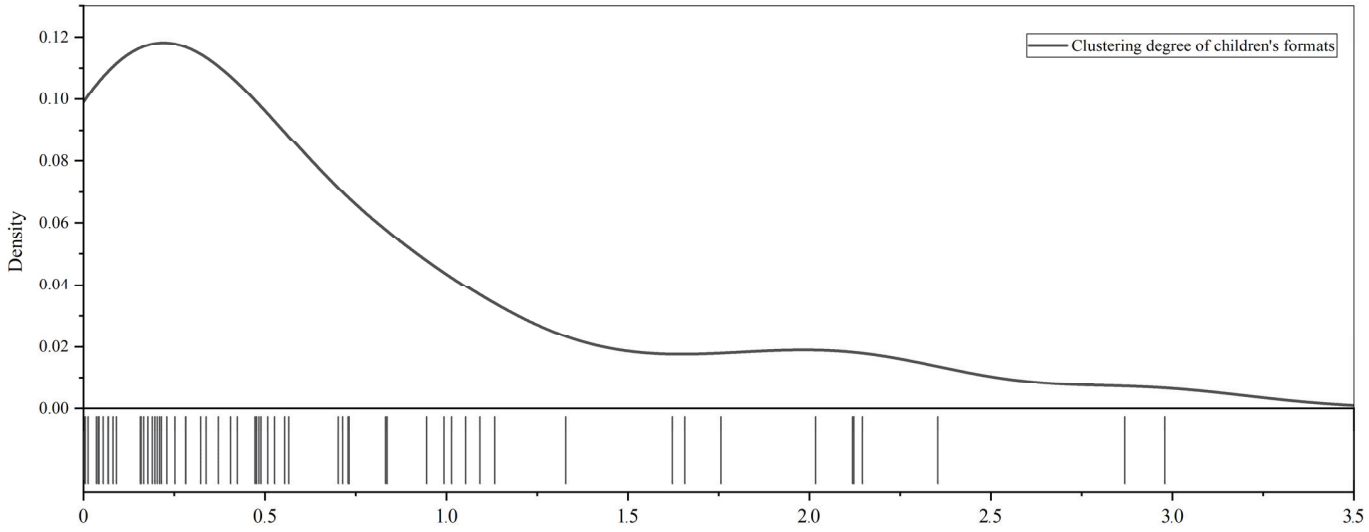


**Figure 3.** Kernel density estimation of clustering degree of children's business format in Wuhan's commercial centers. Data sources: the field investigation data.

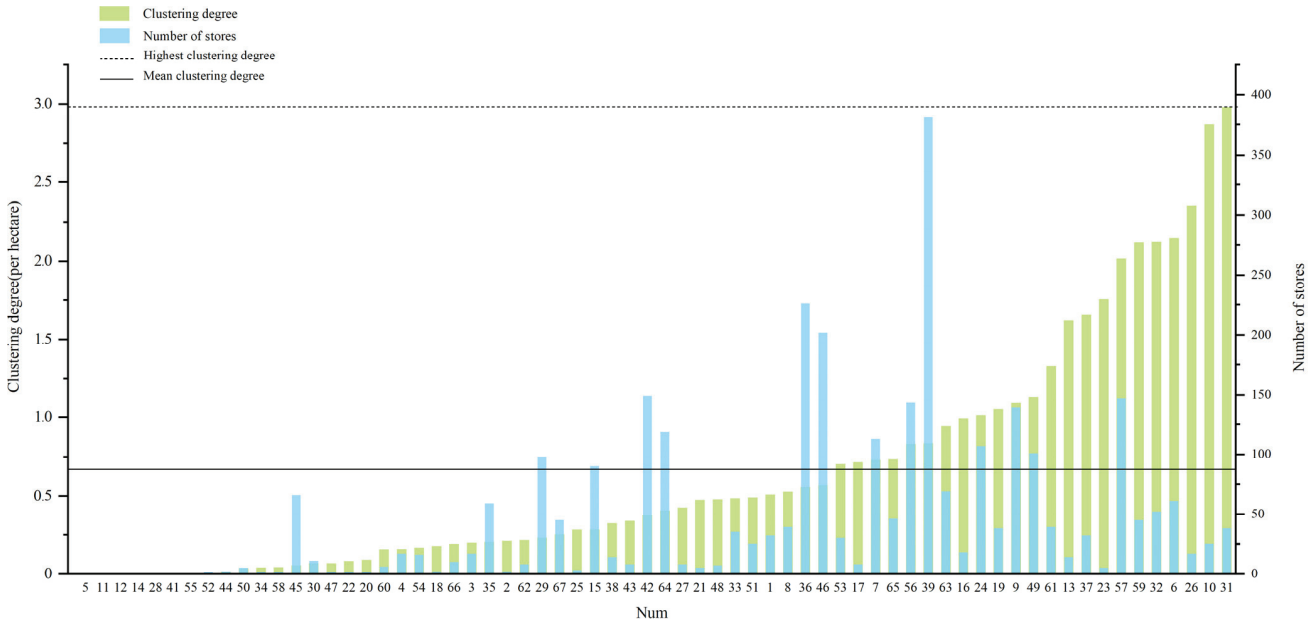


**Figure 4.** The clustering degree of children's business formats and the number of stores in the sample business centers. Data sources: the field investigation data.

#### 4.1.2. Unbalanced Layout of Children's Formats in Different Commercial Centers

First, we find that the standard deviation of the overall clustering degree of children's stores in 66 commercial centers reached 0.74 per hectare. Figure 5 shows that the lower the level of commercial centers, the greater the gap between the median and the mean of the data group and the stronger the imbalance in children's business format layout.

Second, the average clustering degree of children's retail, entertainment, and education stores was 0.18, 0.12, and 0.31 per hectare, respectively. The layout and investment of various children's formats differed significantly—there was a greater number of children's education stores, and its distribution was more extensive.

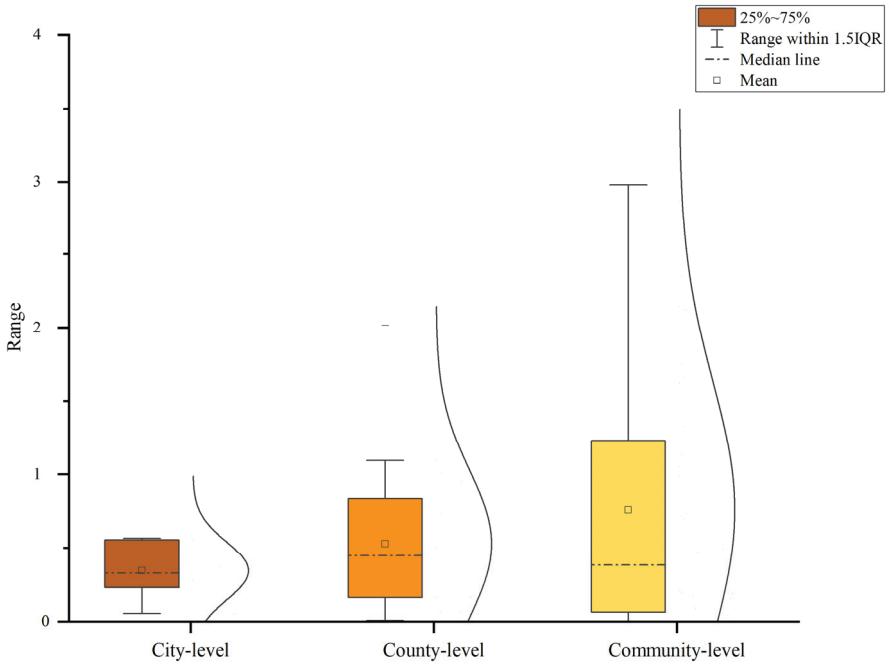


**Figure 5.** Unbalanced distribution of children's formats in Wuhan's commercial centers of different levels. Data sources: the field investigation data.

Furthermore, as shown in Figure 6, the children's business formats with the largest differences were children's education and children's entertainment, with a long "tail", an obvious gap between the high-value and low-value end, and a prominent "single-peak non-equilibrium" structure. The difference in the layout of children's retail formats was relatively small, showing a pattern orientation of "a primary and secondary multi-peak and non-equilibrium". The uneven distribution of various types of children's businesses in 66 commercial centers varied significantly.

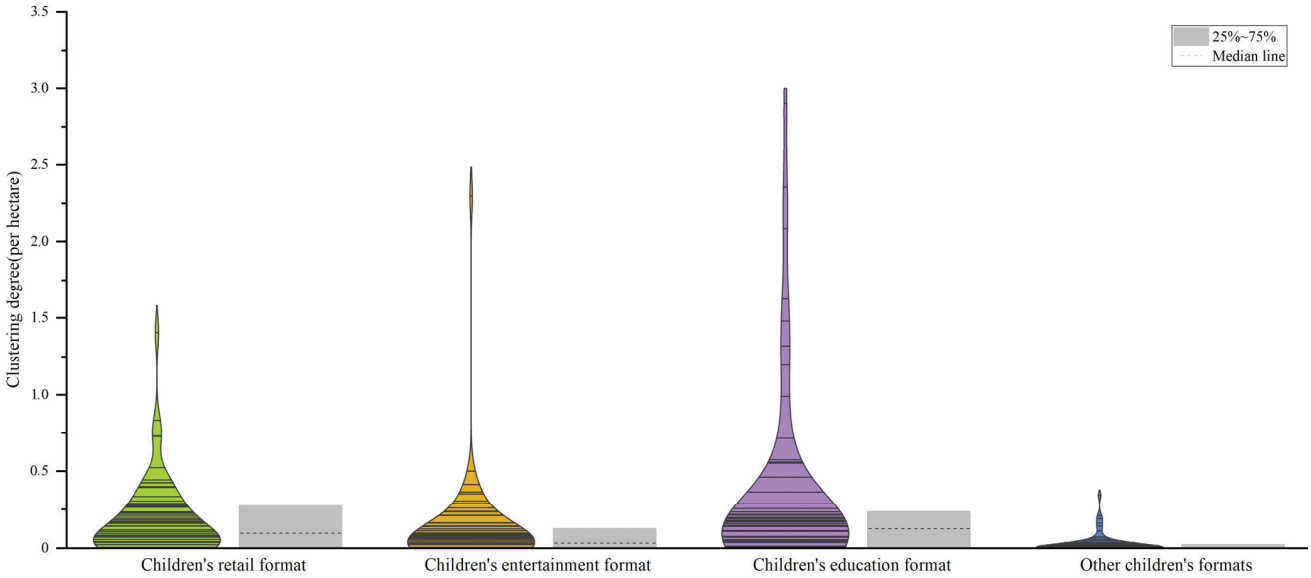


**Figure 6.** Violin diagram of the clustering degree of various children's business formats in 66 commercial centers in Wuhan. Data sources: the field investigation data.

Finally, as shown in Figure 7, in the city- and district-level commercial centers, more than half of the children's business formats were children's retail (accounting for 60.4% and 52.7%, respectively). Their average clustering degrees were 0.18 per hectare and 0.12 per

hectare, respectively. The children's education business format ranked second (accounting for 29.4% and 24.6%, respectively), and the average clustering degrees were 0.10 per hectare and 0.16 per hectare, respectively. The children's entertainment format occupied a larger proportion (55.8%) of stores found in community-level commercial centers, with a high average clustering degree of 0.45 per hectare, followed by the children's retail format (21.6%), with an average clustering degree of 0.14 per hectare. Therefore, there are differences in the proportions of various types of children's businesses at different levels of commercial centers.

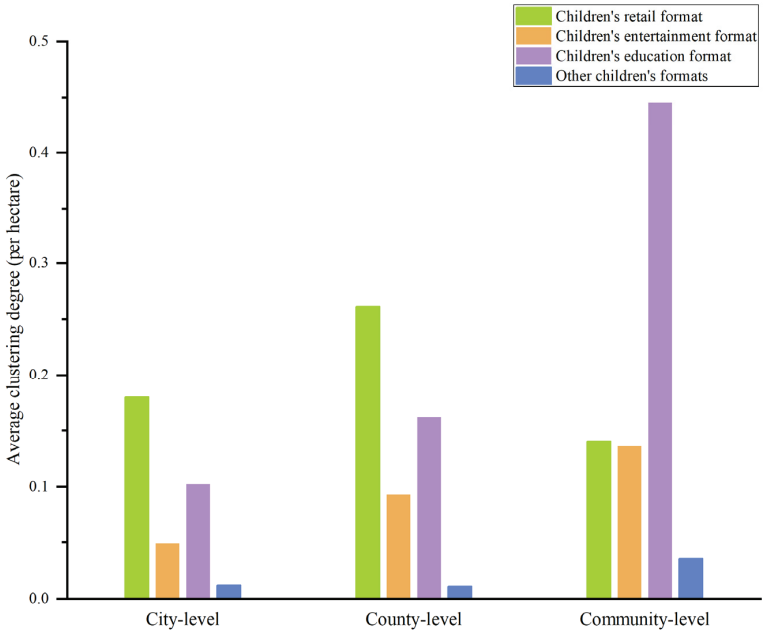


**Figure 7.** The difference in the proportion of 4 types of children's business formats in 66 commercial centers in Wuhan. Data sources: the field investigation data.

### *4.2. Characteristics of the Attractiveness of Wuhan's Commercial Centers*

#### 4.2.1. Gradient Characteristics of Commercial Center's Attractiveness

Based on the measurements of the commercial centers, we created classification statistics on attractiveness. As shown in Figure 8, the attraction force of nearly 90% of the commercial centers shows a gradient characteristic that increases with level. The average values of customer attraction of city-, county-, and community-level commercial centers were 7.7, 2.0, and 0.5, respectively, and there was an obvious gradient difference in the adsorption capacity of commercial centers at each level.

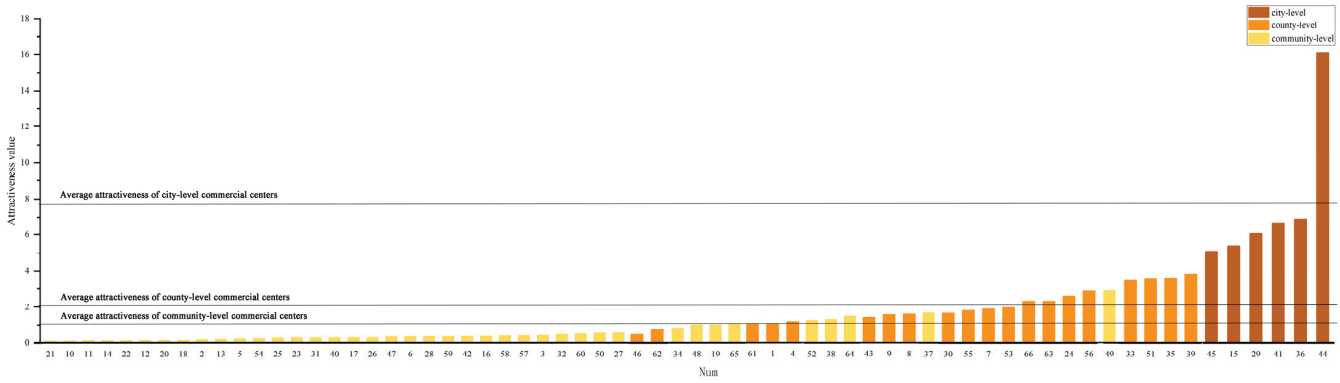


**Figure 8.** Gradients and intra-level differences in attractiveness of Wuhan's commercial centers. Data sources: derived from LBS data (Table 1).

4.2.2. Difference in the Attractiveness of Commercial Centers of the Same Level

Comparing the difference in customer attraction between same-level commercial centers (Figure 8), we found the following. (1) In city-level commercial centers, while most commercial centers tended to have similar levels of customer attraction, the attractiveness of the No. 45 commercial center was slightly lower than that of other commercial centers at the same level, and that of No. 44 was significantly higher than that of other commercial centers. (2) In the county-level commercial centers, the attractiveness of the No. 46 commercial center was lower than that of other commercial centers of the same level, while that of No. 39 was slightly higher than the other commercial centers. (3) In community-level commercial centers, the attractiveness of most commercial centers was low, with No. 49 being significantly higher than the average for its class.

4.2.3. Non-Linear Relationship between the Attractiveness of Commercial Centers and the Clustering of Children's Business Formats

We used the number of commercial centers as the horizontal axis and the standardized value as the vertical axis to draw a line graph of the standardized value of each variable in order to observe its relationship with the attractiveness value (Figure 9). The analysis showed that the relationships between attractiveness and most factors do not conform to the general linear relationship; thus, it is misleading to analyze the relationship between the agglomeration degree of children's business formats and the attractiveness of commercial centers. To describe the non-linear relationship between the variables, it is therefore necessary to study and improve the retail gravity model.

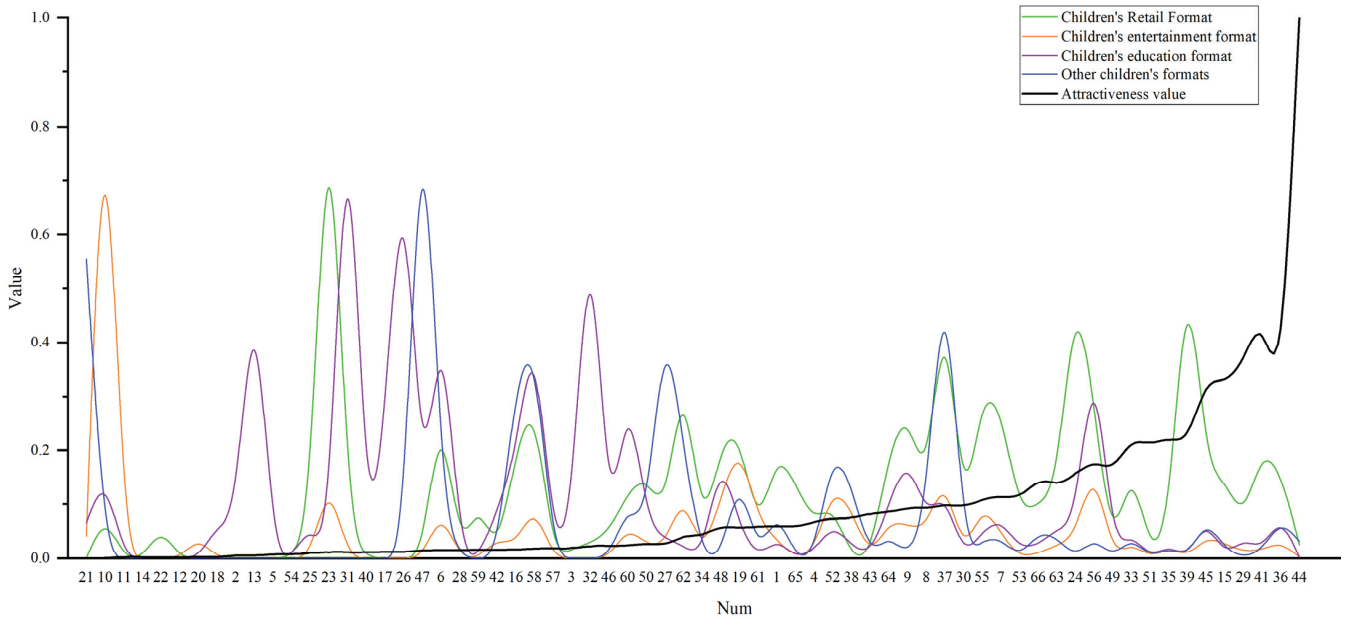


**Figure 9.** Line chart about the relationship between attractiveness and the clustering degree of children's formats. Data sources: the field investigation data, AutoNavi Map API data, and LBS data.

*4.3. Influence Mechanism of the Clustering Degree of Children's Business Formats on the Attractiveness of Commercial Centers*

4.3.1. Modeling Results

In this study, we constructed a retail gravity model by using the interaction probability between commercial centers and township streets as the explained variables and defining the traffic time and agglomeration of children's business forms as the explanatory variables. The clustering degree of children's business formats includes the clustering degree of the children's retail, entertainment, education, and other formats. We used SPSS to test the factors and found no obvious correlations between them (Table 2). Due to the limited number of samples investigated, we completed the modeling and solving by setting up

three control groups—full-level commercial centers, county-level and community-level commercial centers, and community-level commercial centers—to robustly explore the effects of various explanatory variables on different-level commercial centers (Tables 3–5).

**Table 2.** Correlation matrix of explanatory variables.

| | Children's Retail Format | Children's Entertainment Format | Children's Education Format | Other Children's Formats | Traffic Time |
|---|---|---|---|---|---|
| Children's retail format | 1 | 0.203 | −0.008 | 0.099 | −0.023 |
| Children's entertainment format | 0.203 | 1 | 0.056 | 0.052 | 0.089 |
| Children's education format | −0.008 | 0.056 | 1 | 0.013 | 0.048 |
| Other children's formats | 0.099 | 0.052 | 0.013 | 1 | −0.189 |
| Traffic time | −0.023 | 0.089 | 0.048 | −0.189 | 1 |

Data sources: the field investigation data, AutoNavi Map API data, and LBS data.

**Table 3.** Modeling results for commercial centers of all levels.

| Explanatory Variables | Influence Level | | Model Estimation | | Observed Value vs. Calculated Value |
|---|---|---|---|---|---|
| | Correlation Coefficient | T-Stat | $R^2$ | Reliability | |
| Traffic time | −0.031308 | −844.94 | 0.611 | 0.0289 | y = 0.9171x + 0.001256 |
| Children's retail format | −0.0087432 | −15.149 | | | |
| Children's entertainment format | −0.0080871 | −10.452 | | | |
| Children's education format | 0.019973 | 63.941 | | | |
| Other children's formats | 0.16289 | 45.68 | | | |

Data sources: the field investigation data, AutoNavi Map API data, and LBS data.

**Table 4.** Modeling results for commercial centers of county-level and community-level.

| Explanatory Variables | Influence Level | | Model Estimation | | Observed Value vs. Calculated Value |
|---|---|---|---|---|---|
| | Correlation Coefficient | T-Stat | $R^2$ | Reliability | |
| Traffic time | −0.033497 | −753.76 | 0.446 | 0.0236 | y = 0.5352x + 0.000609 |
| Children's retail format | −0.018948 | −29.548 | | | |
| Children's entertainment format | −0.003684 | −4.3877 | | | |
| Children's education format | 0.016845 | 49.463 | | | |
| Other children's formats | 0.16441 | 40.411 | | | |

Data sources: the field investigation data, AutoNavi Map API data, and LBS data.

**Table 5.** Modeling results for commercial centers of community-level.

| Explanatory Variables | Influence Level | | Model Estimation | | Observed Value vs. Calculated Value |
|---|---|---|---|---|---|
| | Correlation Coefficient | T-Stat | $R^2$ | Reliability | |
| Traffic time | −0.039562 | −397.37 | 0.309 | 0.0167 | y = 0.1766x + 0.000425 |
| Children's retail format | 0.01977 | 11.184 | | | |
| Children's entertainment format | −0.036233 | −30.036 | | | |
| Children's education format | −0.0018477 | −4.2597 | | | |
| Other children's formats | 0.23506 | 47.86 | | | |

Data sources: the field investigation data, AutoNavi Map API data, and LBS data.

4.3.2. The Impact of Children's Retail Format

Children's retail format had a limited influence on the attractiveness of commercial centers. By observing the relationship between the two values (Tables 1 and 2), we can see that this type of business format had a weak and unstable effect on the attraction of city-level commercial centers. By comparing Tables 2 and 3, we find that the correlation coefficient of children's department stores changed significantly from negative to positive, indicating that children's department stores have an inhibitory effect on the attraction of county-level commercial centers. The correlation coefficient of children's retail format in Table 3 is 0.01977, indicating that it has a strong appeal to consumers in community-level commercial centers. On the one hand, this may be because children themselves have no spending power, and retail commodities such as children's food, toys, and clothing are not necessities of life for all consumers. Therefore, for more consumers, other types of stores in city- and district-level commercial centers are more attractive. However, the acquisition threshold of such products is low and the space demand for store operations is small. Community-level commercial centers can already meet the needs of most consumers to obtain children's general merchandise. At the same time, with the popularity of online shopping, consumers' expectations of the shopping travel costs for children's daily necessities have decreased. More consumers consider that they do not need to go to high-level commercial centers to buy children's daily necessities. In addition, this phenomenon is closely related to the retail format characteristics. This type of format cannot use the characteristics of "accompanying reading" and "accompanying playing" to further expand the customer attraction effect, such as entertainment and education formats, so it is relatively passive in promoting the role of attracting customers.

4.3.3. The Impact of Children's Entertainment Format

As shown in Table 3, the correlation coefficient of children's entertainment format on the attraction of community-level commercial centers was −0.036233, indicating that it has a significant inhibitory effect. A comparison of Tables 1 and 2 showed that the absolute value of the correlation coefficient of this format and its change are both small, and the effect at the city-level commercial center is not significant. Several reasons explain this phenomenon. First, children's entertainment venues are not limited to commercial centers. Community centers, city parks, and other indoor or outdoor public spaces can also provide playgrounds for children. "Pay to play" has become the norm in major Chinese cities, but Severcan's research found that children prefer free public spaces. This makes children's entertainment facilities in commercial centers not the only or optimal choice for consumers. Therefore, this type of business has a very limited influence on the attraction of commercial centers in general. Second, the scope of design allowed for children's play places in community-level commercial centers was limited, the budget was small, there was only one set of amusement facilities, and there was insufficient daily management and maintenance. Merely placing rudimentary equipment and facilities is not enough to attract children, nor can it meet the needs of most modern consumers. Therefore, the high concentration of children's entertainment formats has inhibited improvement in the attractiveness of community-level commercial centers. Third, city-level commercial centers have more advantages in terms of the novelty and diversity of children's amusement facilities. While there are many types of businesses in these commercial centers, it should be noted that the phenomenon of "an inch of land and an inch of gold" directly conflicts with the large space demand of children's entertainment stores, resulting in relatively poor competitiveness in terms of revenue per store. Consumers in city-level commercial centers generally have diverse visiting purposes; therefore, time spent in a single store is usually limited. However, children often need to stay in such stores for a long time, which leads to single-purpose consumption travel that can better meet the needs of children's play time. That said, in the case that a consumer trip has multiple purposes and cannot provide sufficient time to stay in a children's entertainment store, most consumers often choose to give up visiting such stores.

4.3.4. The Impact of Children's Education Format

A comparison of Tables 1 and 2 revealed that the correlation coefficients of children's education formats are all positive, and the absolute value is decreasing, thereby indicating that this type of format has a promoting effect on city-level customer attraction. In Tables 2 and 3, the correlation coefficient of this type of business changed from a positive to a negative value, demonstrating that the children's education format also has a promoting effect on attracting customers in county-level commercial centers. The correlation coefficient of this type of business in Table 3 was −0.0018477. This small value indicates a weak role for community-level commercial centers. First of all, the "accompanying reading" model generated by education and training stores can bring a large number of consumers and increase the length of consumers' stay. It can also effectively stimulate the potential consumption power of parents, thereby amplifying the "siphon aspect" of high-level commercial centers. At the same time, education and training services possess the characteristics of continuity and periodicity and require consumers to maintain a long-term relationship with service personnel, which provides a long-term and stable passenger flow for the commercial centers. Compared with children's retail stores, such stores are more dependent on the offline physical environment and have strong site adaptability, which makes them more resilient to the impact of online shopping. Second, children's education stores in Wuhan have formed a degree of differentiated division of labor in commercial centers of different levels. The city-level commercial centers have focused on new types of children's quality education and art education, such as sensory integration training, educational thinking enlightenment, and emotional social and language communication guidance. In contrast, county-level commercial centers have emphasized traditional quality education, e.g., instrumental music, art, and dance, and subject education, e.g., Chinese, mathematics, and English. Some stores also provide childcare services. This division of labor is in line with customers' consumption travel expectations, thus enabling children's education stores to be developed in both city- and county-level commercial centers. However, for community-level commercial centers, the high cost, venue, and talent threshold restrictions of such stores make it difficult to adapt to consumer needs.

4.3.5. The Impact of Traffic Resistance

Traffic impedance showed an obvious and stable inhibitory effect on commercial centers at all levels. The accessibility of commercial centers significantly affects consumers' willingness to travel. Moreover, the higher the cost of transportation, the lower the consumers' willingness to shop. Comparatively speaking, consumers have a higher acceptance threshold for shopping travel costs in high-grade commercial centers; therefore, the inhibitory effect of traffic impedance decreases slightly as the commercial center level increases.

4.3.6. Differences in the Influence between Factors

In general, the effects of different factors on different levels of commercial centers vary. Children's retail format has a strong inhibitory and promotional effect on county- and community-level commercial centers but has no significant effect on city-level commercial centers. The children's entertainment format has a relatively large inhibitory effect on the attraction of community-level commercial centers but has a weaker impact on city-level commercial centers. Children's education format has a significant promoting effect on the attractiveness of county-level commercial centers and also appears to have a promoting effect on city-level commercial centers, but has a weak impact on community-level commercial centers. Traffic impedance showed a stable and strong inhibitory effect at all levels of commercial centers.

## 5. Conclusions

### *5.1. Summary*

This study investigated the mechanism of the clustering degree of children's business formats on the attractiveness of commercial centers and examined the similarities and

differences between the effects of the mechanism on different levels of commercial centers. The results of this study are as follows. (1) First, children's business in Wuhan's commercial centers is generally active, and different types of children's business formats have an unbalanced layout at different levels of business centers. (2) Second, there is not only a grade gradient difference in the attraction of commercial centers in Wuhan but also a significant gap in the attractiveness of commercial centers at the same level. (3) Various types of children's business formats show different directions and levels of influence on different levels of commercial centers. For city-level commercial centers, the preference for children's education and entertainment formats, to some extent, plays a role in promoting them; for county-level commercial centers, children's education format is the most important, while too much investment in children's retail format may not meet the expectation of the marketers; and for community-level commercial centers, investment in children's retail format shows the best results. (4) Traffic resistance shows a steady inhibitory effect and is more sensitive in low-grade commercial centers than in high-grade commercial centers.

This study innovatively optimizes the retail gravity model. Utilizing the data of first-tier cities in China to test the validity of the model, it enriches the theoretical research on the retail gravity model and provides a new understanding of the influence mechanism of commercial center attractiveness. Further, we explored the relationship between the clustering degree of children's business formats and the attractiveness of commercial centers and clarified the differences in the impact mechanism at different levels of commercial centers.

### *5.2. Policy Recommendations*

The risks to the current children's businesses' prosperity are obvious. These include the impact of the COVID-19 epidemic, the "double reduction" (reducing the homework burden of students in compulsory education and the burden of off-campus training) policies of the government, increased consumer demand, and regional economic decline. The chain problems these issues cause cannot be underestimated. Therefore, to fully understand the potential of children's consumption, it is critical to control the proportion of business formats and coordinate the relationships between the distribution of children's business formats and various commercial centers. This study puts forward suggestions on the configuration of children's business formats in commercial centers from the following five perspectives:

(1) The revitalization of urban high-level commercial centers in the global post-epidemic era

This study found that investment in children's education formats can effectively improve the attractiveness of urban high-level commercial centers. First, major international cities (London, New York, Hong Kong, etc.) have entered the post-epidemic era, wherein the recovery of urban economies and commercial centers after the epidemic is particularly urgent. Second, families' willingness to invest in children's education continues to increase, and the children's education consumer market is still expanding, which remains a global development trend. Third, experiential business formats (e.g., education, entertainment, etc.) will be hit harder during the epidemic, and these kinds of formats will also rebound faster after the epidemic. Therefore, in the post-epidemic era, integrating children's education formats in high-level commercial centers is an effective means of promoting their vitality.

(2) The strengthening of children's retail formats in commercial centers under the "government-driven" adjustment of market failure

On the one hand, this study found that investment in children's retail formats is extremely effective in community-level commercial centers, while children's entertainment format has a negative impact on their appeal. On the other, the degree of residents' reliance on community business services has gradually increased and their growing preference for retail shopping in community centers and nearby living circles is becoming increasingly obvious. Nowadays, the children's business model of "pay to play" is sweeping the world, and low-level commercial centers, such as community-level commercial centers that meet the daily lives of residents as their main functions, have also followed suit. The children's

retail format in Wuhan's community-level commercial centers accounts for only one-fifth of the total children's businesses at present, lagging far behind the children's entertainment business (55.8%). This makes the configuration of the children's business format misaligned with the needs of residents, thus complicating further investment to meet consumer expectations. Therefore, to benefit users and meet the shopping needs of nearby residents, market capital should be guided to invest in the children's department store format in community-level commercial centers, and the government's public policies should be reviewed and fulfilled. In addition, targeted support should be provided to communities in which the supply and demand of children's retail formats are not well aligned.

(3) Transformation of children's education format in commercial centers in response to China's "double reduction" policy

Although this study confirmed the driving effect of children's education format on the attraction of commercial centers, subject and traditional quality education facilities will inevitably decline under the objective constraints of the Chinese government's implementation of the "double reduction" policy. This will not only limit children's education stores but also affect the stores attached to them. Therefore, the composition of the existing education format should be adjusted by cultivating a new type of children's education format that can continue to play a positive role in the children's education format and make up for the negative reduction effect of the decline in traditional educational facilities on the attraction of commercial centers. In addition, relying on the advantages of relatively low store rents and customer travel costs in county-level commercial centers, another feasible optimization strategy would be to introduce disciplinary and non-disciplinary education and training institutions to provide after-school care services for children.

(4) Flexible format adjustment to improve the mismatch between commercial center level and children's business formats

Research shows that there is an obvious mismatch between the configuration of children's business formats in Wuhan's commercial centers and their impact on customer attraction, which makes it difficult to successfully invest in children's business formats and achieve the desired results. In city-level commercial centers, the increase in children's education, entertainment, and other experiential business formats can be more appealing to consumers, but the current situation is that the dominant business format is children's retail stores. Similarly, investment in the children's education format in county-level commercial centers is the most effective, and it is more beneficial to increase the proportion of children's retail formats in community-level commercial centers. However, the status quo is that the children's retail format accounts for the highest proportion of stores found in district-level commercial centers, while the children's entertainment format accounts for a larger proportion in community-level commercial centers. Therefore, it is necessary to gradually adjust the configuration of children's business formats in commercial centers at all levels in Wuhan in flexible ways, such as business integration and business upgrading.

(5) Targeted optimization of business centers to make up for the shortcomings of children's business formats

Based on the measurement of the attraction of 66 commercial centers in Wuhan, we found that the commercial centers of No. 45 (city level), No. 46 (county level), and No. 47 (community level) had the lowest attractiveness among others of the same grade. From the perspective of children's business configuration, this research attempts to put forward targeted optimization suggestions for these three commercial centers: (i) The proportion of children's retail, entertainment, and education in the No. 45 commercial center (city-level) accounts for 41.1%, 16.3%, and 38.1% of the total children's business, respectively, which is basically in line with the average proportion of children's business in commercial centers at the same level. However, the type of children's education format is too conservative—mainly music education, art education, etc. Therefore, we suggest that the proportion of children's business formats be appropriately adjusted with dependence

on children's education stores reduced, and the aggregation of new children's quality education stores prioritized. (ii) The overall situation of children's business formats in the No. 46 commercial center (county level) is weak, but it is a feasible optimization strategy to moderately increase the education-oriented children's business format. (iii) The children's business format of the No. 47 commercial center (community-level) is primarily children's education. The problem here concerns the mismatch between the children's business formats and the level of commercial centers. Thus, we recommend reducing dependence on children's education and supporting the supply of daily children's general merchandise in cooperation with community children's public service facilities.

## 6. Limitations and Future Research

As with any study, this study has certain limitations. First, owing to its data-driven and model research approach, the generalizability of the results is limited. Second, given the short duration of data collection and the limited scale of the collection sites, the model construction is limited. In addition, the data acquisition method has limitations, resulting in insufficient data accuracy and errors in the extraction of shopping and residential locations. Thus, the generality of this study needs to be further improved.

Future studies could investigate children's business formats in different cities to verify whether the patterns revealed in this study would work in diverse settings. In addition, consumer attributes and behavioral characteristics were not fully covered in this study. It would be interesting to further improve this research by combining subjective consumer surveys and interviews.

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# Analysis of Landscape Pattern Evolution and Driving Forces Based on Land-Use Changes: A Case Study of Yilong Lake Watershed on Yunnan-Guizhou Plateau

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**Abstract:** In order to explore the landscape pattern evolution and driving forces of the Yilong Lake watershed, the combined method of supervised classification with manual visual interpretation based on the landsat5TM/8OLI remote sensing image data sources was used to establish a high-precision spatial distribution information database of the Yilong Lake watershed. Landscape index was used to analyze the distribution and spatial pattern change characteristics of various land-use types. Based on correlation and principal component analysis, we discuss the relationship between the change characteristics of land-use type, distribution and spatial pattern, and the interference of local socio-economic development and natural factors. The results show that: (1) In the past 30 years, the land-use types of the Yilong Lake watershed are mainly forest, garden plot and cultivated land. The forest area decreased significantly by 30.45 $km^2$, of which the fastest reduction stage was from 2000 to 2005, with a total reduction of 20.56 $km^2$. The garden plot conversion is relatively large, with a total of 181.69 $km^2$ transferred out, of which 28.84 $km^2$ has become unused land, respectively. (2) In the past 30 years, the maximum patch index decreased by 9.94% and the patch density index increased by 14.25%, indicating that the landscape fragmentation in the whole basin increased. The Shannon diversity index showed an increasing process; the aggregation index showed a decreasing process. (3) The change in landscape pattern in the watershedwas closely related to economic growth, population growth, social affluence and agricultural development. Natural factors, social factors and economic indicators are significantly positively correlated with patch density, edge density, landscape shape index and Shannon diversity index, and significantly negatively correlated with the largest patch index and the contagion index. On the whole, the wetlands in the basin are shrinking and the landscape diversity is changing. Reducing the excessive impact of human activities on the watershed ecosystem is a key factor for the local protection of wetland resources and the maintenance of wetland ecological functions.

**Keywords:** Yilong Lake watershed; landscape pattern; land use; driving factors

## 1. Introduction

Plateau lake wetlands are an important part of China's "two screens and three belts" ecological security pattern, and play an irreplaceable role in water conservation, biodiversity protection, and carbon fixation [1]. Yilong Lake is a plateau freshwater lake at the southernmost tip of China, an important channel for migratory birds to migrate, a typical wetland resource type in the Yunnan Guizhou Plateau, and one of the nine lakes in Yunnan Province [2]. Compared with other plateau lakes in Yunnan Province, Yilong Lake has a special history and has undergone many large-scale transformations [3,4]. In recent years, due to the dual constraints of the natural environment and human production and life, the wetland ecosystem is fragile and sensitive, and the wetland structure and ecological

function degradation are obvious [5]. The wetland ecosystem is an important condition for maintaining regional social, economic, and environmentally sustainable development [6]. In recent decades, due to the influence of climate and environmental factors and human activities [7–9], the water level of plateau lakes has decreased, the area has decreased [10], the swamp wetland has shrunk and degraded [11], and the area, type, structure, and function of wetlands have changed significantly, especially the change inland use. Land is the most basic natural resource and the material basis of human economic and social activities. Land use/land cover (LULC) change is a direct characterization signal of various human production activities acting on the ecological environment on the earth's surface [12,13]. The diversity of spatial composition and distribution of land use indicates the spatial distribution characteristics of various types of wetland patches [14]. The temporal and spatial evolution of landscape pattern is the most intuitive form of land-use change [15]. The analysis of landscape pattern evolution based on land-use change is an important content of landscape ecology research. It has played a role in promoting the study of plateau lake wetland landscape on a large scale.

It is very important to analyze the driving mechanism of landscape pattern, which can help find out the causes of landscape pattern change [16]. Natural factors dominated by climate change and human activities represented by social and economic development are the main driving factors leading to the continuous reduction in wetland distribution areas [17,18]. In recent years, many scholars have carried out a great deal of research on the wetland evolution process and mechanism by using 3 S technology and landscape ecology theory [19]. The existing research on landscape pattern usually selects landscape-pattern-related indexes such as area, shape, aggregation and diversity to measure and reflect the characteristics and composition of landscape patches. This study examines the role and contribution of natural factor changes and human activity interference in the evolution of the wetland ecosystem, based on qualitative analysis, correlation analysis and regression analysis [20,21]. There are fewer amounts of data used in correlation analysis, which can be better applied to the needs of plateau lake wetland analysis. In view of this, taking the Yilong Lake Basin on the Yunnan Guizhou Plateau as the research object, through the research on the land-use change, landscape pattern evolution and the correlation with natural factors and human factors in the Yilong Lake Basin in the past 30 years, this paper explores the driving factors of landscape pattern evolution under the land-use change in the Yilong Lake Basin. It provides a scientific basis for future sustainable development, ecological environment protection and regional management of the Yilong Lake Basin.

## 2. Materials and Methods

### *2.1. Study Area*

Shiping County is located in the southeast of the Yunnan Province and in the west of Honghe Hani and Yi Autonomous Prefecture. It spans between longitude 102°8′–102°43′ E and latitude 23°19′–24°6′ N. Yilong Lake is the southernmost plateau freshwater lake in China. It is a typical wetland resource type in the Yunnan Guizhou Plateau and one of the nine largest lakes in Yunnan Province. The Yilong Lake watershed mainly includes Yilong Town, Baoxiu town and Bazin town of Shiping County, in an east–west strip. The drainage area is 357.61 $km^2$ (Figure 1).

### *2.2. Data Source and Processing*

The remote sensing image data of the Yilong Lake Basin are landsat5 TM (1990, 1995, 2000, 2005, 2010), landsat8 oli (2015, 2018) Landsat series data. The base map coordinate system is (GCS\china\geodetic\coordinate\system\2000), and the spatial resolution is 30 m. The RGB band synthesis and spatial geographic correction are carried out on the image. Land-use types in the basin are divided according to the land resource classification system [22] and natural language classification [23]. Natural language classification is a process of considering various functions of land in the natural environment and human social development, and dividing it into several functional areas [24]. Among the various

functions of the natural language system, ecological function is the premise and foundation of other functions [25]. At the same time, combined with field investigations, on-site visits and the collection of the latest data, a remote sensing interpretation mark is established after comprehensive analysis. The classification system includes three main categories and seven secondary categories (Table 1, Figure 2).

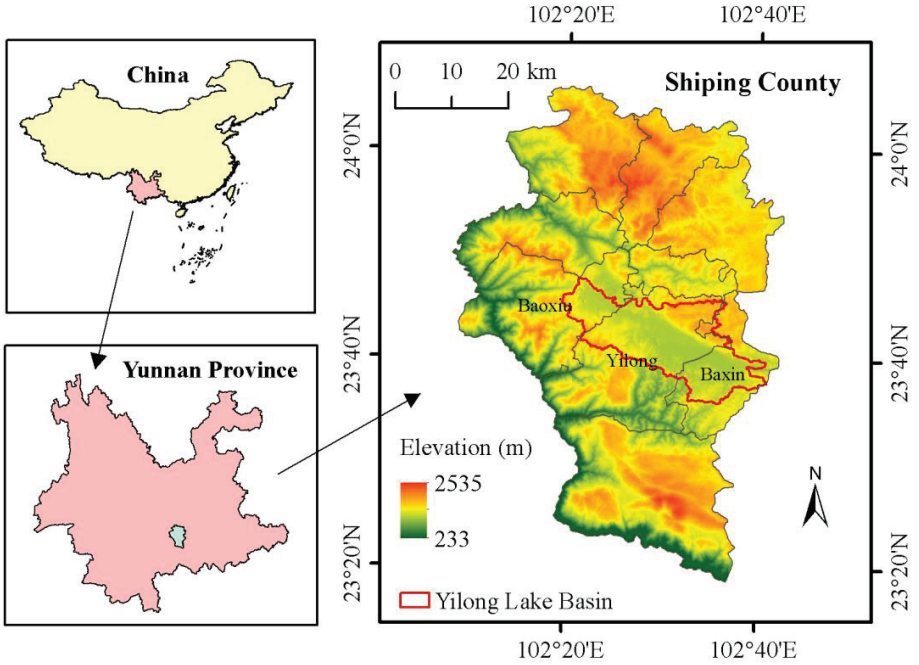


**Figure 1.** The map of Yilong Lake watershed.

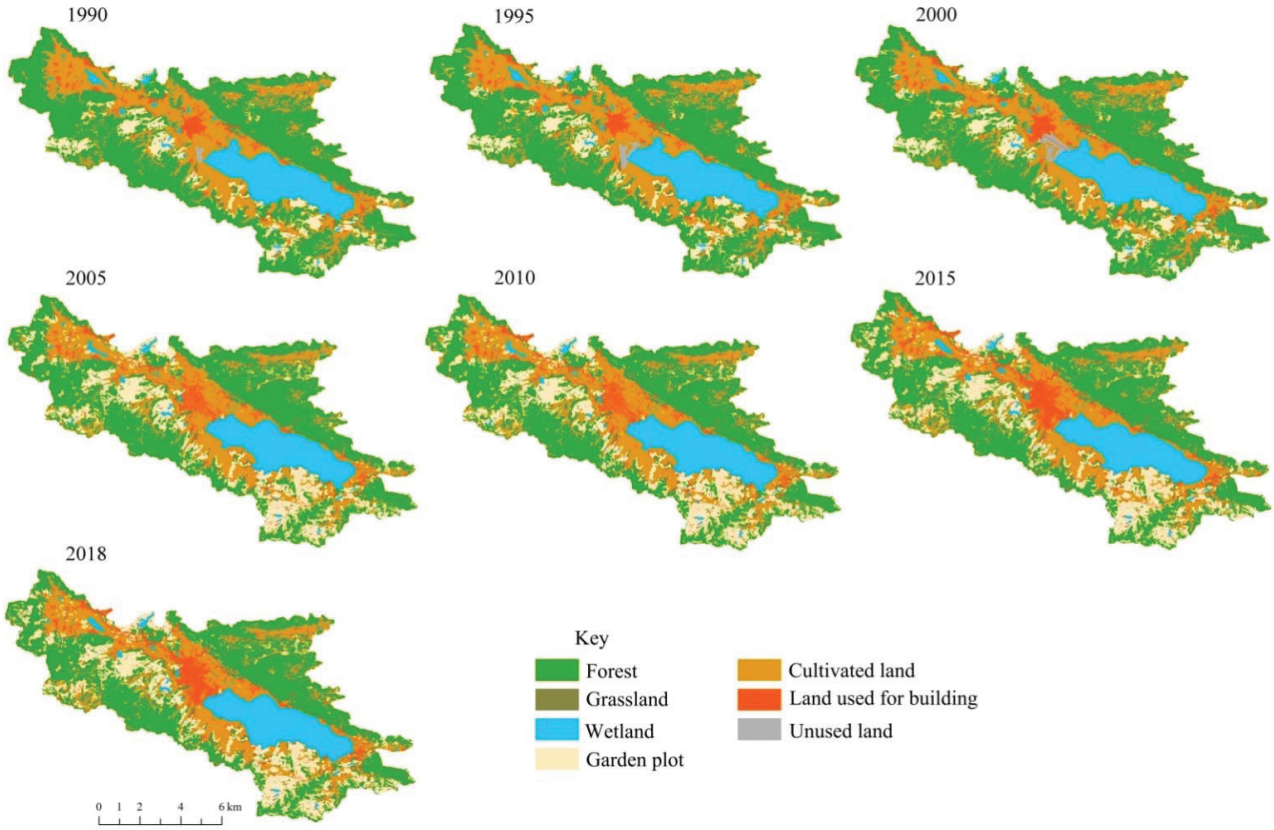


**Figure 2.** Spatial variation of landscape types in time series.

**Table 1.** Classification of land-use system in the Yilong Lake Basin.

| Main Categories | Secondary Category | Corresponding Land-Use Types |
|---|---|---|
| Ecological space | Forest | Bamboo forest land, arbor forest land, shrub land and other forest lands |
| | Grassland | grassland |
| | Wetland | Lakes, river wetlands, swamp wetlands, artificial wetlands |
| Production space | Garden plot | Garden plot |
| | Cultivated land | Paddy field, dry land |
| Living space | Land used for building | Construction land for urban and rural residents, industrial and mining construction land, and transportation land |
| | Unused land | Bare ground |

### *2.3. Method*

#### 2.3.1. Land-Use Change

(1) Dynamic degree of land use; it refers to the quantitative change inland-use types within a certain time range in the study area, reflecting the impact of human activities on land-use types [26]. By quantitatively describing the change speed of land-use types, its development trend can be predicted. The expression of dynamic degree of land-use type is:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%$$

where: $K$ is the dynamic degree of a certain landscape type in a certain period of time; $U_a$ and $U_b$ are the area of a certain landscape type at the initial stage and the final stage of the study, $hm^2$; $T$ is the time, $a$.

(2) Land-use transfer matrix; it contains the static data of land-use types in a certain period of time and the dynamic data of mutual transformation of various land types. The transfer direction and quantity of different types of land use are analyzed through the transfer matrix, and the general form of land-use transfer matrix refers to the relevant literature [27]. This study uses the calculation method to analyze the internal transfer of land-use types in the study area.

$$S_{ij} = \begin{bmatrix} S_{11} & \cdots & \cdots S_{1n} \\ \cdots & \cdots & \cdots\cdots \\ S_{n1} & \cdots & \cdots S_{nn} \end{bmatrix}$$

where $S$ represents the area, $n$ represents the number of land-use types before and after the transfer, $i$ represents the land-use type before the transfer, and $j$ represents the land-use type after the transfer, which is the area from land class $i$ to land class $j$. Each row of elements in the matrix represents the local class source information of each local class before the transfer of land class $j$.

#### 2.3.2. Landscape Index Analysis

Based on the correlation between landscape indexes [28,29], the landscape indexes of landscape pattern evolution in the Yilong Lake watershed were screened and analyzed from three aspects: landscape fragmentation, landscape shape and landscape diversity [30]. From the category level, select the largest patch index (LPI), patch density (PD), edge density (ED) and landscape shape index (LSI); from the landscape level, select the largest patch index (LPI), patch density (PD), edge density (ED), landscape shape index (LSI), the contagion index (CONTAG) and Shannon diversity index (SHDI). FRAGSTATS 4.2 (Home Page, China) software was used to analyze the changes in landscape pattern from three aspects: landscape fragmentation (LPI and PD), landscape patch shape (ED and LSI) and landscape diversity (CONTAG and SHDI).

2.3.3. Collection and Treatment of Human and Natural Factors

Regional socio-economic development indicators can comprehensively reflect the type and intensity of the interference of human activities on natural resources [31]. The watershed is a typical agricultural watershed. Select the total population (TP), urban population (UP), rural population (RP), agriculture, forestry, animal husbandry and fishery industry (AF), the forestry output value (F), the total sown area of crops (TC), the large livestock breeding (LLB) and the pig breeding (PB) as social driving indicators, gross domestic product (GDP), the primary industry (PI), the second industry (SI), and the third industry (TI) as economic driving indicators. The annual average precipitation (P) (mm) and the annual mean temperature (T) (°C) are used as natural driving indicators. Other data are from the statistical yearbook of Shiping County (1990–2018).

SPSS 22 was used to analyze the correlation between the regional landscape index and the output value of social and economic development, as well as natural factors. Principal component analysis was used to analyze the impact and contribution of human activity interference and natural factor changes on the change in regional landscape diversity.

## 3. Results

### *3.1. Dynamic Change Characteristics of Land Use*

According to Figure 2 and Table 2, the land-use types of the Yilong Lake Basin in the last 30 years are mainly forests, gardens and cultivated land. In the last30 years, the forest area has decreased significantly by 30.45 $km^2$, of which the fastest reduction stage is from 2000 to 2005, with a total reduction of 20.56 $km^2$ and a dynamic degree of ("−" U+2.31%). At the same time, the garden area has increased significantly, with an increase of 32.53 $km^2$ in the past 30 years. Among them, the fastest period of increase was from 2000 to 2005, with a total increase of 27.21 $km^2$ and a dynamic degree of 16.23%. The wetland area fluctuates greatly, first increasing, then decreasing, and then increasing. From 1990 to 2015, the lake area decreased by 3.83 $km^2$, and in 2018, the lake area was 40.42 $km^2$, and from 2015 to 2018, the lake area increased by 2.46 $km^2$. In the past 30 years, the construction land and transportation land for urban and rural residents have increased rapidly. The fastest period of area increase is from 2000 to 2015. The construction land for urban and rural residents has increased by 17.19 $km^2$, with a dynamic degree of 7.38%.

**Table 2.** The changes in land-use area in the Yilong Lake watershed from 1990 to 2018.

| Year | Index | Forest | Grassland | Wetland | Garden Plot | Cultivated Land | Land Used for Building | Unused Land |
|---|---|---|---|---|---|---|---|---|
| 1990 | Area/$km^2$ | 181.66 | 41.79 | 0.15 | 30.02 | 89.34 | 13.84 | 0.83 |
| 1995 | | 178.84 | 41.62 | 0.25 | 33.28 | 87.41 | 14.27 | 1.95 |
| 2000 | | 178.32 | 42.06 | 0.25 | 33.53 | 85.01 | 15.53 | 2.9 |
| 2005 | | 157.76 | 40.04 | 0.58 | 60.75 | 76.49 | 21.56 | 0.41 |
| 2010 | | 154.06 | 39.91 | 0.7 | 62.08 | 76.38 | 24.04 | 0.43 |
| 2015 | | 151.28 | 37.96 | 0.91 | 62.56 | 71.22 | 32.72 | 0.94 |
| 2018 | | 151.21 | 40.42 | 0.93 | 62.54 | 69.17 | 32.4 | 0.94 |
| 1990–1995 | Area/$km^2$ | −2.82 | −0.17 | 0.1 | 3.26 | −1.93 | 0.43 | 1.12 |
| | Dynamic degree/% | −0.31 | −0.08 | 13.33 | 2.17 | −0.43 | 0.62 | 26.99 |
| 1995–2000 | Area/$km^2$ | −0.52 | 0.44 | 0 | 0.25 | −2.4 | 1.26 | 0.95 |
| | Dynamic degree/% | −0.06 | 0.21 | 0.00 | 0.15 | −0.55 | 1.77 | 9.74 |
| 2000–2005 | Area/$km^2$ | −20.56 | −2.02 | 0.33 | 27.22 | −8.52 | 6.03 | −2.49 |
| | Dynamic degree/% | −2.31 | −0.96 | 26.40 | 16.24 | −2.00 | 7.77 | −17.17 |
| 2005–2010 | Area/$km^2$ | −3.7 | −0.13 | 0.12 | 1.33 | −0.11 | 2.48 | 0.02 |
| | Dynamic degree/% | −0.47 | −0.06 | 4.14 | 0.44 | −0.03 | 2.30 | 0.98 |
| 2010–2015 | Area/$km^2$ | −2.78 | −1.95 | 0.21 | 0.48 | −5.16 | 8.68 | 0.51 |
| | Dynamic degree/% | −0.36 | −0.98 | 6.00 | 0.15 | −1.35 | 7.22 | 23.72 |
| 2015–2018 | Area/$km^2$ | −0.07 | 2.46 | 0.02 | −0.02 | −2.05 | −0.32 | 0 |
| | Dynamic degree/% | −0.02 | 2.16 | 0.73 | −0.01 | −0.96 | −0.33 | 0.00 |
| 1990–2018 | Area/$km^2$ | −30.45 | −1.37 | 0.78 | 32.52 | −20.17 | 18.56 | 0.11 |
| | Dynamic degree/% | −0.60 | −0.12 | 18.57 | 3.87 | −0.81 | 4.79 | 0.47 |

It can be seen from Table 3 that from 1990 to 2018, the garden land was the most frequently converted in the Yilong Lake Basin, with a total of 181.69 $km^2$, of which 28.84 $km^2$ were turned to unused land, respectively. The second is grassland, with a total area of 89.34 $km^2$, mainly turning to wetlands, with a total area of 13.42 $km^2$. A total of 41.77 $km^2$ of cultivated land has been transferred out, and the main grassland is 2.19 $km^2$.

**Table 3.** The conversion of land-use types in the Yilong Lake watershed from 1990 to 2018 (Unit: $km^2$).

| 1990–2018 | Forest | Grassland | Wetland | Garden Plot | Cultivated Land | Land Used for Building | Unused Land | Total |
|---|---|---|---|---|---|---|---|---|
| Forest | 0.11 | 0.00 | | 0.01 | | | 0.02 | 0.14 |
| Grassland | 0.01 | 57.00 | 13.42 | 6.98 | 1.64 | 0.18 | 10.11 | 89.34 |
| Wetland | 0.01 | 1.05 | 11.55 | 0.75 | 0.01 | 0.11 | 0.37 | 13.86 |
| Garden plot | 0.77 | 6.39 | 4.81 | 140.25 | 0.11 | 0.53 | 28.84 | 181.69 |
| Cultivated land | 0.01 | 2.19 | 0.63 | 0.12 | 38.57 | 0.09 | 0.16 | 41.77 |
| Land used for building | | 0.02 | 0.78 | | | | 0.02 | 0.83 |
| Unused land | 0.03 | 2.45 | 1.27 | 3.09 | 0.11 | 0.03 | 23.00 | 29.97 |
| Total | 0.93 | 69.11 | 32.47 | 151.21 | 40.43 | 0.94 | 62.52 | 357.61 |

### *3.2. Change in Landscape Pattern Index*

As shown in Figure 3, from 1990 to 2018, the maximum patch index at the landscape level decreased by 9.94%, and the patch density index increased by 14.25%, indicating that the landscape fragmentation in the whole basin increased. At the level of land-use types, the patch density index of all land-use types has shown an upward trend in the past 30 years, with the most drastic change in construction land, increasing from 0.62 to 11.29. The largest patch index in the basin increased with construction land and garden land, with construction land increasing from 0.91 to 3.32 and garden land increasing from 0.98 to 3.60. Forest and cultivated land decreased the most, with forest decreasing from 25.85 to 15.91 and cultivated land decreasing from 15.26 to 3.83. In the past 30 years, the patch density index of construction land has increased more than the maximum patch index, indicating that construction land is mainly expanding away from the urban area.

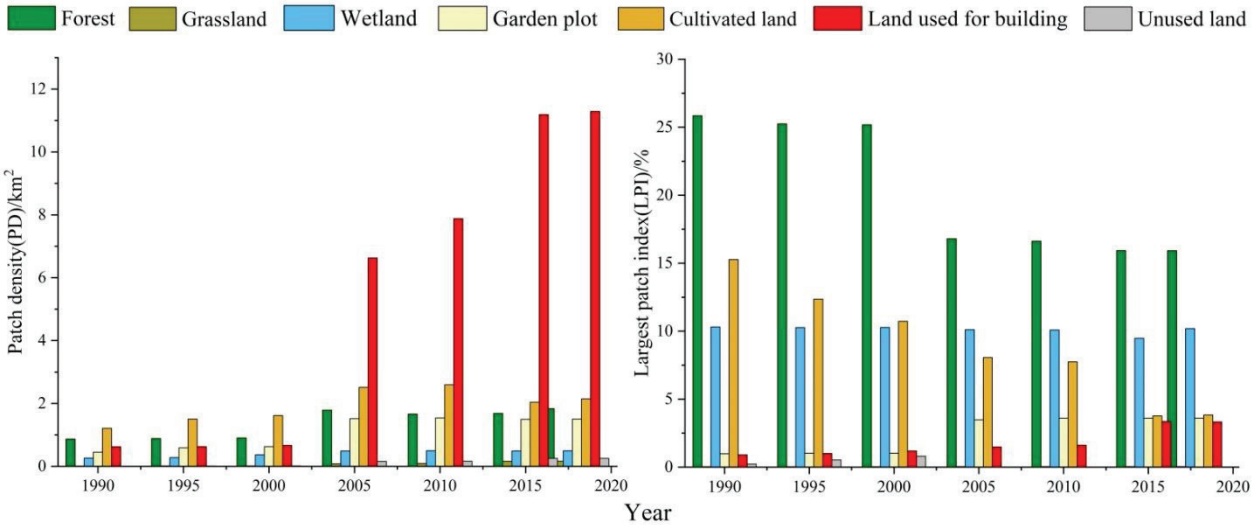


**Figure 3.** Changes in landscape fragmentation in the Yilong Lake watershed.

According to Figure 4, in the past 30 years, the landscape shape index and edge density index have shown a growing trend at the landscape level, indicating that the shape of landscape patches in the basin is becoming increasingly complex. The landscape shape index of all land-use types showed different degrees of growth, including construction land

increased by 27.35, garden land and forest increased by 21.48 and 13.11, respectively. Except for the decrease in the wetland edge density index, the edge density index of other land types increased, and the edge density index of construction land increased the most, by 34.28. It can be seen that the changes in the landscape patch shape in the basin are mainly affected by the changes in urban and rural residents' construction land, transportation land and cultivated land.

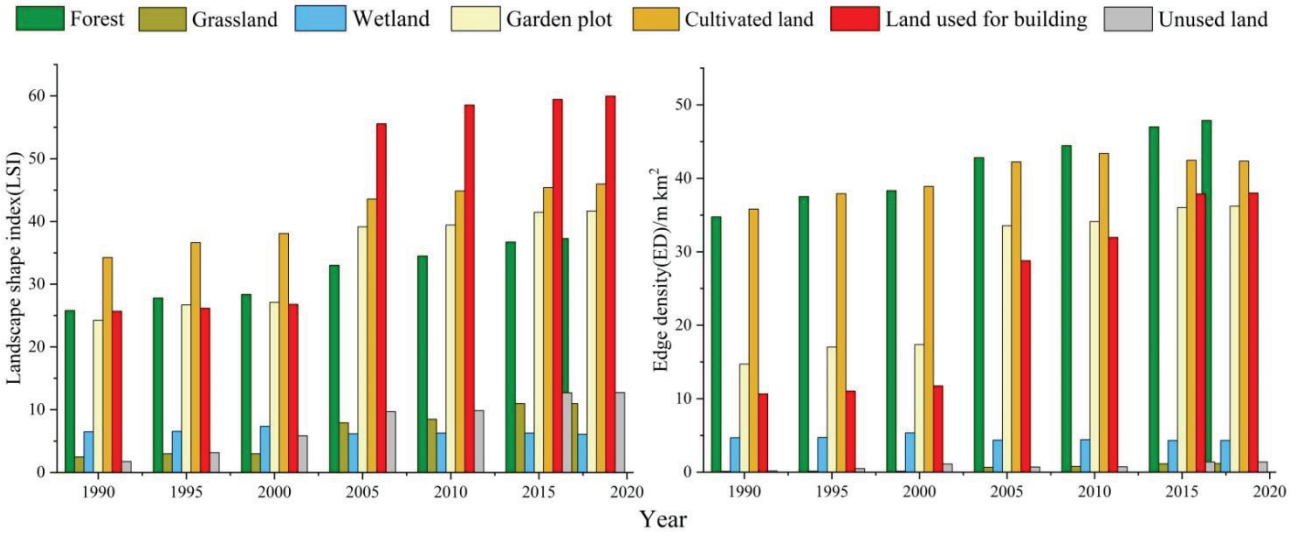


**Figure 4.** Change in landscape patch shape in the Yilong Lake watershed.

It can be seen from Table 4 that in the past 30 years, the landscape diversity in the basin has increased, the aggregation index has decreased by 9.56, and the Shannon evenness index has increased by 0.19, but the change intensity is lower than the landscape fragmentation and the change in landscape patch shape. In the past 30 years, the variation range of landscape diversity index in the basin is small. The change center of the landscape diversity index is around the construction land of urban and rural residents, and the surface of the Yilong Lake. Shannon diversity index showed an increasing process, indicating that the richness of the landscape increased during this period. The aggregation index showed a decreasing process, indicating that during this period, the connectivity between landscape types increased and the overall heterogeneity decreased. The water landscape shows the most significance when the dominance and connectivity of the landscape types increase.

**Table 4.** Landscape pattern index of the Yilong Lake watershed 1990–2018.

| Year | PD (/km$^2$) | LPI (%) | LSI | ED | CONTAG (%) | SHDI |
|---|---|---|---|---|---|---|
| 1990 | 3.4227 | 25.85 | 26.1209 | 50.4526 | 58.2824 | 1.2925 |
| 1995 | 3.8953 | 25.2454 | 27.9968 | 54.4215 | 56.9152 | 1.3242 |
| 2000 | 4.1945 | 25.183 | 28.9619 | 56.4634 | 56.1037 | 1.3426 |
| 2005 | 13.1652 | 16.79 | 38.4485 | 76.5342 | 51.46 | 1.4248 |
| 2010 | 14.4124 | 16.6096 | 40.0508 | 79.9242 | 50.5428 | 1.4431 |
| 2015 | 17.2996 | 15.9195 | 42.5397 | 85.0927 | 48.867 | 1.478 |
| 2018 | 17.6757 | 15.9127 | 42.755 | 85.6456 | 48.7175 | 1.4818 |

### *3.3. Relationship between Watershed Landscape Change and Natural, Social and Economic Development*

According to Table 5, Principal component analysis showed that the influence weight of social key factors on wetland area and landscape diversity was greater than that of the annual average temperature and precipitation. The results showed that the explanatory degrees of the first and second principal components to the total variables were 78.03% and 17.07%, respectively. Among them, human activity factors, namely, the output value of

agriculture, forestry, animal husbandry and fishery, the value of the tertiary industry, the value of the secondary industry and the value of the primary industry, have a large load on the first principal component. These indicators mainly reflect the status of social and economic development. Therefore, it can be considered that the first principal component is the representative of social economy. The annual average temperature and precipitation among the natural driving factors have a large load on the second principal component; thus, the second principal component is considered to be representative of climate factors.

**Table 5.** Correlation between the landscape index and key social and natural factors in the study area.

| Drivers | Landscape Index | | | | | |
|---|---|---|---|---|---|---|
| | **PD** | **LPI** | **LSI** | **ED** | **CONTAG** | **SHDI** |
| TP | 0.963 ** | −0.923 ** | 0.970 ** | 0.970 ** | −0.980 ** | 0.984 ** |
| RP | −0.238 | 0.091 | −0.186 | −0.186 | 0.211 | −0.224 |
| UP | 0.784 * | −0.670 | 0.757 * | 0.758 * | −0.779 * | 0.789 * |
| T | 0.935 ** | −0.908 ** | 0.937 ** | 0.937 ** | −0.935 ** | 0.934 ** |
| P | −0.143 | 0.235 | −0.184 | −0.185 | 0.170 | −0.162 |
| PI | 0.883 ** | −0.789 * | 0.866 * | 0.867 * | −0.884 ** | 0.891 ** |
| SI | 0.780 * | −0.669 | 0.752 | 0.752 | −0.771 * | 0.779 * |
| TI | 0.795 * | −0.683 | 0.767 * | 0.768 * | −0.786 * | 0.795 * |
| AF | 0.907 ** | −0.819 * | 0.888 ** | 0.888 ** | −0.900 ** | 0.905 ** |
| F | 0.922 ** | −0.843 * | 0.901 ** | 0.901 ** | −0.911 ** | 0.914 ** |
| TC | 0.961 ** | −0.917 ** | 0.966 ** | 0.966 ** | −0.976 ** | 0.980 ** |
| LLB | 0.820 * | −0.723 | 0.802 * | 0.803 * | −0.819 * | 0.826 * |
| PB | 0.754 | −0.696 | 0.750 | 0.751 | −0.757 * | 0.758 * |

Note: * $p < 0.05$, ** $p < 0.01$.

It can be seen from Table 4 that, on the whole, the selected social key factors have a strong correlation with the six landscape indexes, indicating that the change in the landscape pattern in the Yilong Lake watershed is closely related to the human factors and social and economic development in the watershed. Based on the analysis of three landscape directions, the fragmentation degree: patch density and largest patch index. Patch density was positively correlated with population, urban population, annual average temperature, value of primary, secondary and tertiary industries, agriculture, forestry, animal husbandry and fishery, forestry output value, total sown area of crops and large livestock breeding. It has a negative correlation with the rural population and precipitation, and the correlation is not significant. Largest patch index is negatively correlated with population, annual average temperature, the value of primary and tertiary industries, agriculture, forestry, animal husbandry and fishery, forestry output value, total sown area of crops, large livestock breeding and pig breeding.

Shape: Edge density and landscape shape index. Edge density was positively correlated with population, urban population, annual average temperature, value of primary, secondary and tertiary industries, agriculture, forestry, animal husbandry and fishery, forestry output value, total sown area of crops, large livestock breeding and pig breeding. It has a negative correlation with the rural population and precipitation, and the correlation is not significant. The landscape shape index is significantly positively correlated with population, urban population, annual average temperature, value of primary, secondary and tertiary industries, agriculture, forestry, animal husbandry and fishery, forestry output value, total sown area of crops, large livestock breeding and pig breeding. It has a negative correlation with the rural population and precipitation, and the correlation is not significant.

Diversity: The contagion index and Shannon diversity index. The contagion index is negatively correlated with population, urban population, annual average temperature, value of primary, secondary and tertiary industries, agriculture, forestry, animal husbandry and fishery, forestry output value, total sown area of crops and large livestock breeding. It

is positively correlated with the rural population, and the correlation is not significant. The Shannon diversity index was positively correlated with population, the value of primary, secondary and tertiary industries, agriculture, forestry, animal husbandry and fishery, forestry output value, total sown area of crops and large livestock breeding. It is negatively correlated with the rural population, and the correlation is not significant.

## 4. Discussion

### *4.1. Dynamic Change Analysis of Land Use*

In this study, a high-precision spatial distribution information database of the Yilong Lake Basin was established based on seven phases of landsat5TM/8OLI remote sensing image data sources from 1990 to 2018 by combining supervised classification and manual visual interpretation, and 15 land-use types were extracted. Our research shows that the land use in the Yilong Lake Basin has changed dramatically in the past 30 years, which is mainly manifested in the reduction in forest and cultivated land area, the substantial increase in construction land, and the fragmentation of the landscape pattern, the complexity of the shape, and the increase in landscape diversity. The increase in the area of construction land has led to a significant reduction in the area of cultivated land. From 1990 to 2018, the total area of cultivated land has decreased by 20.17 $km^2$, a decrease of about 22.58%. Among them, the fastest reduction period is from 2000 to 2015, a total decrease of 13.79 $km^2$. Generally, the interference of human activities on wetlands mainly acts on small spatial and temporal scales, and has the characteristics of diverse methods, high intensity, fast speed, relatively short duration, etc. [32]. The landscape shape index and edge density index are both showing a growing trend, indicating that the shape of landscape patches in the watershed is becoming increasingly complex. In the past 30 years, there has been a frequent process of mutual transformation among various land-use types in the Yilong Lake Basin, with the continuous reduction in cultivated land and a large number converted into garden land and construction land. The cultivated land in the Yilong Lake Basin continues to decrease, which is the fastest among all landscape types. The change trend of forest and construction land in these periods shows a stable growth, of which the construction land is the most stable relative to the growth. The frequent transformation and changes between these lands are related to the specific policy environment at that time, such as the transformation policy of medium- and low-yield forests and the change in regional real estate market policy. While human influence acts on the landscape pattern, the evolution of the landscape pattern will also affect human production and social activities in the process of evolution [33]. From 1995 to 2015, the lake area decreased by 14.64 $km^2$, mainly due to the impact of human activities, social and economic development has a stronger impact on the land-use pattern, and the water level of the Yilong Lake continues to decline [4,34]. At this time, human beings have a negative effect on the impact of natural resource allocation and landscape pattern changes, resulting in the landscape pattern in turn restricting and affecting the development of human society. From 2015 to 2018, the lake area increased by 14.57 $km^2$, mainly due to the treatment projects such as the Yilong Lake retreating and returning to the lake, ecological restoration, and water replenishment of the Yilong Lake since 2013. To some extent, it shows that policy factors have an important impact on land-use change [35].

### *4.2. Driving Forces of Landscape Evolution and Suggestions*

Research on the driving mechanism of land use/cover change worldwide shows that 60% of land use/cover change can be attributed to human economic and social development activities, and 40% of land use/cover change is related to factors such as climate change [36]. However, our research shows that the land use in the Yilong Lake Basin has changed dramatically in the past 30 years, which is mainly reflected in the impact of human economic and social development activities. Due to the development of economic construction and the improvement of living standards, the landscape area and the number of patches have changed dramatically, and the landscape pattern index has also fluctuated significantly.

On the other hand, the conversion of cultivated land into construction land due to urban development and construction, road construction and other activities has also exacerbated the fragmentation of the landscape pattern [37]. Human activities are the main driving factor leading to the change inland-type distribution area and spatial pattern in the Yilong Lake Basin, which is similar to the research results in other regions [38,39]. The expansion of construction land area is usually at the cost of the reduction in cultivated land and forest area. The greater the number of patches, the greater the patch density, which means the higher the landscape fragmentation [40]. The patch density index of all land-use types showed an upward trend in the past 30 years, and the patch density was significantly positively correlated with the population, the non-rural population, and the value of primary, secondary, and tertiary industries. The change in transportation land is the most dramatic. From 1990 to 2018, construction land increased rapidly, and the fastest period of area increase was from2000 to 2015. With the growth of population and the expansion of urbanization, the dramatic changes in landscape types have changed the structure and function of the ecosystem, showing that the construction land is mainly far away from the urban area for expansion and development. Therefore, it is suggested to adopt effective ecological restoration for landscape types with broken landscape and degraded functions to maintain landscape integrity and connectivity, restore ecosystem service functions and values of the basin, and maintain landscape ecological security of the basin.

Natural factors are also the driving factors affecting land-use change. Changes in temperature and precipitation have an impact on land-use types, distribution areas and landscape diversity in the whole basin, but the degree of interpretation is relatively small. Shiping is located in a low-latitude plateau, with a typical monsoon climate and remarkable three-dimensional climate. Under the future climate conditions, the ecosystem of Yilong Lake Basin is at risk of degradation. After ecological water replenishment, the mutual feeding relationship between landscape pattern and driving factors will also be adjusted. Natural factors usually need to affect the land type and landscape by changing the wetland hydrological process, affecting soil nutrients, changing the growth and development of wetland plants, as well as the composition of wetland plant communities, interspecific relationships, etc., and the process has obvious hysteresis [41]. Generally, temperature and precipitation changes can affect the wetland area, type, and spatial distribution pattern of the land through direct and indirect effects on the growth of plants, interspecific relationships, soil nutrient conditions, wetland hydrology, etc., in the basin. The influence of natural factors is mainly on large time scales and spatial scales, with characteristics such as large influence range, long duration, time lag, etc. [42]. Relevant studies have shown that climate change is likely to be the main reason for affecting the water cycle and indirectly affecting water resources [43]. This study also found that the annual precipitation had no significant correlation with the area of all landscape types and the landscape pattern index, and the average temperature was only significant with some indicators, indicating that the correlation between climatic environmental factors and watershed landscape change was not obvious. In addition, the strong interference of human activities makes the watershed landscape evolution mechanism very complex [44]. Therefore, on a small time and spatial scale, compared with the interference of human activities, the contribution of changes in natural factors to the watershed ecosystem is relatively small. It is necessary to analyze and study the process and driving mechanism of wetland landscape change under the combination of multiple factors from a spatial perspective.

## 5. Conclusions

(1) The land use of the Yilong Lake Basin is mainly forest, garden and cultivated land. From 1990 to 2018, the area of construction land continued to increase, and the construction land in the basin was mainly transferred from cultivated land and forests. The disturbance of human activities and the change in natural factors jointly affect the land-use type, spatial distribution and landscape diversity of the Yilong Lake Basin, but their contribution to the ecosystem of the basin is different. The explanation degree

of human disturbance to wetland area and landscape diversity index is 80.97%, and the explanation degree of natural factor change is 13.90%. Economic growth, population growth, social affluence and agricultural development are the main socio-economic driving factors of land-use change in the Yilong Lake Basin, and the driving effects of driving factors on land-use change in the basin are increasing year by year. According to the correlation analysis, the driving effects of socio-economic driving factors on land-use change are different. Among them, economic growth, especially industrial structure adjustment, agricultural development and residents' living standards, are the main driving forces affecting cultivated land and forests; population growth and residents' living standards are the main driving forces of the waters. The main factors affecting construction land are population growth, agricultural development, and economic growth.

(2) With the social and economic development, the land-use structure of the basin has been continuously optimized, and the degree of land-use intensification has gradually increased. The shape of landscape patches in the basin is complicated, and the landscape fragmentation and diversity are increased. Urban land and rural residential areas show continuous growth, whereas cultivated land shows a trend of fragmentation. The leap-forward growth of urban land is the main cause of the complexity of the shape of watershed landscape patches. With the ecological restoration of the Yilong Lake Basin, the implementation of the ecological protection and governance of the Yilong Lake surface mountain, the return of the pond to the lake and the ecological restoration, the replenishment and water supply of Yilong Lake and other governance projects, the study on the change in the landscape pattern index shows that the number and density of patches are decreasing as a whole, which means that the landscape fragmentation is smaller, making the landscape types richer, indicating that the important landscape types in the Yilong Lake Basin are protected, and the ecological environment is gradually improving. Therefore, reducing the excessive impact of human activities on the watershed ecosystem is the key to realize the ecological protection of the Yilong Lake Basin.

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# Changes in Urban Growth Patterns in Busan Metropolitan City, Korea: Population and Urbanized Areas

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**Abstract:** Cities have exhibited spatial patterns of expansion or compacting in the process of economic and population growth. South Korea is a well-known example of a country that has experienced rapid economic growth and urbanization. This study's target area, Busan Metropolitan City (BMC), experienced urban growth but, over the past 20 years, underwent economic and population stagnation. How will urban growth patterns change if economic and population growth stagnates? This study aimed to identify changes in urban growth patterns using population and urbanized areas in BMC, South Korea, from 1980 to 2020. It uses Exploratory Spatial Data Analysis, Bachi's Index and the Standard Deviational Ellipse, and Social Network Analysis to identify population concentration, changes in centrality, inland expansion of urbanized land, and centrality of migration. The results showed that (1) BMC's urban growth pattern extended outward, despite population and economic stagnation since 2000; (2) population and economic stagnation over the next 20 years expanded population polarization in the city's urban center and outskirts; (3) the built-up area expanded in all directions for 40 years—the centrality of the urbanized area was seen in and around the urban center in 1980 but moved northeast in 2020; and (4) since 2000, when population stagnation first emerged, the centrality of the population in migration has been more evident in the outskirts. These results suggest that if there is no sustainable urban planning and development strategy when growth is stagnant, expansionary urban growth will continue, and cities will reach the growth limit.

**Keywords:** urbanization; Bachi's Index; local indicator of spatial association; social network analysis; Busan Metropolitan City

## 1. Introduction

The level of global urbanization exceeded 55% in 2018 and is forecasted to reach 68% by 2050 [1]. While definitions of urbanization vary among scholars, a commonality among them is that they include the expansion of industries and jobs with economic growth and an increase in population density [2,3]. Urbanization, which is closely related to economic growth, refers to the process in which land development expands outward as the population of non-urban areas moves to urban areas and population density increases due to the expansion of jobs and industries in urban areas [4,5]. Western developed countries have experienced urbanization over a long period of time, but in many developing countries, urbanization occurs in a short period due to the effect of economic growth [6].

Recent discussions on urbanized areas and populations have noted the phenomenon of imbalance. They reveal the appearance of urbanization patterns that differ from those of the past growth period because of aging, population decline, and so on, particularly focusing on patterns in which population loss appears in tandem with an increase in built-up areas [7,8]. Furthermore, they discuss that even in growing areas, the patterns formerly represented by urban sprawl or suburbanization are changing in that the expansion of urbanized land occurs more rapidly than population growth [9–11].

The research questions of this study are as follows: What does the urban growth pattern of a city experiencing two stagnation periods after rapid urbanization look like? How did the urbanized area and population, representative indicators of the urban growth pattern, and their centrality change?

This study targets Busan Metropolitan City (BMC), the second-largest city in South Korea, as the most representative example of the situation raised in the research questions above. In South Korea, the expansion of urbanized areas from 1970 to 1990 was led by rapid economic growth, population movement to urban areas, and population growth [12]. However, rapid population aging since 2010 and the population's concentration in the capital region, including Seoul, has led to a population decline in metropolitan cities in non-capital regions [13]. In particular, this has caused issues such as the shrinkage and hollowing out of the inner city (the central business district [CBD] and the surrounding old town) in metropolitan cities in non-capital regions, resulting in changes in urban structure [14]. Such changes are aggravated when population and economic stagnation manifest in combination [14,15]. Among the various cities in South Korea that have undergone rapid urbanization, BMC is a representative example of two continuous stagnations. It experienced its most rapid growth through industrialization after the Korean War, but since 1995, the economic growth rate has decreased, and the population has continued to decrease as well.

This study aims to identify changes in urban growth patterns using the indicators of population and urbanized area in BMC. Population and urbanized area (or built-up area) are representative indicators of urbanization levels and spatial patterns. In this study, the spatial pattern of the population was examined to distinguish between residents and migrants, and land cover developed into urban areas was used to represent the urbanized area. Regarding the spatial scope, a 40-year period from 1980 to 2020 was applied to include both the period of rapid economic and population growth and the period of decline after growth peaked in 1995. After examining the Local Moran's I of the population on a 10-year basis, the changes in the urbanized area and its resulting centrality were determined through Bachi's Index and the Standard Deviational Ellipse (SDE). The migration centrality of the population, a key variable reflecting urban growth pattern change, was then identified through Social Network Analysis. Finally, we examined this change.

This study does not address urban expansion patterns as suburbanization; rather, it focuses on how the inner area of a large city that is experiencing both growth and decline shows changes. It clarifies (a) the changes in population concentration within the city during the period of decline after a period of growth, (b) the changes in urbanized area expansion and centrality, and (c) the changes in the migration of people within the city. This study is meaningful in terms of how cities in developing counties where rapid urbanization takes place implement planning and development strategies. In particular, it shows empirical facts related to how cities reach the limit of growth if they follow existing development methods without sustainable planning and development strategies at a time when population and economic growth are stagnant.

## 2. Previous Studies

The approach to urban growth patterns depends on what the result of urban growth is, and the theoretical approach depends on how far out the spatial range is set. Discussions on identifying urban growth as a characteristic of urban sprawl focus on the spatial patterns as well as the density and distribution of the population or activities in which the urbanized area has expanded [16–18].

Existing studies approaching urban growth patterns as urban sprawl have long researched Western cities, discussing those cities' leapfrog development characterized by low density, suburban development, motor-vehicle-oriented transportation, and fragmented land development [16,19]. Since the main purpose of these discussions is to identify the form of expansion leading to urban growth, this study included not just one urban bound-

ary but also the surrounding boundary as its spatial scope and quantified changes in that scope. The new spatial patterns of urban growth, which have recently become a topic of discussion, are divided into edge growth, outlying growth, and infilling growth [20]. The new spatial patterns appear as a result of the interaction between the pre-grown and the newly grown urban areas [21]. These two areas indicate that the roles of urban planning and land use regulation are considered in the process of urban growth, resulting in different urban growth patterns for each city [22]. These discussions include the surrounding boundaries around the existing city boundaries.

Numerous studies have been conducted on the urbanization patterns arising from economic and population growth, such as population density, the spatial patterns of urbanized land, and urban sprawl. In particular, various methods have been proposed to quantify urbanization patterns. Such studies are diverse and include those (a) using population, land consumption, and multidimensional indicators [7,23,24], (b) based on remote sensing data [16,25–27], and (c) identifying changes in the density and distribution of explanations using exponential, quadric exponential, and power functions [28–33].

Urbanization has two prominent features: urban population growth and urban area expansion [34]. The two interact closely in the process of urbanization [35]. Urban population growth increases the demand for urban land, resulting in the inevitable expansion of urban areas. Studies on urbanization, including those on urban sprawl, have been conducted from various perspectives. Such studies include discussions on changes in urban population growth as a major indicator of urbanization [36–38], the spatial patterns of urban areas [39–42], and urban density [19,23]. Much of the discussion on the spatial patterns of urbanization primarily focuses on the sprawl and suburbanization phenomena that emerged during the period of rapidly increasing urban population and economic growth.

Existing discussions indicate that similar forms of urbanization expansion emerged in various developed areas, such as the United States and Europe, following the Industrial Revolution and World War II, and lasted until the 1990s [19,43,44]; they also indicate that similar spatial patterns are seen in developing countries [11,45]. This process is caused not only by population growth, income growth, and low commuting costs, which are powerful initiators of socioeconomic transformation [46,47], but also by inappropriate public finance policies issued by a government relying heavily on the land market [48], ill-suited urban growth boundaries [49], local government decisions [50], and excessive investment in public transportation [51].

Recent studies argue that there is an imbalance in the close relationship between population growth and the expansion of urban areas, which was deliberated as orderly market forces in terms of urban economies, thus leading to various issues [52]. Urbanized areas exceeding the urban population cause severe diseconomies, leading to the ghost city phenomenon [11]; additionally, they cause environmental problems and human and land conflicts [35,53]. Furthermore, they suggest that urbanization patterns are emerging in forms different from those of the past period of growth and are centered on cities in developed countries. Based on an analysis of urbanization patterns in European cities after the 1990s and using the indicators of population and density of land use, Wolff et al. [7] found an occurrence of sprawl-without-growth. Liu and Meng [54] also identified functional urban areas in European cities after 1990 through the indicators of population and discontinuity of the urban area and, as a result, suggested that factors of population loss and sprawl were emerging simultaneously. Urbanization patterns also appear in a form contrary to conventional sprawl development [55–57]. These studies demonstrate a return flow of small- and high-income households into the city borders and indicate regrowth or redensification of existing urban areas rather than suburban areas.

Many studies have attempted to analyze the urban growth patterns of various cities. Recent comparative studies of urban growth patterns in several cities have targeted cities in China and the United States. Jia et al. [58], who studied the urban area of Beijing-Tianjin-Hebei (BTH), discussed the dynamics of the urban growth patterns shown distinctively in Chinese cities in terms of urban land, inner structure, mixed uses of land, accessibility,

and environmental impact. Analysis between 2015 and 2018 suggested that there was a difference in the urban growth patterns of both large and small cities in BTH. As small cities expanded, they became spatially fragmented and decentralized [58]. He et al. [59] also compared urban growth patterns of Chinese and American cities between 1995 and 2005 and between 2005 and 2015. These studies investigated three major cities in the United States—the Northeast megalopolis, the California megalopolis, and the Great Lakes megalopolis—and the three urban agglomerations of China—the Beijing-Tianjin-Hebei megalopolis, the Yangtze River Delta urban megaregion, and the Pearl River Delta urban agglomeration. For the U.S., outlying urban sprawl occurred within 4 km of the primary urban center; for China, it occurred within 4–10 km. Edge urban sprawl appeared to be a key urban growth pattern in the two countries. Xu et al. [60] identified the change in urban sprawl using population density. They confirmed that population density is decreasing in 35 Chinese and 20 American cities and suggested that, while urban sprawl appeared in both countries, it was more evident in the United States.

In addition, studies on the urban growth pattern over 20–30 years have been conducted for cities that have grown rapidly. Cengiz et al. [61] studied the urban growth that occurred from 1984 to 2018 for Ankara, Turkey. Their study identified that irregular expansion occurred using land use and land cover change and density analysis; in particular, they found that edge expansion was significantly increasing. Dou and Chen [62] identified urban growth patterns in the Shezhen area in Guanding Province, China, from 1988 to 2015, which was characterized by an extensional urbanization of urbanized land cover; they found that foreign capital investment and government policies played an important role in the area's growth. Verstegen and Goch [63] applied cellular automata modeling to Dublin, Ireland, Milan, Italy, and Warsaw, Poland, from 1990 to 2018, and confirmed that monocentric edge expansion occurred in Dublin, ribbon sprawl occurred in Warsaw, and polycentric infill development occurred in Milan. Dadashpoor et al. [17] confirmed that the edge growth pattern appeared, as well as that a dispersed growth pattern appeared in some subregions, as a result of applying the cellular automata method to the Tabriz metropolitan area in Iran. Sharma and Kumar [64] analyzed India's Rohtak City using land cover and land use data; a four-fold growth occurred in the built-up area, which is characteristic of planned and unplanned residential and commercial arrangement. Nong et al. [65] identified the urban growth pattern of Hanoi, Vietnam, between 1993 and 2010. The spatiotemporal dynamics of the built-up land confirmed that it was extended by 10–35 km from the urban center, and infilling and edge expansion growth primarily appeared. Zhang et al. [66] confirmed the urban growth pattern of Wuhan, China, through the change in urban land between 1990 and 2010. Wuhan experienced redevelopment, infilling, and edge expansion, which were confirmed to have been influenced by industrial upgrading, educational leveling up, and population aging. Baqa et al. [67] identified the urban growth pattern of Karachi, Pakistan, between 1990 and 2020 through cellular automata of land cover. They showed that the built-up area extended outward in an unpredictable manner. Sun et al. [68] identified the urban growth pattern of Shenyang, China, between 1989 and 2018 through changes in the residential area. It was suggested that urban planning and economic growth resulted in the expansion of residential space.

Existing studies have primarily focused on identifying the expansion modes of growing cities, with their basis on the growth mechanism that urban growth is the result of the expansion of urban land, stimulated by population growth following economic growth. Studies on urban growth patterns are based on finding the common laws [69] and determining types of cities based on generalized types. Existing studies have focused on the positive relationship between the economic and population growth pattern and the urban growth pattern but have overlooked cases in which economic and population growth have stagnated. Therefore, this study focuses on determining whether urban growth patterns vary or the existing patterns are maintained through step-by-step comparison, including periods of both growth and stagnation.

In addition, existing studies have primarily focused on the relationship between the urban center and suburban areas in the urban growth pattern and overlooked changes within the city. The form of suburbanization, which has been explored in many studies, and the new types recently considered, such as edge, outlying, and infilling growth, have been discussed with a focus on the relationship between the city and the periphery. Existing studies have suggested that the roles of urban planning and development policy were the key factors behind such change. However, urban planning and development policy is defined within the administrative boundaries of the city and is independent of the urban planning and development policy of the city that constitutes the suburban areas. Therefore, this study focuses on the process of internal change in a city, a unit of urban planning and development policy, and identifies how the expansion of the urbanized area changes the urban centrality and what type of pattern the internal movement of the population embodies.

## 3. Material and Methods

### *3.1. Study Area*

The study area is BMC in South Korea, a representative city where economic and social stagnation persists. BMC is located in the southeastern part of the Korean Peninsula and consists of 16 sub-city administrative areas (gu and gun) and 206 community areas (dong; Figure 1). BMC experienced a rapid increase in population due to unregulated population growth after the Korean War [70] as well as dramatic economic and massive suburban expansion during the high growth period from 1970 to 1980 [71]. Although BMC has been the second-largest city in South Korea since 1914 when cities first began to form, it has experienced significant depopulation, industrial hollowing out and deindustrialization, aging, and gaps in living conditions between the city center and suburban areas. This has led the city to enter a state of economic and social stagnation [70,71].

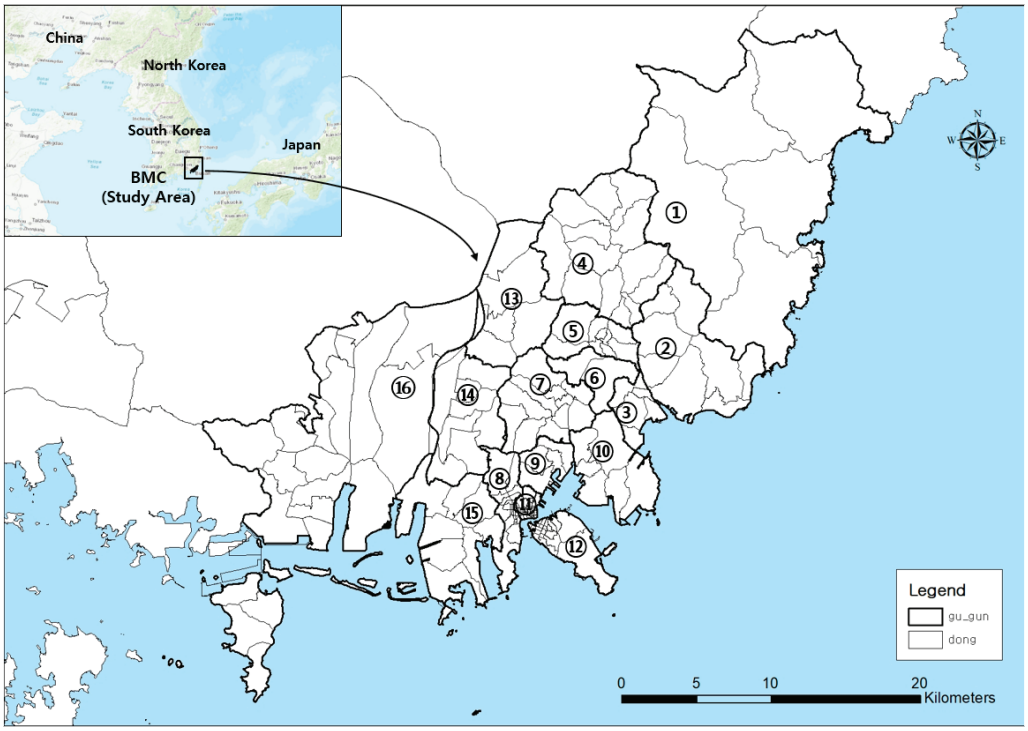


**Figure 1.** Location and Map of BMC. Note: ① Gijang-gun, ② Haeundae-gu, ③ Suyeong-gu, ④ Geumjeong-gu, ⑤ Dongrae-gu, ⑥ Yeonje-gu, ⑦ Busanjin-gu, ⑧ Seo-gu, ⑨ Dong-gu, ⑩ Nam-gu, ⑪ Jung-gu, ⑫ Yeongdo-gu, ⑬ Buk-gu, ⑭ Sasang-gu, ⑮ Saha-gu, ⑯ Gangseo-gu. The base map was adopted from the National Spatial Data Infrastructure Portal of Korea (www.nsdi.go.kr (accessed on 12 August 2022)).

BMC reveals a growth of 20 years as well as a decline of 20 years based on the data from 2000. These characteristics typically signify economic and population stagnation (see Table A1 and Figure A1 in Appendix A). Further, BMC is a representative city for understanding how urban growth patterns change in big cities that experience a decline after a period of growth. There are three reasons for selecting BMC as the target area for this study. First, BMC is the second-largest city in South Korea. However, despite the general trend of population growth in South Korea, in BMC, there has been a continuous decline since 1995. Second, the youth formed a major segment of BMC's population previously, but in recent times, the city primarily comprises a rapidly aging population. In 2009, it topped the list of aging cities in South Korea, with the degree of aging increasing by 1% every year. Third, despite South Korea's continuous economic growth, BMC has not kept pace with other cities. With a shrinking population, the gap in GDP per capita between BMC and other cities in South Korea is gradually increasing. These three reasons constitute the typical characteristics of a declining city.

### *3.2. Unit of Analysis and Data*

The units of analysis used are the community area (dong) and sub-city administrative area (gu/gun). The spatial features of the lowest units are used as bases to identify the spatial patterns of urban growth throughout the city. The community area (dong) is used for studying the population, a 30 m × 30 m grid and the community area (dong) are used for studying urbanization, and the sub-city administrative area (gu/gun) is used for examining migration. The variables, time ranges, and data used for analysis are presented in Table 1.

**Table 1.** Data and unit of analysis.

| Variable | Methodology | Data Type | Year | Unit of Analysis | Data Source |
|---|---|---|---|---|---|
| Population | Exploratory Spatial Data Analysis | Shape file | 1980, 1990, 2000, 2010, 2020 | Dong | Population and Housing Census (Statistics Korea) |
| Urbanization | Bachi's Index, SDE | Raster file Shape file | 1980, 1990, 2000, 2010, 2020 | 30 m × 30 m grid and dong | Land Cover Map (Ministry of Environment) |
| Domestic Migration | Social Network Analysis | Network file | 2000, 2010, 2020 | Gu and gun | Internal Migration Statistics (Statistics Korea) |

Three methodologies were used to analyze changes in the patterns of urban growth. First, for spatial clusters of population analysis, the Exploration Spatial Data Analysis (ESDA) method was used. The shape files of the community area (dong) unit were used for the data. The data include the attributes of the population and housing census and were analyzed every 10 years from 1980 to 2020. Second, for the analysis of changes in urbanized patterns, Bachi's Index and the SDE method were used. The shape files of the community area (dong) unit and a 30 m × 30 m grid file were used for the data. The data include the properties of land cover and population and were analyzed every 10 years from 1980 to 2020. Finally, for the centrality of migration analysis, the Social Network Analysis method was used. The network files for the sub-city administrative area (gu/gun) unit were used for the data. The data include the property of O-D matrix attributes for traffic volume and were analyzed every 10 years from 2000 to 2020 when the data were statistically collected. ArcMap 10.8 and NetMiner 4 software were used for analysis. The flow of the study is presented in Figure 2.

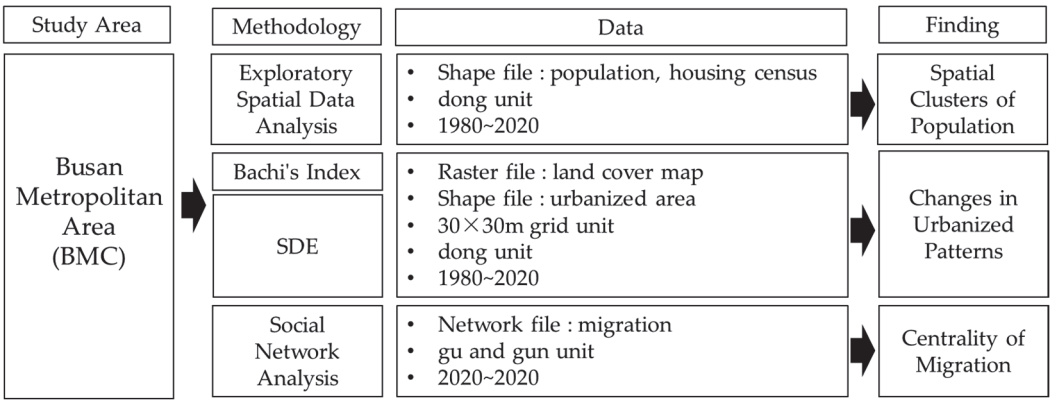


**Figure 2.** Analytic flow.

### *3.3. Exploratory Spatial Data Analysis*

Local Moran's I was used as a local indicator of spatial association (LISA), as proposed by Anselin [72], to identify the spatial concentration based on population quantity. Local Moran's I can distinguish clusters of spatial features into four types with 95% statistical significance. HH (High-High) indicates that an object with a high value is clustered around a surrounding object with a high value. LL (Low-Low) indicates that an object with a low value is clustered around a surrounding object with a low value. HL (High-Low) indicates that an object with a high value has a spatial correction with a surrounding object with a low value, and LH (Low-High) indicates that an object with a low value has a spatial correction with a surrounding object with a high value [72]. Local Moran's I was calculated using Equation (1).

$$I_i = \frac{(X_i - \overline{X})}{S_i^2} \sum_{j=1,\ j \neq i}^{n} w_{ij}(x_j - \overline{X}),\ S_i^2 = \frac{\sum_{j=1,\ j \neq i}^{n} w_{ij((x_j - \overline{\overline{x}})^2}}{n-1} \quad (1)$$

$x_i$: an attribute for feature $i$; $\overline{X}$: the mean of attribute; $W_{ij}$: spatial adjacent weight between features $i$ and $j$; $n$: total number of features.

This study used the fixed distance band method as the spatially adjacent weight ($W_{ij}$) of the LISA. The fixed distance band method is useful for evaluating the statistical properties of data on a particular spatial scale. The fixed distance was calculated using Ripley's K function (Equation (2)). Spatially adjacent weight was assigned if the adjacent spatial weight fell within a distance based on the calculated distance.

$$L(d) = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{i=1, j \neq i}^{n} k(i,j)}{\pi n(n-1)}} \quad (2)$$

### *3.4. Bachi's Index and Standard Deviational Ellipse*

This study first compared urbanization patterns from 1980 to 2020 on a 10-year basis using the urbanized area of the 30 m × 30 m land cover maps to determine the changes in urbanization in terms of land use. The urbanized area in the land cover map refers to the developed or built-up area, including residential, industrial, commercial, recreational, and transport areas. Next, the community area (dong) was integrated into areas changing into urban areas, and Bachi's Index and SDE were applied to identify the forms of spatial changes in urbanization. These two measurement tools are used to derive the spatial distribution characteristics as oblong, principal axis, and ellipsoid in space, using the mean center and the Standard Deviation Distance (SDD) of distribution [73,74]. It is possible to understand, through the average center, how the center of the urbanization area moves, and the concentration of the urbanization area can be understood according to the SDD increase and decrease. Furthermore, the orientation of the variance and concentration of

the urbanized area can be determined through the oblong and Standard Deviation Ellipse. The mean center and SDD were calculated according to Equation (3), and oblong was calculated according to Equation (4). The orientation and size of the SDD were calculated according to Equation (5).

$$\overline{X} = \frac{\sum_{i=1}^{n} q_i X_i}{\sum_{i=1}^{n} q_i}, \overline{Y} = \frac{\sum_{i=1}^{n} q_i Y_i}{\sum_{i=1}^{n} q_i}, SDD = \sqrt{\frac{\sum_{i=1}^{n} q_i (X_i - \overline{X})^2 + q_i (Y_i - \overline{Y})^2}{\sum_{i=1}^{n} q_i}} \tag{3}$$

$$O = \frac{1}{2}\left(\frac{\sigma_x}{\sigma_y} + \frac{\sigma_y}{\sigma_x}\right), \sigma_x = \sqrt{\frac{\sum_{i=1}^{n} q_i (X_i - \overline{X})^2}{\sum_{i=1}^{n} q_i}}, \quad \sigma_y = \sqrt{\frac{\sum_{i=1}^{n} q_i (Y_i - \overline{Y})^2}{\sum_{i=1}^{n} q_i}} \tag{4}$$

$$tan2_\alpha = \frac{2\gamma\sigma_x\sigma_y}{\sigma_x^2 - \sigma_y^2}, \; SDE_x = \sqrt{\frac{\sum_{i=1}^{n} (X_i - \overline{X})^2}{n}}, \quad SDE_y = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - \overline{Y})^2}{n}} \tag{5}$$

$\overline{X}, \overline{Y}$ : mean center coordinates; $q_i$: urbanized area of community area $i$; $X_i$, $Y_i$: coordinates of community area $i$.

### *3.5. Social Network Analysis*

Regarding sub-city migration within a metropolitan city, the interregional connectivity and centrality of in-migration and out-migration of the population were measured using Social Network Analysis. Social Network Analysis is a method used to describe an overall structure that considers the relational properties between regions [75]. The centrality index refers to the most important node among various nodes in a network [76]. In-migration centrality $(IC_{ik})$ and out-migration centrality $(OC_{ik})$ were calculated according to Equation (6) to identify the centrality distinguishing between in-migration and out-migration, and the eigenvector centrality $(P_i)$ was calculated according to the same equation to identify centrality considering the relative proportion within the city as a whole.

$$IC_{jk} = \sum_{i=1}^{n} Z_{ijk} = Z_{jk}, \; OC_{ik} = \sum_{j=1}^{n} Z_{ijk} = Z_{ik}, \; P_i = \sum_{j=1}^{N-1} P_j P Z_{ji} \tag{6}$$

## 4. Results

### *4.1. Spatial Clusters of Population*

Figure 3 presents the areas of population concentration from 1980 to 2020 identified using Local Moran's I. In 1980, an HH cluster of population concentration emerged around the CBD and the surrounding old town (Busanjin-gu, Seo-gu, Dong-gu, Nam-gu, Jung-gu), which had formed around the Busan port. In 1990, the HH cluster moved inland to the northeast of the CBD. However, in 2000, there was no emergence of clusters of populated areas; instead, the clusters tended to be dispersed across the region. Nonetheless, HH clusters appeared in some areas of Haeundae-gu and Buk-gu, which are believed to have been influenced by Hwamyung New Town (Buk-gu) and Haeundae New Town (Haeundae-gu), among others, toward which occupants began to move during the late 1990s. In 2010, population-intensive HH clusters emerged around some parts of Haeundae-gu, Yeonje, and Dongrae in the eastern area of BMC. This is attributed to the influence of Centum City (Haeundae-gu) and Dongbusan New Town (Haeundae-gu and Gijang-gun), among others, which began to develop rapidly after 2005. Many development projects emerged in the outskirts, and the depopulation in the CBD and the surrounding old town accelerated due to the dilapidated infrastructure, resulting in spatial polarization of the eastern and the western areas. The population-intensive HH cluster in 2020 is completely different from that of 1980. Most areas where HH clusters manifested in 1980 exhibited LL clusters,

and HH clusters were concentrated in the eastern area of BMC. Table 2 demonstrates that 88.9% of community areas had population-intensive HH clusters in the CBD and the surrounding old town (Busanjin-gu, Seo-gu, Dong-gu, Nam-gu, Jung-gu) in 1980, but this shifted to 82.4% with LL clusters in 2020. Conversely, most of the population-intensive HH clusters in 2020 were found in the eastern areas (Gijang-gun, Haeundae-gu, Geumjeong-gu, Dongrae-gu). Figure 3 and Table 2 can be summarized into two main findings. (1) Between 1980 and 2000, when the city's population and economy were growing, areas in which the population was concentrated moved to the outskirts of the CBD. (2) Between 2000 and 2020, when economic and population growth was stagnant, such areas moved further to the outer boundaries of the city. As a result, the differences between east and west population-intensive areas were evident.

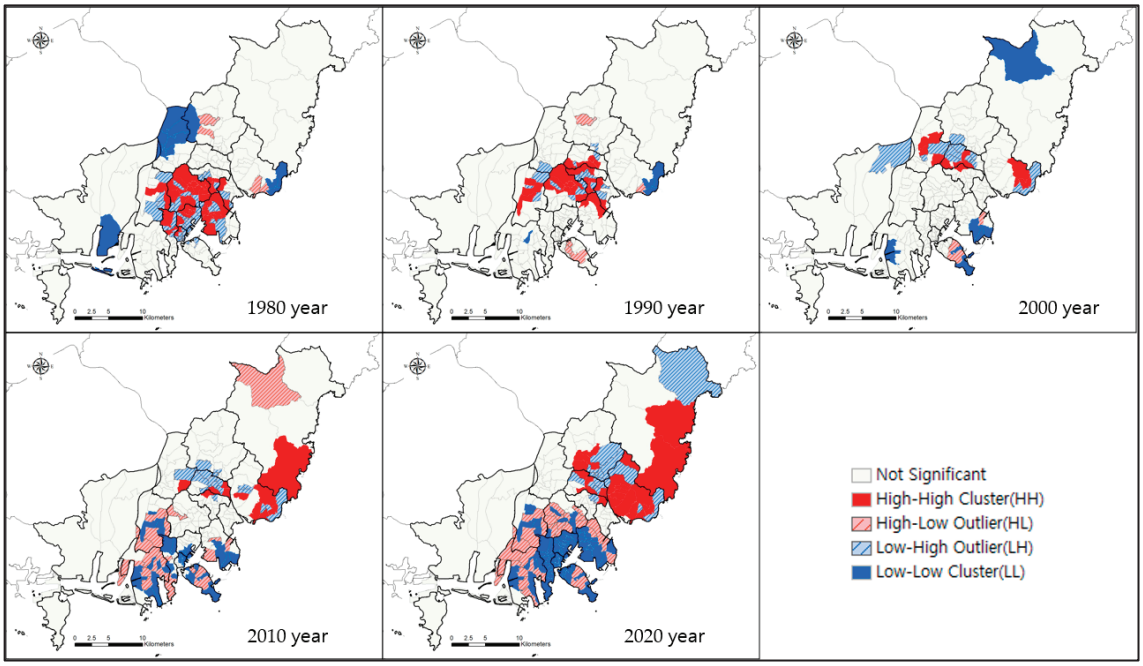


**Figure 3.** Spatial clusters of population in BMC. Note: The base map was adopted from the National Spatial Data Infrastructure Portal of Korea (www.nsdi.go.kr (accessed on 12 August 2022)).

**Table 2.** Numbers of High-High (HH) and Low-Low (LL) clusters in BMC.

| Gu-Gun | 1980 | | 1990 | | 2000 | | 2010 | | 2020 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | HH | LL | HH | LL | HH | LL | HH | LL | HH | LL |
| Gijang-gun | - | - | - | - | - | 1 | 1 | - | 2 | - |
| Haeundae-gu | - | 4 | - | 4 | 4 | - | 5 | - | 12 | - |
| Suyeong-gu | 2 | - | 2 | - | - | - | - | - | - | - |
| Geumjeong-gu | - | 1 | - | - | - | - | - | - | 4 | - |
| Dongrae-gu | - | - | 5 | - | 4 | - | 3 | - | 5 | - |
| Yeonje-gu | 2 | - | 5 | - | 1 | - | 1 | - | 1 | - |
| Busanjin-gu | 14 | - | 8 | - | - | - | - | - | - | 6 |
| Seo-gu | 3 | - | - | - | - | - | - | 5 | - | 13 |
| Dong-gu | 5 | - | - | - | - | - | - | 3 | - | 12 |
| Nam-gu | 8 | - | 2 | - | - | 3 | - | 4 | - | 13 |
| Jung-gu | 2 | - | - | - | - | - | - | 5 | - | 9 |
| Yeongdo-gu | - | - | | - | - | 2 | - | 6 | - | 9 |
| Buk-gu | - | 6 | - | - | 3 | - | 1 | - | - | - |
| Sasang-gu | 2 | - | 3 | - | - | - | - | 4 | - | 5 |
| Saha-gu | - | - | - | 1 | - | 2 | - | 7 | - | 7 |
| Gangseo-gu | - | 1 | - | - | - | - | - | - | - | - |
| Total | 38 | 12 | 25 | 5 | 12 | 8 | 11 | 34 | 24 | 74 |

### *4.2. Changes in Urbanized Patterns*

As presented in Figure 4, the urbanized area of BMC has expanded from the CBD and the surrounding old town to the outskirts, which were previously underdeveloped. Compared with 1980, urbanized 30 m × 30 m area units expanded in 1990 to areas such as Dongrae-gu, Haeundae-gu, and Saha-gu. The urbanized area expanded in Haeundae-gu, Buk-gu, and Gangseo-gu in 2000; in Gijang-gun, Haeundae-gu, and Gangseo-gu in 2010; and in Gijang-gun and Gangseo-gu in 2020.

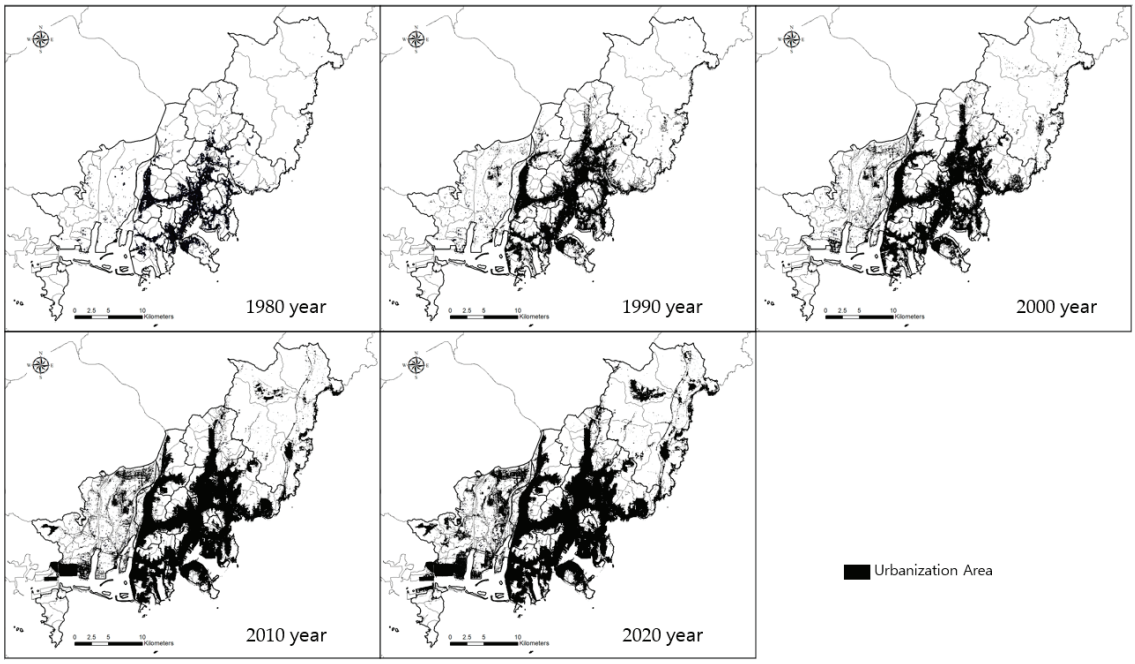


**Figure 4.** Changes in the urbanized area in BMC. Note: The base map was adopted from the National Spatial Data Infrastructure Portal of Korea (www.nsdi.go.kr (accessed on 12 August 2022)).

Two facts can be identified by looking at the change in urbanized 30 m × 30 m area units shown in Table 3. First, the urbanized unit was continuously increasing at all times. The urbanized unit increased in two stagnation periods, by 192.48% between 1980 and 2000 during the period of population and economic growth and by 76.98% between 2000 and 2020. In particular, the total area increased further during those stagnation periods. Second, the degree of increase in the urbanized unit at the urban boundary continued, and the gap was even larger when considering the average growth degree. In the case of Gijang-gun, located at the eastern boundary of the city, the rate of increase was 587.68% during the growth period and 494.15% during the stagnation periods, showing the tendency above. Gangseo-gu, located at the western boundary of the city, also followed such a tendency, increasing by 351.07% during the growth period and 247.69% during the two stagnation periods. Gijang-gun, which accounts for 5% of the urbanized units that increased during the growth period, grew to 21% during the two stages, and Gangseo-gu grew from 15% to 33%.

**Table 3.** Number of urbanized area units (30 m × 30 m) and Bachi's Index.

| | | 1980 | 1990 | 2000 | 2010 | 2020 |
|---|---|---|---|---|---|---|
| Number of Urbanized Area Units (30 m × 30 m) | Gijang-gun | 641 | 2689 | 4408 | 13,174 | 26,190 |
| | Haeundae-gu | 2539 | 9281 | 13,162 | 18,565 | 20,357 |
| | Suyeong-gu | 4018 | 5872 | 6368 | 7614 | 8176 |
| | Geumjeong-gu | 3295 | 7687 | 10,301 | 12,547 | 15,536 |
| | Dongrae-gu | 3965 | 8966 | 9950 | 11,623 | 12,011 |

**Table 3.** *Cont.*

| | | 1980 | 1990 | 2000 | 2010 | 2020 |
|---|---|---|---|---|---|---|
| | Yeonje-gu | 4658 | 7479 | 7727 | 8379 | 9603 |
| | Busanjin-gu | 12,143 | 13,183 | 14,405 | 17,025 | 18,117 |
| | Seo-gu | 4255 | 4405 | 4977 | 6322 | 6976 |
| | Dong-gu | 5894 | 5997 | 6195 | 6865 | 7159 |
| | Nam-gu | 9292 | 11,508 | 12,935 | 17,742 | 19,579 |
| | Jung-gu | 2272 | 2346 | 2458 | 2746 | 2776 |
| | Yeongdo-gu | 4238 | 5438 | 6125 | 8099 | 9224 |
| | Buk-gu | 820 | 4501 | 8044 | 10,442 | 12,695 |
| | Sasang-gu | 10,276 | 13,128 | 15,518 | 16,323 | 17,914 |
| | Saha-gu | 6280 | 14,112 | 16,953 | 21,868 | 23,956 |
| | Gangseo-gu | 3139 | 5805 | 14,159 | 27,692 | 49,230 |
| Bachi Index | Mean Center $(\overline{X}, \overline{Y})$ | (386,281.2, 185,179.9) | (386,744.6, 186,163.3) | (386,255.3, 186,454.6) | (386,226.3, 186,839.5) | (387,375.1, 187,475.6) |
| | Distance of Mean Center | - | 1087.2 m | 569.5 m | 385.9 m | 1313.1 m |
| | Direction of Mean Center | - | 64.8° | 149.2° | 94.3° | 29.0° |
| | SDD | 6703.9 | 7855.5 | 8511.6 | 9602.2 | 10,717.5 |
| | Oblongity (O) | 1.0008 | 1.0003 | 1.0096 | 1.0051 | 1.0005 |

The center and form of the urbanized area, identified using Bachi's Index, can be seen in Table 3, and the SDE appears in Figure 5. The SDD of Bachi's Index demonstrates an increase from 6703.9 in 1980 to 10,717.5 in 2020. This indicates that the distribution of urbanization patterns expanded throughout the space. The mean center represents the centrality of the urbanized area, with the average center moving 1087.2 m northeast (64.8°) in 1990 compared with 1980, having moved 569.5 m northwest (149.28°) in 2000, 385.92 m north (94.38°) in 2010, and 1313.1 m east (29.0°) in 2020. The oblong value did not change significantly between 1980 and 2020, indicating that the form of urbanization expansion increased evenly in all directions except the south. The orientation of urbanization expansion progressed in all directions but to varying degrees. As seen in Figure 5, the SDE extended in along the east-west direction, owing to a significant expansion of urbanized areas in Gijang-gun and Gangseo-gu. Compared with 1980, urbanized areas in Gijang-gun increased by 3.986%, and those in Gangseo-gu increased by 1.468%.

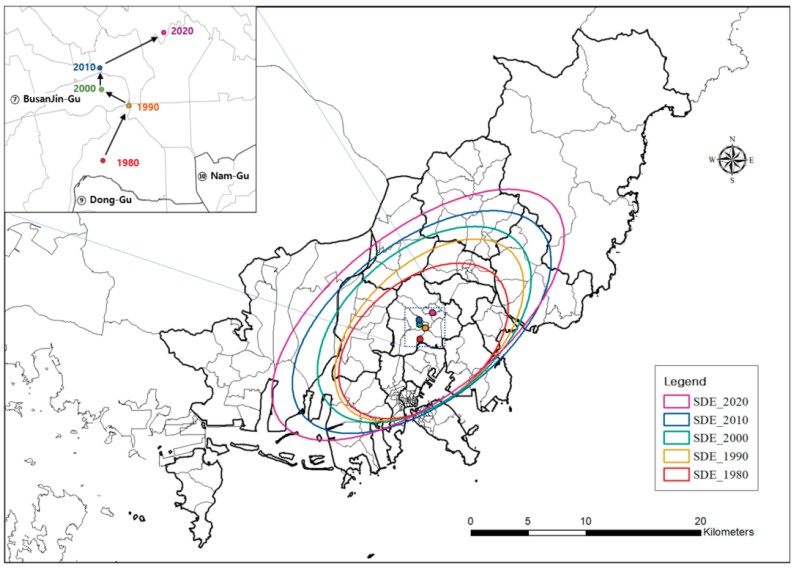


**Figure 5.** SDE in BMC. Note: The base map was adopted from the National Spatial Data Infrastructure Portal of Korea (www.nsdi.go.kr (accessed on 12 August 2022)).

### *4.3. Centrality of Migration*

Figure 6 presents the centrality of migration for BMC in 2000, 2010, and 2020, prepared using Social Network Analysis. The highest figures were seen in Dongrae-gu and Haeundae-gu in all years. Since 2000 was a time of expansion toward the city's outskirts, population migration was centered on Dongrae-gu and Haeundae-gu in the eastern area of BMC, and the movement toward Gangseo-gu in the western area of BMC also continually increased. Apart from such outskirts, areas in Suyeong-gu and Nam-gu emerged where centrality was higher for in-migration than out-migration. However, similar to the previous analysis, areas of the CBD and the surrounding old town area demonstrated higher centrality for out-migration and movement toward the outskirts.

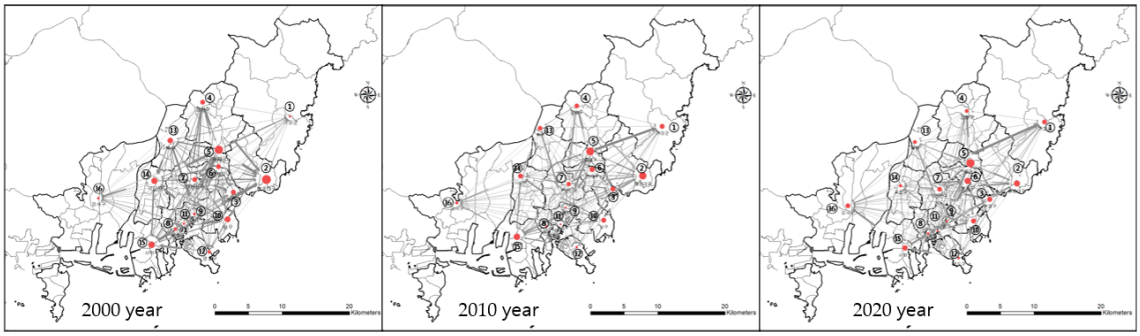


**Figure 6.** Social Network Analysis of migration in BMC. Note: The base map was adopted from the National Spatial Data Infrastructure Portal of Korea (www.nsdi.go.kr (accessed on 12 August 2022)).

The results shown in Table 4 also support the movement patterns toward the outskirts. Among the areas located on these outskirts, Haeundae-gu, Gangseo-gu, and Geumjeong-gu demonstrated higher centrality for in-migration than for out-migration in 2000, 2010, and 2020, while Gijang-gun demonstrated higher in-migration than out-migration following 2010. The eigenvector centrality shown in Table 4 indicates the central influence of movement, considering both in-migration and out-migration. Haeundae-gu, Dongrae-gu, Yeonje-gu, Busanjin-gu, Dong-gu, and Sasang-gu were among the areas with high population mobility. Among them, in-migration affected Haeundae-gu, out-migration affected Busanjin-gu, Dong-gu, and Sasang-gu, and both in-migration and out-migration affected Dongrae-gu and Yeonje-gu. The eigenvector centrality, while not high, steadily increased for Gijang-gun and Gangseo-gu due to in-migration.

**Table 4.** In-migration centrality, out-migration centrality, and eigenvector centrality.

| Gu-Gun | In-Migration Centrality ($IC_{ik}$) | | | Out-Migration Centrality ($OC_{ik}$) | | | Eigenvector Centrality ($P_i$) | | |
|---|---|---|---|---|---|---|---|---|---|
| | **2000** | **2010** | **2020** | **2000** | **2010** | **2020** | **2000** | **2010** | **2020** |
| Gijang-gun | 377 | 1041 | 1003 | 795 | 514 | 459 | 0.13 | 0.22 | 0.21 |
| Haeundae-gu | 2295 | 1584 | 1281 | 330 | 371 | 497 | 0.32 | 0.28 | 0.26 |
| Suyeong-gu | 1186 | 1024 | 1072 | 284 | 294 | 504 | 0.16 | 0.18 | 0.22 |
| Geumjeong-gu | 1194 | 978 | 728 | 959 | 568 | 458 | 0.24 | 0.21 | 0.16 |
| Dongrae-gu | 2176 | 1687 | 1705 | 1749 | 1425 | 1306 | 0.38 | 0.37 | 0.37 |
| Yeonje-gu | 1147 | 1108 | 1287 | 1414 | 1157 | 1199 | 0.27 | 0.30 | 0.34 |
| Busanjin-gu | 1186 | 880 | 971 | 1316 | 1167 | 1274 | 0.24 | 0.26 | 0.31 |
| Seo-gu | 721 | 450 | 480 | 1376 | 941 | 967 | 0.19 | 0.16 | 0.18 |
| Dong-gu | 594 | 380 | 433 | 2122 | 1787 | 1546 | 0.31 | 0.31 | 0.29 |

**Table 4.** *Cont.*

| Gu-Gun | In-Migration Centrality ($IC_{ik}$) | | | Out-Migration Centrality ($OC_{ik}$) | | | Eigenvector Centrality ($P_i$) | | |
|---|---|---|---|---|---|---|---|---|---|
| | **2000** | **2010** | **2020** | **2000** | **2010** | **2020** | **2000** | **2010** | **2020** |
| Nam-gu | 1438 | 1069 | 1038 | 710 | 429 | 340 | 0.20 | 0.18 | 0.18 |
| Jung-gu | 482 | 326 | 304 | 1364 | 1014 | 833 | 0.21 | 0.19 | 0.17 |
| Yeongdo-gu | 771 | 511 | 504 | 1167 | 1036 | 1054 | 0.18 | 0.19 | 0.20 |
| Buk-gu | 1422 | 952 | 747 | 1305 | 984 | 841 | 0.27 | 0.23 | 0.20 |
| Sasang-gu | 1601 | 1066 | 639 | 1934 | 1810 | 1638 | 0.35 | 0.37 | 0.32 |
| Saha-gu | 1668 | 1357 | 1112 | 1522 | 1223 | 1124 | 0.24 | 0.26 | 0.25 |
| Gangseo-gu | 553 | 614 | 1000 | 463 | 307 | 263 | 0.10 | 0.12 | 0.18 |

## 5. Discussion

### *5.1. Urban Growth Pattern*

This study identified the population and urbanized land cover patterns from 1980 to 2020 in BMC, a representative city in South Korea that is currently experiencing economic and population stagnation following a period of economic and population growth. Until 1990, the population concentration patterns expanded to the outskirts along with population growth; however, the trend toward the outskirts intensified even after 2000, when population and economic stagnation emerged. Particularly in 2020, population polarization was also evident between the CBD and the surrounding old town and the outskirts. The expansion of the urbanized area has manifested in a rapid increase in the volume of built-up area, and the expansion toward the outskirts has further intensified since 2000, when population expansion and economic stagnation occurred. The centrality of the built-up area also moved from near the CBD in 1980 to the outskirts in 2020, with expansion in all directions but to significantly varying degrees in the east and west directions. The population migration analysis also demonstrated high centrality of in-migration in the outskirts.

The urban expansion in BMC identified in this study is similar to the growth pattern of cities found in previous studies, specifically showing the edge growth among the types raised by Richardson and Chang-Hee [20], which have recently begun to be widely discussed. This finding is similar to that of Cengiz et al. [61], who studied Ankara's urban growth pattern for a similar period, that of Dadashpoor et al. [17] targeting Tabriz, Iran, and that of Zhang et al. [66] targeting Wuhan, China. However, in BMC, economic and population growth, which are the drivers of urban growth, have been stagnant for 20 years. Despite these two stagnations, urban growth patterns with edge expansion appeared in BMC, which was more evident during the period of stagnation rather than during the period of growth.

The results, which show an urban growth pattern similar to that of the sprawl-without-growth concept presented by Wolff et al. [7] and Liu and Meng [54], have two implications. First, despite population loss and aging, the simultaneous migration of the population center to the outskirts and the expansion of urbanized areas indicates strong path dependence in which the behavioral cause of land consumption leading to urbanization follows behaviors based on the past period of growth rather than on rational decision-making. Numerous studies on coordination in the relationship between humans and land present various driving mechanisms in terms of the urban economies of urban human-land change [46,54,77,78]. However, the reinforced movement and expansion toward the outskirts despite the absence of population and economic growth, which are considered fundamental forces for the expansion of urbanized areas, can be understood as a manifestation of the path dependence of urban sprawl, as presented by Atkinson and Oleson [79], in the development-inducing urban growth management planning and policy of the local government. This implies that the phenomenon of path dependence, demonstrated in the bottom-up process of land

consumption by each actor, as presented in the discussion by Brown et al. [80], is projected to the urban growth pattern as a result.

Second, urban growth management policies and planning to date aim to effectively induce the allocation of various sizes of land in cities [81]. In particular, urban growth management approaches for managing the urbanization process have focused on finding an appropriate balance between the negative and positive effects of urbanization [82]. The results of this study, which demonstrate a simultaneous pattern of population loss and expansion to the outskirts, show that even within a single city, the expansion of abandoned spaces and polarization between spaces may have negative effects. This means that in discussions of conventional suburbanization, the hollowed-out core and growing hinterland phenomena between urban and rural areas can emerge within a single metropolitan city [43,83,84], which suggests the need for a shift in policy and planning orientation to recognize different urban growth patterns and their consequent negative effects on cities facing population decline and aging following a period of growth and the need to consider them in the course of urban growth management.

### *5.2. Contributions*

This study contributes to the field by providing empirical examples of what happens when cities in developing counties that are currently growing rapidly show stagnant growth. Existing studies have focused on identifying growth patterns between urban and suburban areas under circumstances of economic and population growth. However, many cities face economic and population stagnation or decline after a period of growth. In this regard, existing studies are limited in that they have not been able to present the dynamics of how urban growth patterns change in such circumstances. As a city that experienced both rapid growth and staging, BMC was a suitable case study for identifying changes according to the situation. This study found that BMC followed existing urban growth patterns and that those patterns were, in fact, strengthened. Only 5.8% of the total area remains to be developed [85], which means that the city has reached the limits of urban growth. This shows that urban planning tools should be developed and applied to prepare for the rapid expansion of cities in developing counties while in an economically stagnant period and help them achieve sustainability.

### *5.3. Limitations and Recommendations for Future Work*

Although this study identifies patterns of change in population and urban expansion over 40 years, it cannot explain the cause of such change based on rationales. Despite population and economic stagnation, there are various economic and social driving forces in the urban expansion of land development and population concentration toward the outskirts. In particular, discussions are needed on the path-dependent characteristics of the local government, which requires a qualitative study of the institution and policy decisions associated with urban growth management policy and planning. In addition, this study is limited in that it targets one city, BMC, in which the representative shrinkage of South Korea is seen. BMC was chosen because it is a city where the population is rapidly flowing out and where super-aging was first expected in South Korea. While it is significant to find that new patterns can emerge in a city, future research must be conducted on multiple cities with similar conditions to develop more generalized patterns. Finally, patterns between 1980 and 2000 could not be identified in this study in terms of understanding the characteristics of population migration due to data limitations.

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**Data Availability Statement:** All data were provided by Statistics Korea (kosis.kr).

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

**Table A1.** Population in BMC and Korea.

| Year | Population | | | Elderly Population (Above 65 Years of Age) | | | |
|---|---|---|---|---|---|---|---|
| | (A) BMC | (B) Korea | Ratio (A/B) | (C) BMC | (D) Korea | Ratio (C/A) | Ratio (D/B) |
| 1975 | 2,580,472 | 34,706,620 | 7.44% | 48,898 | 1,206,599 | 1.89% | 3.48% |
| 1980 | 3,248,232 | 37,436,315 | 8.68% | 71,145 | 1,446,114 | 2.19% | 3.86% |
| 1985 | 3,595,405 | 40,448,486 | 8.89% | 91,707 | 1,749,549 | 2.55% | 4.33% |
| 1990 | 3,854,960 | 43,410,899 | 8.88% | 127,130 | 2,162,239 | 3.30% | 4.98% |
| 1995 | 3,883,880 | 45,858,029 | 8.47% | 172,389 | 2,640,205 | 4.44% | 5.76% |
| 1996 | 3,867,125 | 46,266,256 | 8.36% | 181,045 | 2,715,598 | 4.68% | 5.87% |
| 1997 | 3,851,312 | 46,684,069 | 8.25% | 190,078 | 2,829,674 | 4.94% | 6.06% |
| 1998 | 3,829,098 | 46,991,171 | 8.15% | 199,622 | 2,959,957 | 5.21% | 6.30% |
| 1999 | 3,817,270 | 47,335,678 | 8.06% | 210,278 | 3,103,512 | 5.51% | 6.56% |
| 2000 | 3,796,506 | 47,732,558 | 7.95% | 222,697 | 3,268,058 | 5.87% | 6.85% |
| 2001 | 3,770,536 | 48,021,543 | 7.85% | 235,609 | 3,444,542 | 6.25% | 7.17% |
| 2002 | 3,730,125 | 48,229,948 | 7.73% | 248,393 | 3,623,048 | 6.66% | 7.51% |
| 2003 | 3,691,445 | 48,386,823 | 7.63% | 261,439 | 3,808,805 | 7.08% | 7.87% |
| 2004 | 3,666,345 | 48,583,805 | 7.55% | 277,081 | 4,014,965 | 7.56% | 8.26% |
| 2005 | 3,638,293 | 48,782,274 | 7.46% | 294,356 | 4,224,735 | 8.09% | 8.66% |
| 2006 | 3,611,992 | 48,991,779 | 7.37% | 312,402 | 4,440,629 | 8.65% | 9.06% |
| 2007 | 3,587,439 | 49,268,928 | 7.28% | 333,756 | 4,709,105 | 9.30% | 9.56% |
| 2008 | 3,564,577 | 49,540,367 | 7.20% | 354,566 | 4,965,375 | 9.95% | 10.02% |
| 2009 | 3,543,030 | 49,773,145 | 7.12% | 372,705 | 5,168,491 | 10.52% | 10.38% |
| 2010 | 3,567,910 | 50,515,666 | 7.06% | 388,047 | 5,348,182 | 10.88% | 10.59% |
| 2011 | 3,550,963 | 50,734,284 | 7.00% | 402,511 | 5,525,630 | 11.34% | 10.89% |
| 2012 | 3,538,484 | 50,948,272 | 6.95% | 422,575 | 5,759,793 | 11.94% | 11.31% |
| 2013 | 3,527,635 | 51,141,463 | 6.90% | 446,877 | 6,030,555 | 12.67% | 11.79% |
| 2014 | 3,519,401 | 51,327,916 | 6.86% | 471,465 | 6,296,931 | 13.40% | 12.27% |
| 2015 | 3,513,777 | 51,529,338 | 6.82% | 494,583 | 6,552,528 | 14.08% | 12.72% |
| 2016 | 3,498,529 | 51,696,216 | 6.77% | 515,918 | 6,781,159 | 14.75% | 13.12% |
| 2017 | 3,470,653 | 51,778,544 | 6.70% | 540,955 | 7,066,201 | 15.59% | 13.65% |
| 2018 | 3,441,453 | 51,826,059 | 6.64% | 567,603 | 7,389,474 | 16.49% | 14.26% |
| 2019 | 3,413,841 | 51,849,861 | 6.58% | 594,404 | 7,718,616 | 17.41% | 14.89% |
| 2020 | 3,391,946 | 51,829,023 | 6.54% | 627,724 | 8,134,675 | 18.51% | 15.70% |

Note: Data were drawn from Statistics Korea, and the population was adjusted according to the present spatial scope.

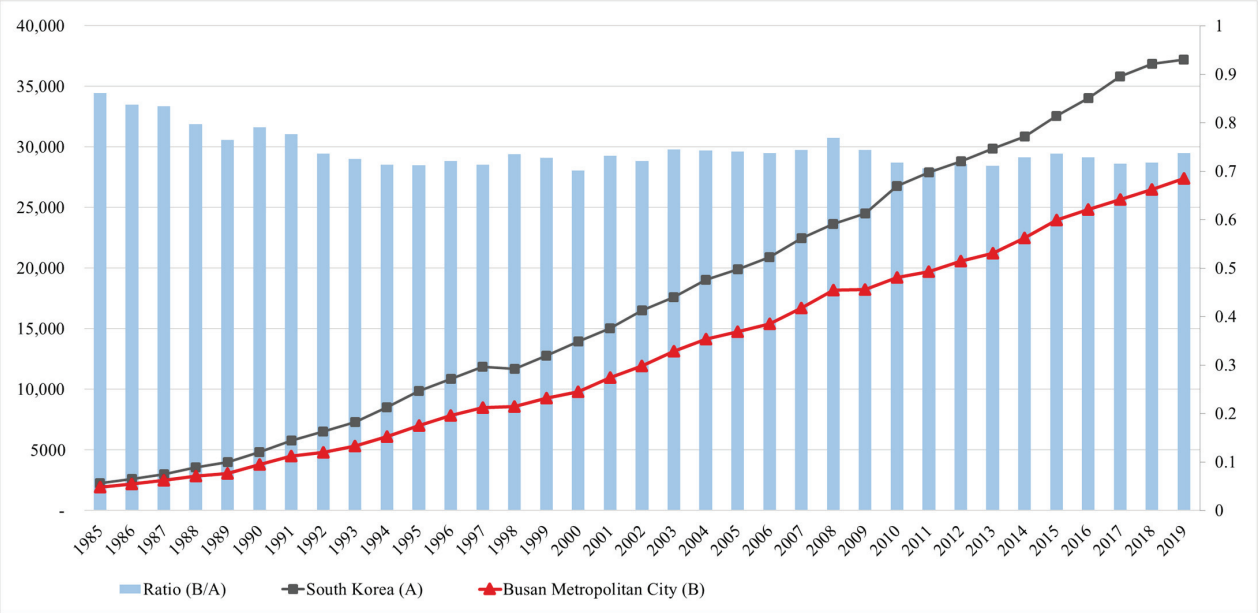


**Figure A1.** GDP per capita (unit: 1000 won; base year: 2015). Note: Data were drawn from Statistics Korea.

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# Sustainable Urban Development for Heat Adaptation of Small and Medium Sized Communities

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**Abstract:** Due to climate change, urban populations will be affected by worsening heat stress. The use of blue–green infrastructure can be an effective countermeasure for urban planners. In this study, the ENVI-met modelling system is used to investigate the impacts of different heat adaptation strategies, such as additional urban trees, irrigation policies, and the use of high reflective surface materials. However, under certain local conditions, these measures can have conflicting effects, e.g., trees can provide shadow but also reduce the cooling ventilation. To address such conflicts, we developed an online tool visualising urban climate simulation data and applying a new decomposition algorithm that translates the biophysical processes (i.e., radiation, ventilation, evapotranspiration, and heat storage) into surface temperature changes during heat wave events. This approach allows us to (1) identify factors responsible for heat, (2) comparatively evaluate heat mitigation of different land development scenarios, and (3) find trade-offs for conflicting adaptation measures. This online tool can support the decision-making of local stakeholders.

**Keywords:** urban climate; green infrastructure; heat adaptation; micrometeorology; ENVI-met

## 1. Introduction

Climate change is one of the greatest challenges of the 21st century and already influencing many weather extremes in all regions of the world. With increasing temperatures, the probability of the occurrence of heavy rainfall events, floods as well as droughts, and heat waves, among others, is growing [1]. In particular, heat waves, which are extended periods of unusually high atmospheric temperatures, are expected to become more frequent and severe, as well as longer-lasting in the future [1–3]. This may lead to adverse health effects and increased heat-related mortality [4–6].

The climate of urban areas is strongly influenced by building development and sealing. The increase in absorbing surfaces due to vertical walls, the heat release from the more concentrated combustion of fossil fuels, the decrease in latent heat loss due to the sealing of the surface, and the increased heat absorption by urban materials can be identified as reasons for a change in the urban energy balance [7]. As a result, phenomena such as the urban heat island (UHI) effect arise, which describes the occurrence of higher temperatures in urban areas compared to the rural surrounding during nighttime [8]. Hot weather periods are exacerbated by the UHI effect, making cities more vulnerable to heat waves [2]. Thus, the urban population experiences a reduced quality of life, and negative impacts on human health [9]. The risk of heat stress also notably increases in regions experiencing demographic change with a growing proportion of elderly people since the thermophysiological adaptability to heat decreases with age [10].

Small and medium-sized communities in Germany, which often have very dense and compact town centres, are particularly vulnerable to heat waves, as demographic change is more pronounced there. Surveys conducted in representative municipalities as part of the project showed that climatic changes are perceived in the region, with the rise in

summer temperatures being mentioned in particular. However, such cities often do not have the financial resources to employ staff to handle issues concerning climate change and climate adaptation.

Therefore, effective and cost-efficient concepts to increase urban resilience and adapt urban structures to the heat need to be developed and evaluated. Against this background, urban green spaces have gained importance. The effect of street trees on the urban climate in different urban environments as well as in different climate zones is described in various studies worldwide [4,11–15]. Foliaged trees are very effective in reducing direct shortwave radiation and lower surface and radiant temperatures in their shade [16]. Therefore, they can contribute to a significant improvement of thermal heat load since human thermal sensation is mainly affected by radiant temperatures [17,18]. In addition, cooling by trees can be achieved through evapotranspiration. Due to evapotranspiration processes, solar energy is increasingly converted into the latent rather than sensible turbulent heat flux [5]. This moderates air temperature and increases humidity [19]. However, the efficiency of evapotranspirative cooling depends on the availability of water, which is often limited due to sealing and the rapid runoff of rainwater in urban areas [20]. Furthermore, green spaces can provide additional ecosystem services as well [21].

Another approach to reduce urban heat involves an increase of the surface albedo of typical urban structures to diminish the energy input available for warming the urban climate [22,23].

The urban climate and the respective influencing factors to heat stress can be considered at different scales (city level, neighborhood level and individual buildings). Thus, climate adaptation concepts must not only take into account climatic effects at the city level, but have to recognize the fine-structure of urban heat at very small scales inside of urban quarters [24].

In this study, we present an online visualization tool utilizing simulations of the micrometeorological model ENVI-met, which can be used by local stakeholders to explore the effects of several local climate adaptation measures on a neighborhood scale. To explain the causes of the variations in urban temperatures, we applied a decomposition algorithm that converts the components of the energy balance into the respective temperature increments. In this way, strategies targeted at heat mitigation can be developed based on scientific findings.

## 2. Materials and Methods

### *2.1. The Microscale Urban Climate Model ENVI-Met*

All simulations in this study were performed with the three-dimensional microscale model ENVI-met, version 4.4.6, which enables the calculation and simulation of climate variables in urban areas [25]. The model consists of three components: an atmospheric model, a soil model, and a vegetation model, which are used to simulate the interactions between urban surfaces, vegetation, and the atmosphere [26]. The typical resolution of the model ranges from 0.5 m to 10 m in space and up to 2 s in time, which makes it suitable for micrometeorological investigations in complex urban environments [24]. Numerous studies have evaluated the accuracy of the model and it has been successfully applied to simulate the meteorological and human-biometeorological impacts of urban geometry, surface materials as well as urban greening [10,27–29].

### *2.2. Study Area*

The case study was conducted for Naumburg, a Central-European small-size city which is situated in eastern Germany (51°9.37′ N, 11°48.5′ E, 130 m asl) and is classified according to Köppen-Geiger as Cfb (warm temperate with warm summers, fully humid) [30] with mean annual temperature of 9.8 °C and mean annual precipitation of 584.6 mm at the German Weather Service (DWD) station Osterfeld (ID 3821; located 11km south-east of the study site). The spatial extent of the city including the neighbouring districts is 129.9 $km^2$ [31] with a total of 32,053 people living in this area [32].

The study area, which encompasses a square area of 0.96 km$^2$, focuses mainly on the city center of Naumburg (see Figure 1) which is a dense medieval old town characterized by narrow streets and a large proportion of sealed surfaces. The proportion of green spaces and street trees is very low. However, the core of the city is surrounded by small green areas in the south and east. On the western border of the city center, there are many street trees. In the north, the city park is adjacent to the city center.

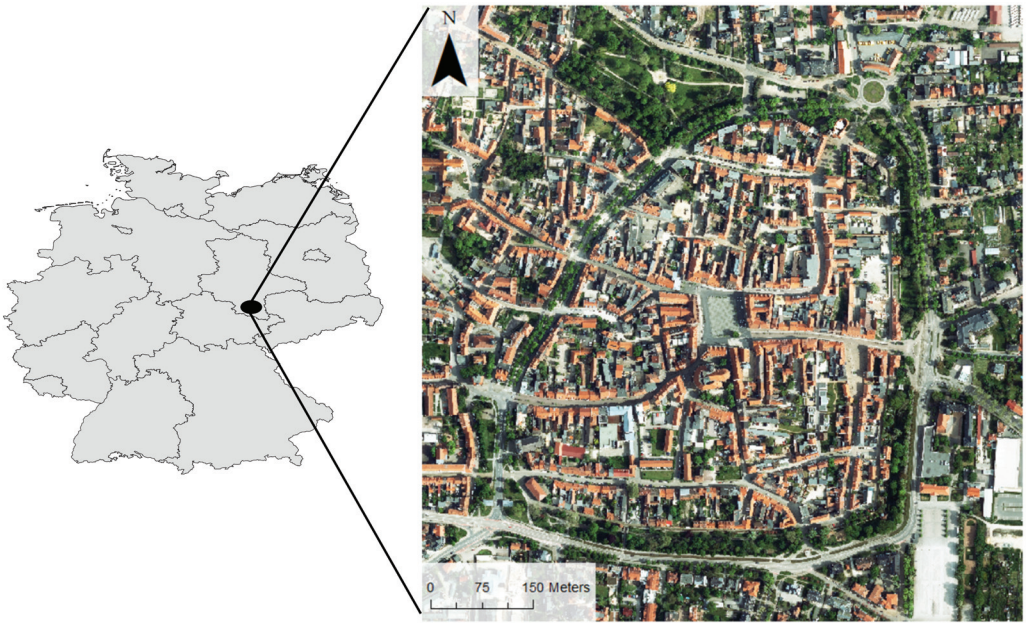


**Figure 1.** Orthophoto of the study area (right part) and the location within Germany.

### *2.3. Setup for Numerical Simulations*

Heat adaptation is particularly important during hot days. Therefore, we browsed the weather data (DWD weather station Osterfeld) for the last 10 years and selected two very hot days (3 and 4 July 2015) representing a heat wave event for the simulations. Half-hourly measured values of air temperature, wind speed, and relative humidity were used for the entire simulation period as input. Wind direction was predominantly south on both days (180°). An overview of the model initialization and the meteorological data used is provided in Table 1.

**Table 1.** Input parameters specified in the ENVI-met input file and guiding the performed simulations.

| | |
|---|---|
| Start of simulation | 2015-07-03 00:00 |
| Duration | 48 h |
| Temporal resolution | 1 h |
| Spatial resolution | 3 × 3 × 2 m |
| Total amount of grid cells | 288 × 288 × 22 |
| Air temperature | 20.5–36.5 °C |
| Relative humidity | 25.4–74.3% |
| Wind speed | 1.5–3.85 m s$^{-1}$ |
| Wind direction | 180° |
| Cloud cover | Cloud free |
| Initial albedo | Roofs: 0.5; Walls: 0.4; Asphalt: 0.2; Grass: 0.2, Trees: 0.18 |
| Initial soil temperature | 0–20 cm: 25.1 °C, 20–50 cm: 22.5 °C, 50–200 cm: 18.5 °C, below 200 cm: 16.0 °C |
| Initial soil moisture | 0–20 cm: 50%, 20–50 cm: 60%, 50–200 cm: 60%, below 200 cm: 60% |

Dimensions, heights and coordinates of the buildings, as well as zoning, were derived from a vector-based 3D-city model [33] and a land-use plan, which was made available in consultation with the Naumburg municipal administration. Green spaces were detected from othophotos (NDVI > 0.5) [34]. To determine the positions and characteristics of trees within the study site, a tree register provided by the Naumburg city administration was used. Median tree height (10 m), crown diameter (3.5 m), and crown base (3 m) were calculated and applied in the ENVI-met tool Albero to create a corresponding model tree. The default settings for all other tree properties were retained (albedo: 0.18, transmission: 0.30, leaf area density: 1.1 $m^2/m^3$). This model tree may represent, e.g., a Field Maple (*Acer campestre*).

As a compromise between sufficient spatial accuracy and a reasonable computing time (circa 2 weeks per scenario), the horizontal resolution was set to 3 × 3 m and the vertical grid cell size to 2 m. Furthermore, the lowest grid cells were vertically divided into five smaller cells, which allowed surface interactions to be calculated more accurately. To reduce the simulation time, the grid cells were enlarged vertically by 20% each from 25 m (5 m above the highest buildings) via telescoping. The simulations were started at 0:00 a.m. (CEST) for a total of 48 h. We excluded the first simulated day from further analyses since we considered it as a tuning phase. All analysed parameters refer to either the surface or a height of 1.4 m, which corresponds approximately to the human biometeorological reference height of 1.1 m [35].

### *2.4. Climate Adaptation Scenarios*

The most acknowledged approaches for climate adaptation in cities include an increase of green infrastructures in the urban environment, the use of high reflective materials for sealed surfaces (scenario 2), and irrigation management of green surfaces (scenario 3). To assess the impact of the climate adaptation scenarios (see Figure 2) on urban heat, we compared them to the current state (Scenario 0; see Figure 1). The simulated scenarios are briefly described in the following:

- **Scenario 0:** Current state of the model area with trees and grass areas
- **Scenario 1:** Current state of the model area without any vegetation; i.e., only bare soil, buildings, and asphalt surfaces in order to estimate the effect of the existing urban trees since the study shows a rather high amount of the already existing vegetation
- **Scenario 2:** Scenario 0 with an increased street albedo (0.6 instead of 0.2) which can be achieved using highly reflective paints applied to the surface material [22,36]
- **Scenario 3:** Scenario 0 with an increased soil moisture (90% instead of 50% usable field capacity)

**Figure 2.** Schematic visualisation of the climate adaptation scenarios: These include the removal of all vegetation in the study area leading to bare soil surfaces (**left** panel), an increase of albedo for sealed surfaces (**middle** panel), and an increase in soil humidity (**right** panel).

Further information on these scenarios are summarised in Table 2. Additional simulations were performed and integrated in an online tool, which is described in detail in Section 2.6.

**Table 2.** Area fractions of the total area for the individual model compartments in % as well as the number of trees in the respective scenarios.

| Scenario | 0 (Current) | 1 (no veg.) | 2 (Albedo) | 3 (Irrigation) |
|---|---|---|---|---|
| Buildungs | 26% | 26% | 26% | 26% |
| Asphalt (albedo: 0.2) | 50% | 50% | 0% | 50% |
| Asphalt (albedo: 0.6) | 0% | 0% | 50% | 0% |
| Grass areas | 24% | 0% | 24% | 24% |
| Unsealed soil | 0% | 24% | 0% | 0% |
| Number of trees | 3855 | 0 | 3855 | 3855 |
| Initial soil moisture | 50% | 50% | 50% | 90% |

*2.5. Quantification of the Biophysical Contribution on the Surface Temperature*

The thermal impacts of different climate adaptation scenarios are reflected in the surface energy balance (SEB):

$$R_n = Q_H + Q_E + Q_G \tag{1}$$

with net radiation $R_n$, sensible heat flux $Q_H$, latent heat flux $Q_E$ and ground heat flux $Q_G$.

The micrometeorological model ENVI-met is based on the SEB, wherein the turbulent fluxes ($Q_H$ and $Q_E$) are determined using an E − $\epsilon$ 1.5-order model. This is a good compromise between the convenient K-theory and the numerically complex closure of second-order and allows us to appropriately incorporate urban structures as well as advection while ground heat fluxes are determined using Fourier's law [37,38]. The components of the SEB can be interpreted as the biophysical contributions [39]. The sensible heat flux $Q_H$, which arises from the temperature difference between the surface $T_{SFC}$ and air $T_a$ at a height $z$, warms the atmosphere in the proximity of the surface and can be expressed as:

$$Q_H = \rho c_P \frac{T_{SFC} - T_a(z)}{r_a} \tag{2}$$

with the density of air $\rho$, the specific heat of air at constant pressure $c_P$, and the aerodynamic resistance to heat transfer $r_a$. The latent heat flux $Q_E$ involves the processes between surface and atmosphere which are related to water exchange and the ground heat flux $Q_G$ describes the heat conduction between surface and soil [40,41].

In order to quantify the mechanism of action of the climate adaptation scenarios, we applied and extended a decomposition approach according to [39], who considered the urban heat island on a neighborhood scale. Using the definition of the dimensionless Bowen ratio $\beta = Q_H/Q_E$, inserting Equation (2) in Equation (1) the surface energy balance can be obtained as:

$$(1-\alpha)S_\downarrow + L_\downarrow - \epsilon\sigma T_{SFC}^4 = \left(1 + \frac{1}{\beta}\right)\frac{\rho c_P}{r_a}(T_{SFC} - T_a) + Q_G \tag{3}$$

with surface albedo $\alpha$, incoming short-wave radiation $S_\downarrow$, incoming longwave radiation $L_\downarrow$, surface emissivity $\epsilon$.

Since our climate adaptation scenarios mainly affect the atmosphere in the proximity of the surface, the air temperature $T_{a,\,ref}$ at a reference height ($z_{ref}$ = 30 m) was not affected by the respective climate adaptation scenario. Thus, the long-wave radiation term can be linearised in Equation (3) which yields after replacing $T_a$ in Equation (2) by $T_{a,\,ref}$

$$T_{SFC} - T_{a,\,ref} = \frac{\lambda}{1+f}(R_n - Q_G) \tag{4}$$

with

$$f = \frac{\lambda \rho c_{\mathrm{P}}}{r_{\mathrm{a}}}\left(1 + \frac{1}{\beta}\right) \text{ and } \lambda = \frac{1}{4\epsilon\sigma T_{\mathrm{a,\,ref}}^{3}} \tag{5}$$

with an energy redistribution factor $f$ and a local climate sensitivity parameter $\lambda$ which translates the heat flux to a corresponding change in temperature [39,42,43].

Considering the difference between the respective climate adaptation scenario (subscipt i = 1,2,3) and the current scenario (subscript 0) regarding Equation (4) leads to

$$T_{\mathrm{SFC,i}} - T_{\mathrm{SFC,0}} = \frac{\lambda}{1 + f_{\mathrm{i}}}(R_{\mathrm{n,i}} - Q_{\mathrm{G,i}}) - \frac{\lambda}{1 + f_0}(R_{\mathrm{n,0}} - Q_{\mathrm{G,0}}) \tag{6}$$

Due to a climate adaptation scenario surface parameters $P$ (i.e., $T_{\mathrm{SFC}}$, $R_{\mathrm{n}}$, $\beta$, and $Q_{\mathrm{G}}$) are altered by a small perturbation $\Delta$ compared to the respective parameter of the reference scenario $P_0$

$$P_{\mathrm{i}} = P_0 + \Delta P \tag{7}$$

Substituting these into Equation (4) and deriving the quantities associated with $\Delta$ results in the temperature effect $\Delta T$ due to the climate adaptation scenario. After neglecting of higher-order terms, it follows for $\Delta T$:

$$\Delta T = \frac{\lambda_0}{1 + f_0}\Delta R_n + \frac{-\lambda_0}{(1 + f_0)^2}(R_{n,0} - Q_{G,0})\Delta f_1 + \frac{-\lambda_0}{(1 + f_0)^2}(R_{n,0} - Q_{G,0})\Delta f_2 + \frac{-\lambda_0}{1 + f_0}\Delta Q_G \tag{8}$$

with

$$\Delta f_1 = \frac{-\lambda_0 \rho c_{\mathrm{P}}}{r_{\mathrm{a},0}}\left(1 + \frac{1}{\beta_0}\right)\frac{\Delta r_{\mathrm{a}}}{r_{\mathrm{a},0}} \tag{9}$$

$$\Delta f_2 = \frac{-\lambda_0 \rho c_{\mathrm{P}}}{r_{\mathrm{a},0}}\frac{\Delta \beta}{\beta_0^2} \tag{10}$$

Using this approach, the energy fluxes of the SEB can be converted to differences in surface temperature due to the biophysical contributions of the climate adaptation scenarios.

### *2.6. Description of the Online Tool*

Due to the lack of useful public tools which allow local stakeholders to identify the characteristics of such adaptation scenarios, we developed an online tool (in R language [44]) to visualize the effects of adaptation measures (Data flow in Figure 3). Significantly reducing the amount of data and processing time, the entire ENVI-met output (in NetCDF format) was condensed to the relevant parameters, the data were restricted to surface or pedestrian level (z = 1.4 m), and saved as a database in the RData format which serves as the basis for the visualisation tool. A second database was constructed for the results of the decomposition algorithm.

The online tool was constructed with the help of the R-shiny package, which requires the specification of a user interface and a corresponding server component [45]. The user interface consists of drop-down menus for the selection of the meteorological parameters and the simulated scenario. Using a slider, the time of the day can be specified. There is also an option to consider differences between the selected climate adaptation scenario and the current state included.

The server component of the program handles the specified inputs of the user interface and applies them to the database. Thus, the outputs containing a spatial representation of the selected parameter, a time series, a histogram, some basic statistics, and the spatio-temporal outcome of the decomposition algorithm are generated.

Finally, the tool is hosted via a Kubernetes server guided by a Docker file [46].

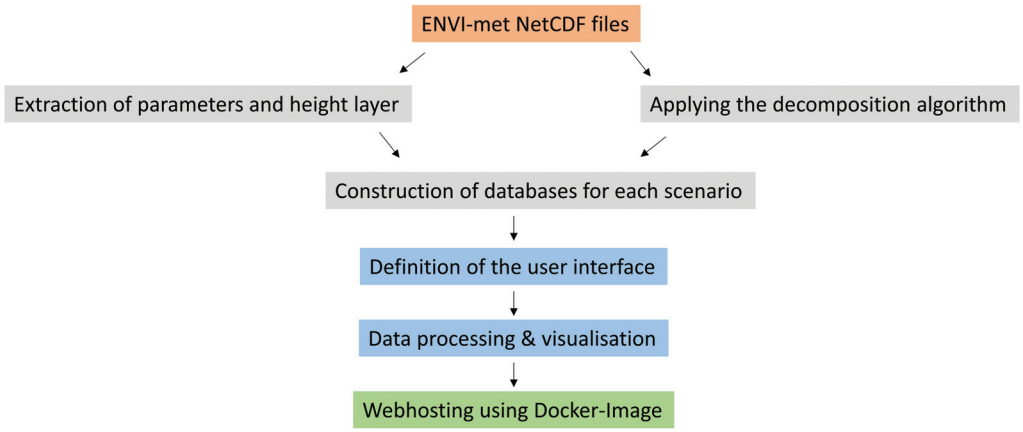


**Figure 3.** Data flow for the online visualisation tool.

## 3. Results

### *3.1. Online Visualisation Tool*

The developed user-friendly, interactive web tool consists of a graphical user interface (GUI) that integrates the data simulated by ENVI-met and allows the exploration of different adaptation strategies regarding their impact on the urban climate at the neighborhood scale. In Figure 4, an example of the air temperature of the current state is shown. By a drop down menu, the meteorological parameters of interest are selected (air temperature, surface temperature, specific humidity factor, sensible heat flux, ground heat flux, latent heat flux, wind direction, wind speed, radiation temperature and physiological equivalent temperature (PET)). Further menus ask for the selection of the time of the pre-simulated day and the choice of the climate adaptation scenario (removed vegetation, current state, green roof scenario, increase in urban trees, irrigation scenario, drought scenario, increase in surface albedo and increase in roof albedo). For an assessment of the impact of a climate adaptation scenario, the difference to the current state can be mapped. For visualization, the meteorological parameters are plotted on a map according to predefined color scales, while the building ground areas are shown in a grey color. The spatial maps offer the possibility to enlarge the area of interest by dragging and zooming. For a deeper understanding, a histogram of the grid values and some basic statistics, as well as the mean diurnal variation, are also shown for the selected parameter and time.

Furthermore, a spatial mapping of biophysical processes (i.e., radiation, convection efficiency, evapotranspiration, and heat storage) contributing to the modified surface temperature is provided in an additional tab (see Figure 5).

The online tool is publicly available at https://webapp.ufz.de//KlimaKonform//urbansimulation//Naumburg. While we focused on climate adaptation strategies for the city center of Naumburg, the tool can easily be applied to the ENVI-met output for any other study areas as well.

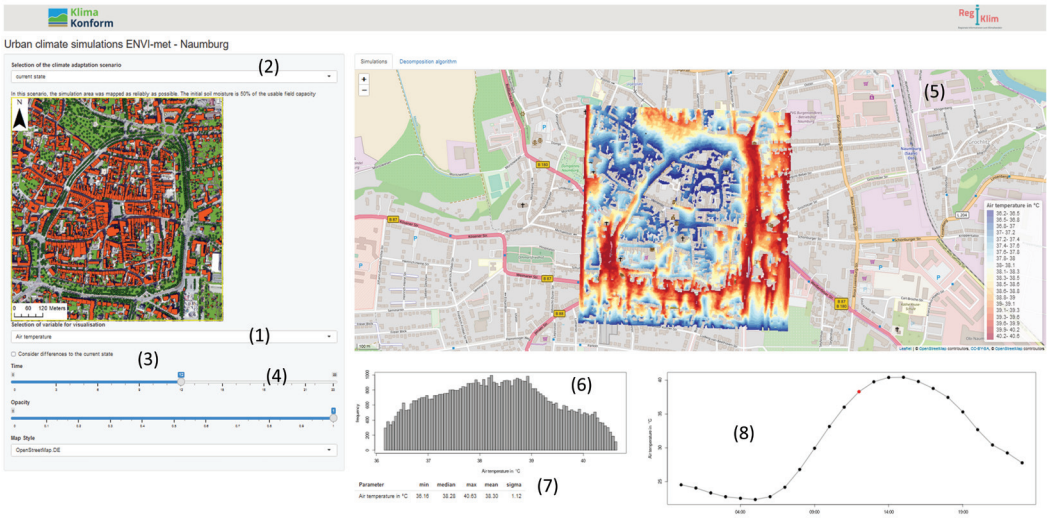


**Figure 4.** Screenshot of the online visualization tool: This example shows the spatial distribution of the air temperature (z = 1.4 m) for the current state at noon. The tool is accessible at https://webapp.ufz.de//KlimaKonform//urbansimulation//Naumburg. This dashboard consists of a user interface (**left**—greyish shaded part) and the corresponding output (**right**). The selection options include (1) the meteorological parameter (2) the simulation scenario, (3) the option to consider the difference compared to the current state and (4) the selection of the time. The output consists of representations for the selected input parameters which covers (5) a spatial map display, (6) a histogram of the grid values, (7) a table of some summary statistics and (8) a diurnal plot.

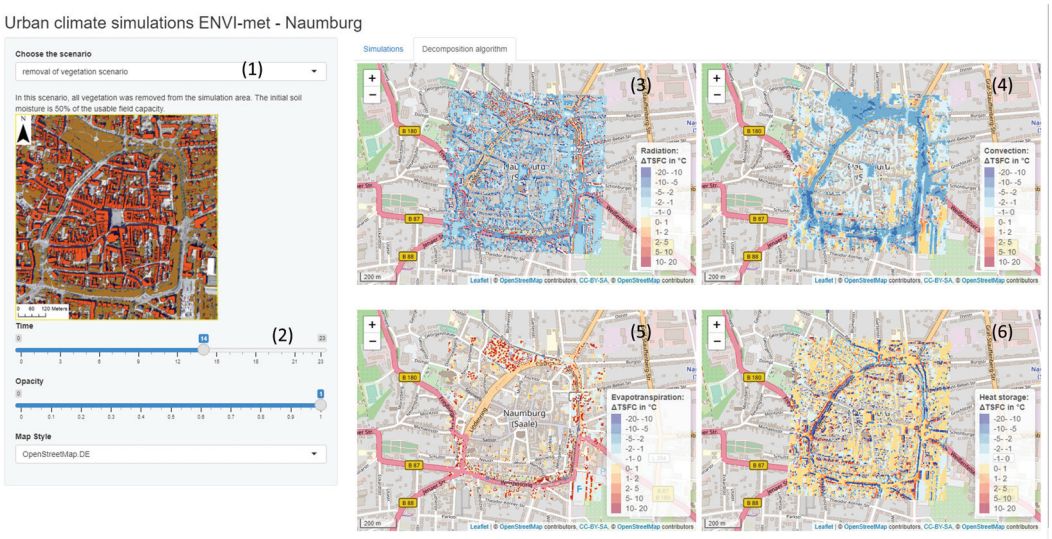


**Figure 5.** Screenshot of the online visualization tool for the output of the decomposition algorithm: This dashboard consists of a user interface (**left**—greyish shaded part) and the corresponding output (**right**). The selection options include the simulation scenario (1) and the selection of the time (2). The output consists of spatial representations of the temperature contributions by the surface energy balance components, i.e., radiation (3), convection efficiency (4), evapotranspiration (5) and heat storage (6). This example shows the temperature contributions for scenario 1 (removal of vegetation) at 14:00. The tool is accessible at https://webapp.ufz.de//KlimaKonform//urbansimulation//Naumburg.

### *3.2. Effects of Climate Adaptation Scenarios on Local Air Temperature ($T_a$) and Thermal Comfort (PET) at Pedestrian Level*

During the simulation period, very high temperatures ($T_a$ at a height of 1.4 m above the surface; see Figure 4) accompanied by extreme heat stress conditions (high PET values)

were prevalent. However, significant spatial variations in air temperature can be observed in the study area due to the heterogeneity of the urban structures. Differences in the layout and orientation of buildings and streets, locally differentiated proportions of urban vegetation, and differences in surface cover lead to altered radiation, heat, and humidity characteristics of urban areas and thus also to local nuances of $T_a$ [8,10,47]. During the day, the least warmed areas are in the shade of buildings while the warmest are found along wide streets and large open spaces, as the influence of urban morphology is lower there [14,48]. In Figure 6, the effects of the studied climate adaptation scenarios (Section 2.4) regarding $T_a$ and PET are shown. Both the irrigation of unsealed surfaces and an increase of surface albedo lower $T_a$ in the urban environment, whereby the effect is most pronounced at noon since net radiation is highest. In our study area, the reduction of temperature due to the used reflective surface material (maximum reduction of $T_a$= 0.88 K) tends to be more amplified compared to the increased evaporative cooling by the irrigation scenario (maximum reduction of $T_a$= 0.41 K). Rather surprisingly, the removal of vegetation showed a reduction of $T_a$ except for a short period in the morning (10:00–11:00). A persistent pattern following the diurnal variation of radiation can not be identified, though. Nevertheless, a warming tendency of urban trees was identified which seems to be less pronounced during the morning and afternoon hours.

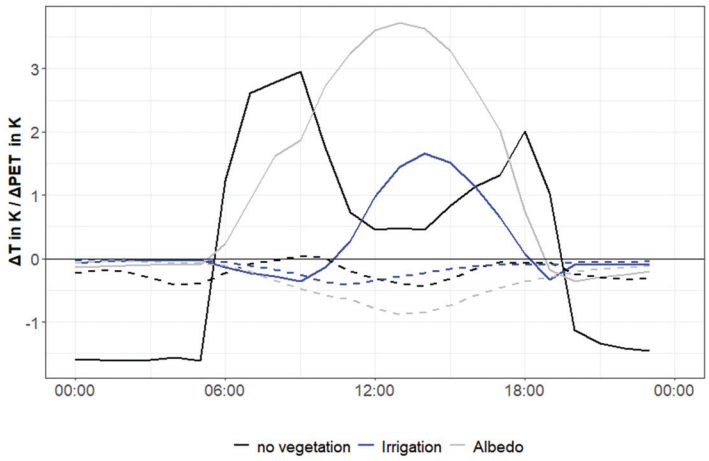


**Figure 6.** Diurnal variations of the total differences of the spatial mean values of PET (solid lines) and $T_a$ (dashed lines) for the climate adaptation scenarios compared to the current state.

For the human perception of heat, the physiologically equivalent temperature (PET), which takes further meteorological variables such as the wind velocity $v$, the mean radiant temperature $T_{mrt}$, and the water vapor pressure VP into account, is a suitable index [10,49]. Determined values for PET (using the ENVI-met tool Biomet with the usual default settings for body and clothing characteristics and the metabolic rate of a reference person) can be assigned to a thermal sensation scale based on surveys. In addition to PET, there are several other measures of thermal comfort (e.g., mPET, PMV, UTCI, and PPD). However, PET is the most basic and widely used measure and allows for a thermo-physiologically meaningful assessment of the thermal environment and is sufficient to analyze the potential of various approaches to attenuate urban heat stress [10]. Therefore, we decided to present our results in terms of the PET. Interestingly, the effects of the climate adaptation scenarios with regard to $T_a$ are reflected in the change in PET just to a limited extent: Despite reduced $T_a$ the albedo scenario increases PET values drastically during daytime since the reflected shortwave radiation contributes to a rise in $T_{mrt}$ and thus in PET. Due to the absence of shortwave radiation, there is almost no alteration of nighttime thermal comfort for this scenario.

Similar to the albedo scenario, the irrigation scenario shows a rise in daytime PET values even though $T_a$ was lowered. This worsening of thermal comfort can be observed

between noon and the evening while during the night and around dawn time a reduction of PET was found. However, in this scenario, the reason for a worsening of thermal comfort is an increase in air humidity.

The absence of urban trees affects PET differently at night and during the day. At night, there is a reduction of PET since trees increase $T_a$, $T_{mrt}$ (mainly due to downward long-wave radiation), VP and reduce wind speed. However, trees can significantly improve daytime thermal comfort due to shading leading to a reduction of $T_{mrt}$. The change of elevation and azimuth of the sun affect PET and lead to deviations from the diurnal radiation since shadow areas are reduced at noon.

In Figure 7, the spatial effects of the climate adaptation scenarios on the air temperature and PET are depicted for 16:00. The cooling effect by the removal of the vegetation is particularly pronounced in the wide streets, while the strong cooling due to the increased surface albedo can be observed in the sealed old town center. The reduction of air temperature is notably less distinctive in the case of intensive irrigation management. Regarding the PET, the removal of vegetation is associated with a stark decrease in human thermal comfort, and the effects are on a much smaller scale compared to $T_a$.

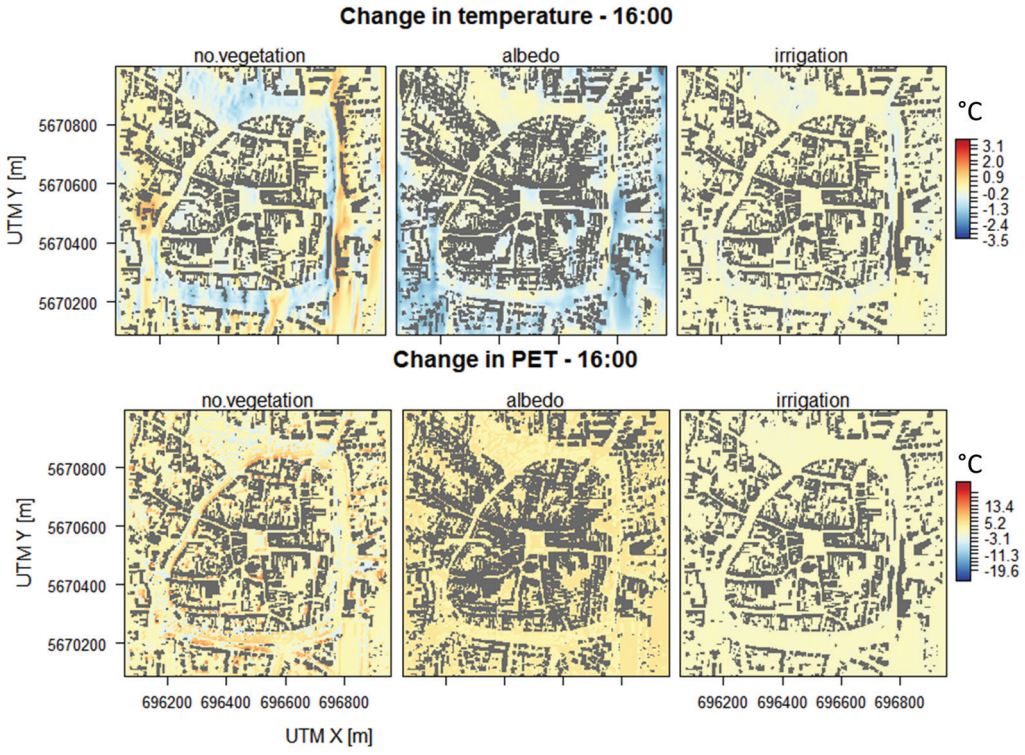


**Figure 7.** Differences in $T_a$ (upper panel) and PET (lower panel) between the scenarios 1, 2, and 3 and the current state at a height of 1.4 m above the ground on 04.07.2015 at 16:00. (Grey areas: buildings).

### *3.3. Temperature Contributions in Terms of Biophysical Processes for Climate Adaptation Scenarios*

While considering changes in temperature does not allow the identification of the precise causes of respective alterations, a physically comprehensive assessment can be achieved by examining the surface temperatures in terms of energy fluxes. Using the decomposition approach (Section 2.5), we can quantify the mechanism of action of the respective climate adaptation scenarios. While, in the following, we mainly refer to diurnal changes of spatial mean values (Figure 8), our online tool shows the spatial variation of each time step as well, and, thus, might be able to support the decision-making for local stakeholders.

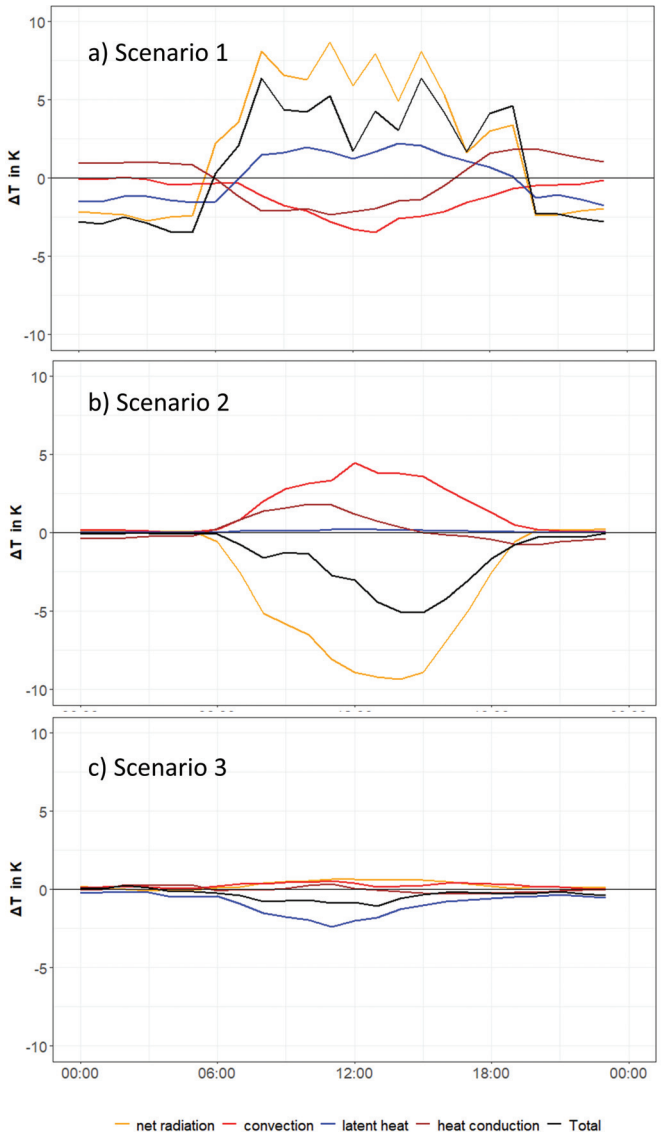


**Figure 8.** Diurnal variation of the total differences of the spatial mean values of $T_{SFC}$ in terms of the biophysical processes for the absence of vegetation (**a**—Scenario 1), an increase in surface albedo (**b**—Scenario 2), and surface irrigation (**c**—Scenario 3) compared to the current state.

#### 3.3.1. The Effect of the Absence of Vegetation

The removal of vegetation leads to a reduction in the surface temperature during the night, while the surface temperature increases significantly during the day (black line in Figure 8a).

Changes in radiation are the main contributing factor to this pattern (yellow line in Figure 8a). During the day, vegetation removal is associated with significantly less shading and increasing net radiation at the surface. At night, urban trees prevent cooling due to a significant reduction of the sky-view factor under the tree canopy, as the long-wave radiation emitted from the ground is reflected, absorbed, and also re-emitted [50].

The general trend of the influence of convection shows a daytime cooling effect and thus is reversed compared to the change in radiation balance (red line in Figure 8a). In the absence of vegetation, the sensible heat flux is significantly higher, and due to the lower $r_a$, which is associated with a higher convection efficiency, reduces the difference between surface and air temperature. Furthermore, the turbulent spectrum contains larger convection cells that are more effective at removing heat from the surface than smaller ones [39]. This is because $r_a$, which can be interpreted as the resistance of the interface to

the temperature gradient, decreases with increasing wind speed due to the greater mixing of the air masses. The lower $r_a$ is, the higher $Q_H$ is, which leads to higher heat dissipation. At night, this effect is much less pronounced due to the low $Q_H$.

Since the tree canopies can contribute to evapotranspiration, a warming effect can be observed for the removal of vegetation scenario (blue line in Figure 8a) during the midday period. However, since stomatal resistance of the leaves was very high at noon, the cooling potential due to transpiration was significantly reduced (local minimum of the blue line at noon). This could be attributed to the heat stress conditions of the vegetation resulting in a closing of the stomata [51,52].

Vegetation prevents heat transfer to the soil to some extent, resulting in less heat storage in the soil (brown line in Figure 8a). Therefore, decreased surface temperatures can be observed in the scenario without vegetation, as more heat is transported away from the surface. During the night, the stored heat is released and warms the surface.

Nevertheless, in scenario 1 processes leading to warming tend to dominate during the daytime, wherefore a significant increase of the surface temperature can be observed through the absence vegetation.

#### 3.3.2. The Effect of an Increase of Surface Albedo

A notable daytime decrease of $T_{SFC}$ can be observed (see Figure 8b). Due to an increase in surface albedo, the net radiation at the surface level is significantly reduced. Thus, significantly less energy is absorbed and available at the surface.

The influence of evaporative cooling is almost nonexistent in this scenario. This is plausible since this scenario mainly refers to changes in properties of sealed surfaces where almost no evapotranspiration takes place.

Through significantly reduced net radiation, both the convection of heat and the conduction of heat into the ground are reduced since less energy is available for partitioning into SEB components. Thus, the transport of heat from the surface is prevented, wherefore the surface temperature tends to increase. Nevertheless, the cooling effect of less absorbed radiation still overcompensates the warming tendencies by convection and heat storage.

#### 3.3.3. The Effect of Surface Irrigation

Increased soil moisture leads generally to a slight cooling effect ($\leq$1 K) throughout the day, which is most pronounced at noon but almost diminishes at nighttime (see Figure 8c).

This cooling effect is mainly due to the increased evapotranspiration rates. Notably, the cooling effect still endures during the night due to the existence of the oasis effect. Irrigation of areas lowers the respective surface reflectance (albedo decreases from 0.222 to 0.213). This results in a slightly positive $\Delta T$ during daytime; opposite to the radiation effect in the albedo scenario.

The temperature effect due to changes in the storage of heat is not very pronounced for the moisture scenario. Higher water availability tends to increase surface temperatures slightly in the morning, while the trend reverses around noon. The most important factor for this pattern is the very high specific heat capacity of water so that more energy is required to warm the soil in the morning.

Due to the increased evapotranspiration, the Bowen ratio falls while net radiation and heat storage rise just slightly which implies a lowered convection and cooling of the surface.

Even though convection, radiation and heat storage tend to increase the $T_{SFC}$, the evaporative cooling still prevails.

## 4. Discussion

### *4.1. The Role of Street Trees for Urban Climate Adaptation*

#### 4.1.1. The Role of Street Trees for Urban Climate Adaptation during Daytime

Numerous studies indicate the potential of trees to reduce air temperature $T_a$ through measurements and simulations [53–56], but the simulation results of this work show an increase of $T_a$ by trees during the day. Nevertheless, urban trees have a positive effect

on daytime thermal comfort, which is mainly due to the reduction of $T_{mrt}$ associated with shading since mostly the wind speed is relatively low on heat wave days in Central Europe [10,57]. However, urban trees also lead to a densification and an increase in roughness of the urban environment which may attenuate dominant wind flow patterns and hinder turbulent air exchange. Both are decisive for the removal of heat and can lead to higher air temperatures below the tree canopy [15,57].

The mechanisms of action of trees on the urban climate, which could be quantified in terms of biophysical processes (see Section 3.3) which include the provision of shading, an increase in evapotranspiration, and a reduction in ventilation (see Section 3.3). The evapotranspirative cooling is minor, though. Thus, if urban trees are to be used as efficient climate adaptation measures, there is mainly a conflict between shading and ventilation that necessitates finding good compromises [58,59].

Many authors emphasize the importance of specific cold air corridors to improve thermal comfort through advection of cool air masses [59–61]. Thus, a too large amount of trees might act as obstacles and hinder an effective ventilation in the urban environment and the selection of the respective locations of the trees needs to be chosen carefully for climate adaptation.

#### 4.1.2. The Role of Street Trees for Urban Climate Adaptation during Nighttime

During nighttime urban vegetation tends to increase both $T_a$ and PET, as the long-wave radiation loss is attenuated by the tree crowns and transpiratory cooling no longer occurs. To enable efficient nighttime cooling, a sufficiently large distance between the trees is necessary. However, this increase in nighttime PET is less dramatic than during daytime since outdoor thermal stress conditions are less pronounced. The impact on indoor climate should be evaluated as well, though. Therefore, urban trees, can not be considered as a suitable tool to attenuate effects such as the nocturnal UHI.

#### 4.1.3. Implications

As the impact of trees on the urban climate shows different effects during daytime and nighttime, the goal of the respective climate adaptation scenario needs to be specified. This study focuses on thermal adaptation in small and medium-sized communities where nighttime UHI formation is much less pronounced than in metropolitan areas. Therefore, the improvement in daytime thermal comfort tends to outweigh the nighttime warming effect.

For an improvement of daytime thermal comfort, the optimum tree configuration consists of maximum shading while the attenuation of ventilation should be as low as possible. Since wide, east-west facing streets get exposed to solar radiation for a longer time than narrow north-south facing street canyons, which increases the likelihood of thermal discomfort, the presence of vegetation there is particularly important [62,63]. Furthermore, large open spaces where people are prevailing for longer times need to be shaded as well.

To minimize the disadvantages of vegetation by densification leading to reduced ventilation and reduced heat removal, a site analysis should be performed which accounts, e.g., for flow corridors for cold air advection. Since narrow street canyons are already shaded throughout the most time of the day, additional urban trees tend to warm the environment there.

Finally, urban green areas provide further ecological benefits such as an increase in urban biodiversity, water retention during storm water events, and visual enhancements [64,65].

### *4.2. Climate Adaptation Using Irrigation Policies and Highly Reflective Materials*

Despite a reduction of $T_a$, irrigation worsens thermal comfort because of higher air humidity superimposing the evaporative cooling (Figure 6). Thus, intensive irrigation policies during extreme heat wave events can not be recommended. Nevertheless, irrigation of the plants during dry periods is essential to promote vegetation health and suitable growing conditions. Ref [24] emphasizes the importance of preserving existing trees because

newly planted trees are usually young plants with a small crown volume. In addition, new plantings are time-consuming and often associated with high costs, wherefore the loss of large shady trees is not easily compensated.

While an increase in street albedo can reduce $T_{SFC}$ and $T_a$ of the overlaying air layers significantly, the implementation can not be recommended since it is accompanied by a substantial increase in $T_{mrt}$ and a worsening of thermal comfort at pedestrian level. Nevertheless, an increase of roof surface albedo might be a promising approach as the increase in $T_{mrt}$ would not affect the inhabitants.

### *4.3. Limitations of the Study*

The performed analysis focuses on an extreme heat wave event with maximum $T_a > 36$ °C which so far occurs not so often (a total of 14 days during the last climatological reference period 1991–2020, according to the DWD weather observation station). However, the likelihood of such heat wave events is going to rise due to climate change, so this could be a typical summer scenario in the coming decades [1,21]. In our simulations, extreme heat stress conditions were predominant, which even prevailed beneath the trees wherefore an improvement in thermal comfort can only be achieved to a limited extent. The need for climate adaptation is particularly required in these periods, though. As the formation of urban heat depends on many factors, other meteorological conditions may alter the results concerning $T_a$, PET and $\Delta T$ contributions of the climate adaptation scenarios significantly [66].

The simulation results are representative for urban areas with similar building configurations as those typical for many town centers of small and medium-sized communities in Germany/Europe. The selected days had a relatively constant wind direction (south), which can be observed during enduring heat events. However, mostly the study area is affected by westerly winds, and this might significantly alter the simulation results in terms of ventilation and the removal of heat in the urban environment. Ref [39] found notable and pronounced differences due to the variation of the wind direction on the effects of convection efficiency and heat storage. Therefore, further studies with different wind speeds and directions are recommended to be conducted in order to evaluate the impact of the various scenarios.

Furthermore, the tree register used in this study did not have complete data on the characteristics of the trees. Therefore, trees with unknown properties were defined and digitized with default characteristics (size, diameter, leaf area density, etc.). However, the climatic effectiveness of trees depends, in addition to the location, on these respective plant characteristics as well [67,68]. Ref [69] reported overestimations of $T_{mrt}$ leading to very high values of PET in ENVI-met. Finally, due to the very high computational time required for micrometeorological simulations, only selected scenarios can be considered - an operational forecast for every day would not be feasible at present.

## 5. Conclusions

This study investigated the potential of various climate adaptation approaches (i.e., urban green spaces, surface albedo, and irrigation of unsealed areas) to improve urban heat resilience in the city center of a medium-sized community. These approaches to climate adaptation are accompanied by undesirable trade-offs requiring compromises by local stakeholders. Therefore, we provided a user-friendly online visualization tool that allows the exploration of the effects of various climate adaptation scenarios. Based on model simulations using the urban climate model ENVI-met, these approaches were compared in terms of $T_a$, PET, and $T_{SFC}$. Furthermore, we applied a decomposition algorithm in order to quantify the mechanism of action.

The shading provided by urban trees could be identified as the main contribution to the reduction of $T_{SFC}$ and PET as well. Thus, human thermal comfort can be significantly improved by using trees due to the shading effect during the daytime. Evapotranspiration contributes much less to urban cooling compared to other biophysical processes. Reduced

ventilation counteracts these cooling effects, though. During the night hours, however, urban trees cause less cooling and an increased heat perception due to the radiation getting trapped under the treetops.

While both an intensive irrigation of the unsealed areas and an increase of surface albedo can reduce $T_a$, and $T_{SFC}$, they can not be recommended for the improvement of daytime thermal comfort during a heat wave event.

Nevertheless, since an increase of surface albedo can significantly reduce $T_a$ of the overlying air layers, the implementation might be a promising approach at roof surfaces as the increase in $T_{mrt}$ would not affect the inhabitants.

As was shown in our discussion, the selection of the most suitable approach for urban climate adaptation varies with time as well as the site characteristics and a generalization is not possible. For that reason, the presented software is a useful tool for climate adaptation of cities.

**Author Contributions:** Conceptualization: N.W., F.Z. and U.S.; methodology: N.W. and F.Z.; software: N.W.; validation: N.W. and F.Z.; formal analysis: N.W. and F.Z.; writing—original draft preparation: N.W.; writing—review and editing: N.W. and U.S.; visualization: N.W.; supervision: U.S.; project administration: N.W. and U.S.; funding aquisition: U.S. All authors have read and agreed to the published version of the manuscript

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**Data Availability Statement:** A visual representation of the simulation results is available at https://webapp.ufz.de//KlimaKonform//urbansimulation//Naumburg.

**Conflicts of Interest:** The authors declare no conflict of interest.

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# Locational Dynamics of Luxury Hotels in Shanghai Metropolis, China: A Spatial-Temporal Perspectivev

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**Abstract:** This study aims to investigate the spatial associations of luxury hotels by using geographical information system (GIS) tools and the multiscale geographically weighted regression (MGWR) model to examine the relationships between the distribution of luxury hotels and exogenous (regional) determinants of urban subdistricts in which the luxury hotels are located. Shanghai City is used as an example. The study first introduces the spatial-temporal characteristics of luxury hotels in Shanghai City, and the key exogenous determinants that contribute to luxury hotel location choice are identified with the MGWR model. The nearest neighbor index decreased from 1.01 to 0.47 and Moran's I statistics increased from 0.268 to 0.452, revealing that the spatial-temporal evolution pattern of luxury hotels presents a cluster trend from 1995 to 2015. The significance level of the standard regression coefficient shows that the institutional proximity, room rate, green space and the World Expo are the primary determining factors that influence the distribution of luxury hotels in Shanghai City. The analysis is important theoretically, as it presents new and novel methodologies for shedding light on the influencing factors of the locational dynamics of luxury hotels. Meanwhile, it enriches the methodologies for analyzing the relationships between luxury hotels and urban structures, and it is important for practitioners, as it provides strategic information that would enable them to globally select appropriate locations for luxury hotels.

**Keywords:** luxury hotels location; spatial-temporal characteristics; influencing factors; Shanghai City

## 1. Introduction

Locational choice has been listed as one of the most influential factors for a hotel's long-term business prosperity and success [1–3]. A superior location is significantly associated with higher demand [4], customer purchasing intention [5], and thus higher revenue, better performance and market profitability [6] and elevated customer satisfaction [7]. In contrast, poor choices of locations increase capital costs, reduce hotel performance, and increase failure rates [8]. Once a hotel is located in a spatial location, relocating it will incur great cost [9]. As such, an understanding of the spatial-temporal dynamics of the location choices of hotels and the potential factors, consisting of a superior location, is of great importance for the hotel industry and urban development. On one hand, the analysis of hotel location can help local governments and tourism organizations better develop and implement strategies to attract new hotels, which will facilitate local economic development [10]. For the urban planners, the study of hotel location choices facilitates the understanding of urban spatial structures and their dynamics [11]. On the other hand, an understanding of the spatial-temporal evolution of hotel location is important for private hotel investors to understand hotel market competition and equilibrium [12].

Although the significance of hotel location is self-evident, the hotel location choice is a highly complex process, involving multi-faceted factors that are often difficult to measure [13]. A large body of literature has been devoted to deciphering hotel location patterns

and mechanisms through different perspectives and disciplines, such as tourism and hospitality management, geography, economics, marketing, and urban planning. Moreover, theories of different disciplines have been introduced to shed light on hotels' location selection, such as geographical theories [14,15], economic theories [16] and marketing theories [9,17]. Several research methodologies, such as qualitative descriptions, the zoning regression model and discrete choice model, have been employed to calculate the pattern of hotel location or mechanisms and summarize the refined hotel location rule based on empirical observations [18–20]. Linear regression has been dominantly used to recognize the preferred site with considerable potential in most existing empirical studies [12], but the limitations associated with simple linear regression result in failure to consider spatial dependency and spatial heterogeneity [21]. To bridge this research gap, significant demand has arisen regarding the use of GIS tools and spatial statistical models to investigate the spatial relationships between hotel location distribution and related factors.

Although the importance of hotel location selections has been long recognized by members of both academia and industry, the relationship between regional factors and hotel locations requires careful consideration. Only a single or a very limited set of location factors have been investigated by researchers [10] and these factors mainly include municipal regulations [22], hotel characteristics, and market positioning [15,23]. These studies were restricted to specific regions or destinations [6,24] and it is still unclear whether and how regional factors affect hotel location distribution in a metropolis. Examining the exogenous factors, such as the business environment, regional attractions and economic development, can help to guide hotel investors in making better location decisions, because the hotel industry requires customers to visit and stay and it is deeply embedded in local regional conditions [25]. A wide variety of factors should be scrutinized for each potential site; nonetheless, to our knowledge, previous empirical studies have not fully addressed the interactions and associations between regional factors and hotel location, and the external environment characteristics, which are likely to affect customers' choice of destination, have seldom been systematically investigated.

With China's fast economic development and increasing globalization, the hotel industry serves the accommodation needs of a burgeoning number of domestic and international travelers [26], as indicated by that fact that the total number of guest rooms in China's star-rated hotels developed rapidly, with a compound annual growth rate of 10%, from 2000 to 2012. Among them, the supply of guest rooms in five-star hotels developed rapidly, with a compound annual growth rate of about 20% (https://m.keyunzhan.com/knews-350972/, accessed on 12 June 2022). Luxury hotels have played an essential role in fostering tourism and stimulating local economic development. Given the significance and consequence of luxury hotels to China's tourist industry, it is essential to investigate how luxury hotels choose their location and the resulting spatio-temporal patterns. The present study aims to answer the following two questions: (1) what are the spatio-temporal patterns in the distribution of luxury hotels in the study area? (2) What are the key factors of the locational choices of luxury hotels? To answer these questions, we present the spatio-temporal characteristics in the distribution of luxury hotels from 1995 to 2015 by using a set of spatial statistical tools. In addition, an innovative multiscale geographically weighted regression (MGWR) model was employed to investigate the driving forces behind the spatio-temporal pattern of luxury hotels from 1995 to 2015.

This paper contributes to the existing hotel location choice literature in four aspects. First, the paper presents a spatio-temporal characterization of the distribution of luxury hotels. Second, this paper investigates and tests the spatial heterogeneity in locational choices of luxury hotels. By using rich geo-referenced firm-level data with detailed information about each luxury hotel in Shanghai City, we can investigate the spatial patterns of luxury hotels in more depth. The location patterns and their dynamics of luxury hotels have been analyzed and compared by using a range of spatial statistical tools, such as the standard deviation ellipse (SDE), nearest neighbor analysis and exploratory spatial data analysis (ESDA). This spatial analysis of the geographic distribution of luxury hotel location assists

in discovering the factors that shape this distribution [20]. Additionally, by investigating this spatial pattern, the set of spatial statistics improves our understanding of luxury hotel location mechanisms and the MGWR model applied in this paper is another innovative feature, and contributes to the literature from the methodology perspective. The MGWR model is a new statistical method used to detect a spatial heterogeneity pattern and reveal potential driving factors behind it [27]. This model improves the classical GWR model by considering different bandwidths of various variables, and then obtains more reliable estimation results. At the same time, the spatial scales of different variables are given, which can effectively explore the spatial heterogeneity and scale effect of the influencing factors of the luxury hotel distribution. This study presents the extended application of the model to examine locational choices in the hotel industry [28].

The remaining parts of this paper are organized as follows. In Section 2, we review location choice of hotels and key literature on hotel location patterns and determinants. In Section 3, we describe our data sources and explain the empirical methodology. In Section 4, we present the estimation results from the specified models. Lastly, in Section 5, final conclusions will be drawn by discussing the theoretical and policy implications of the study, and future research directions will be provided. The technical flowchart is shown in Figure 1.

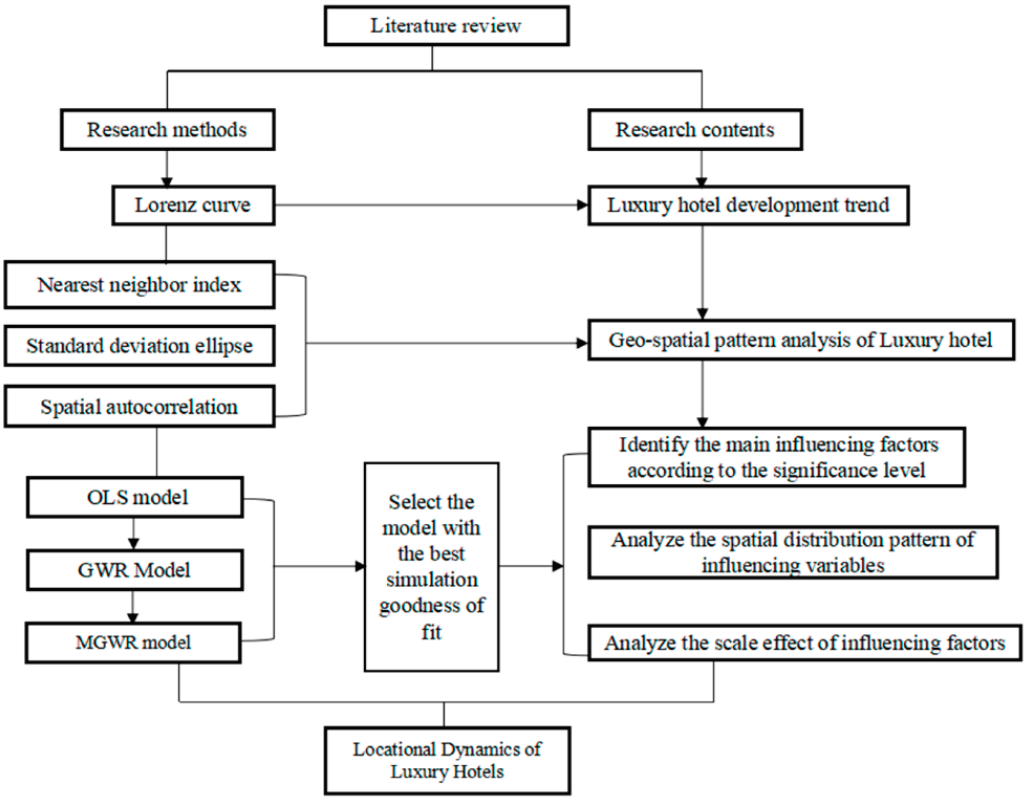


**Figure 1.** The technical flowchart of this study.

## 2. Literature Review

### *2.1. Luxury Hotel Location Models*

According to the previous studies, several theories models have been proposed in the literature to better understand hotel location. Egan and Nield derived a mono-centric model from the partial-equilibrium bid-rent approach, and explained the spatial hierarchy of different hotels' levels in terms of the distance to the city center, suggesting that luxury hotels choose central locations, whereas budget hotels are located at the edge of the city [14]. In fact, because hotels are not randomly distributed, their locations are usually clustered with other heterogeneous or homogeneous hotels to achieve an agglomeration effect, which refers to hotel co-location patterns that potentially lead to competitive advantages

and benefits from clustering [29]. The agglomeration model specifically sheds light on the relative location of new hotels and how to position a hotel relative to other hotel incumbents [12]. Some studies found that lower-end hotels are more likely to receive positive spillover effects by co-locating in a cluster with high-end hotels [30]. Other scholars also pointed out that a price premium is associated with locations close to more upscale and luxury hotels; nevertheless, high-end hotels undergo substantial price erosion by being located close to low-end hotels [31]. In general, the abundance of prior studies on theoretical hotel location models implements different research disciplines. It is important for the luxury hotels to depict the spatial hierarchy of hotel distribution, and it is also significant for the luxury hotels to choose a relative location as suggested by the agglomeration model.

In addition, substantial sophisticated empirical models were also used to explain the choices and spatial patterns of hotel locations; these methods can also shed light on the factors that determine hotel location and help us to understand the driving factors behind the hotel location decision. Two types of empirical models can be used, the count data model (CDM) and the discrete choice model (DCM) [12]. The count data model (CDM) is used to treat the dependent variable as a count number to analyze which characteristics of a zone will affect hotels based on the number of new entrants established there [20,32]. The discrete choice model (DCM) explains hotel location choice based on the economic principle of profit maximization; it is used to examine which characteristics make a zone more attractive than others [12,33,34]. Some scholars applied a binary logistic model to understand the location choices of upper-grade and lower-grade hotels in Hong Kong [35]. In numerous intra-metropolitan and intra-regional studies, many sophisticated spatial statistical tools have emerged to shed light on the spatial distribution of hotel location and these spatial statistics can be used to investigate the dependence and relationship of observations over a particular space [26], such as geographically weighted regression tools [36], the nearest neighbor analysis, standard deviational ellipses and so on. Along with a wide range of available geographic information data and computerized technology, GIS has been a powerful and credible tool to analyze hotel location distribution. This paper will employ some new GIS tools to investigate the luxury hotel location questions in Shanghai City of China.

### *2.2. Factors Influencing the Location Distribution of Luxury Hotels*

Previous studies focused on hotel-level factors, such as capital investment, star rating, the quality of facilities, ownership and service diversity [20,37,38]. Egan and Nield found that large hotels generally tend to be located far from the city center to reduce the land cost [14]. In addition, the larger a new hotel is, the closer it will choose to be to other hotels [17]. Hotels with different star ratings cater to different potential markets and luxury hotels commonly attract affluent business travelers, so these hotels prefer a central location in the city [20]. Newell and Seabrook revealed that the main influences on hotel investment decisions were financial factors [39], while Ruggero and Rodolfo found that structural social capital was the stronger positive determinant of hotel performance [40]. Some researchers argued that service diversification was a helpful strategy to improve the stability of hotel performance [41,42] and other studies emphasized the importance of entrepreneurship and various promotion strategies [43,44]. These determinants can be considered individual hotel characteristics and consist of the hotel's internal management.

Compared to the extensive studies on internal factors, the influences of regional or external factors on hotel location, especially on luxury hotels, are relatively under-researched. The hotel industry is closely linked to tourism and economic activities, which are in turn driven by general economic conditions, the business environment, and market supply and demand. For instance, some studies found that a wide range of destination-related external factors are the most important determinants among the competition for international hotel chains, such as business regulations market size and socioeconomic factors [45]. Other scholars argued that the economic efficiency of the hospitality industry in Spain was significantly affected by regional tourist flow [46].

Tourism resources are an important element of hotel location choice and the eclectic paradigm clearly indicates that "opportunities for tourism" are an important influence on international hotels' choice of a host location [47]. In addition, international meetings, incentives, mega-events, and exhibitions have boosted local economic development [48]. This business and also shopping activities help to form an important nexus that links the hotel industry with regional economic development. The impact of mega-events, such as international festivals and sports competitions, has drawn the attention of some researchers [49,50]. Other scholars found that mega-events (the Olympic Games, for example) were significant factors in the choice of hotel location in China, because hosting a mega-event requires the host city to provide sufficient accommodation for guests and visitors [51].

Good accessibility to travel destinations and traffic facilities is found to be an important factor that influences hotel locations [52,53]. Some studies argued that hotels were likely to choose locations with a high supply of public goods and an abundant supply of services, because proximity to rich public infrastructures can influence a hotel's room rates and generate higher revenue for hotels [54,55]. Barros found that hotels close to potential markets outperform their counter parts with poor accessibility in terms of efficiency [56]. From the tourists and consumers' perspective, when making a hotel location decision, it is thought that the objective of selecting a good hotel location can be accomplished if accessibility to facilities such as commercial districts, airports or railway stations, and tourism attractions can be taken into consideration [53].

In addition, the economic conditions affect the occupancy rates and the revenue generated per available room of hotel firms [57]. It is arguable that the level of economic development affects the level of competition at various hotel locations [58]. In urban areas, the choice of hotel location is highly dependent on urban development, which inevitably changes urban structures. For instance, Bégin recognized that with urban structure change, the locations of hotel had altered accordingly in Xiamen of China [59]. Available evidence from other literature also confirmed that the location of hotels established in different periods is highly associated with urban development [60,61].

Aside from the aforesaid regional factors, spatial agglomeration is also regarded as an important determinant of hotel locations [62]. Generally, hotels that choose to spatial agglomerate can gain a significant positive spillover effect from their neighbors in hotel efficiency [56]. Freedman and Kosová found that hotels particularly prefer locations with a high concentration of mid-and up-scale neighboring hotels [63]. In Chinese cities, the spatial agglomeration is more obvious because the role of agglomeration economies may hold more importance due to the large size of the city [10,64].

## 3. Methods and Data

### *3.1. Study Area*

Shanghai City is an important economic, trade, finance and tourism center of China. It covers a land area of approximately 6340.50 $km^2$, and the population was 24.15 million in 2015 (https://tjj.sh.gov.cn/ydsj/index.html, accessed on 12 August 2022). As of 2015, Shanghai City had a total of 247 star-rated hotels in the Shanghai metropolitan area, including 68 five-star hotels and 66 four-star hotels (https://tjj.sh.gov.cn/ydsj/index.html, accessed on 12 August 2022). Shanghai City attracts a substantial amount of business people and tourists from home and abroad. In 2015, the business revenues of the star-rated tourism hotels were CNY 19,815 million. With increasing income and changes in attitudes towards consumption, tourism consumption is gradually transforming from sightseeing to a high-quality vacation experience, providing a large consumer market for new development of high-star hotels. Several ring roads form the metropolitan transportation skeleton and we restricted our sample to the metropolis area of Shanghai City, which is conventionally defined as eight central urban districts (Huang pu, Jing'an, Hongkou, Xuhui, Changning, Putuo, Zhabei and Yangpu), four inner suburban districts (Pudong, Minhang, Baoshan and Jiading) and five outer suburban districts (Songjiang, Qingpu, Fengxian, Jinshan and

Chongming). The basic census geographic units in Shanghai City are subdistricts (or jiedao). There were about 285 subdistricts within our study area.

### *3.2. Spatial Statistics Approaches*

#### 3.2.1. Exploratory Spatial Analysis Tools

The standard deviation ellipse (SDE) method is commonly used in analyzing the spatial distribution of a point data set, covering the mean center and the standard distance. The long axis of the ellipse aligns with the direction of maximum diffusion, while the short axis aligns with the direction of minimum diffusion. The acreage of the ellipse determines the degree of dispersion of luxury hotels. A smaller acreage indicates that the hotel distribution is closer to the center of gravity. The azimuth indicates the directional trend of the hotel distribution, with angles of 0° and 180° indicating that the distribution of hotels is predominantly in a north–south direction and an angle of 90° indicates that the distribution is predominantly in an east–west direction. Some researchers employed this tool to evaluate the distribution of tourism resources in different destinations [65]. This paper uses the SDE tool to examine the spatial pattern and distribution trend of luxury hotels in Shanghai City.

The nearest neighbor index (*NNI*) can measure the overall characteristics of spatial distribution of the luxury hotels. The *NNI* can be calculated as follows [66]:

$$NNI = d(nn)/d(ran) \tag{1}$$

where $d(nn)$ denotes the nearest neighbor distance; $d(ran)$ denotes the expectation of the average nearest neighboring distance if all luxury hotels are randomly distributed and they can be calculated as follows:

$$d(nn) = \sum_{i=1}^{n} \frac{\min(d_{ij})}{n};\ d(ran) = 0.5\sqrt{A/n} \tag{2}$$

where $n$ is the number of luxury hotels; and A denotes the area. When $NNI < 1$, the sample points represent a clustered distribution; when $NNI > 1$, the sample points tend to be dispersed; when $NNI = 1$, the sample points are randomly distributed.

In order to measure the agglomeration effects of luxury hotels, we will employ a set of exploratory spatial data analysis (ESDA) tools to measure the degree of dependency among luxury hotel locations. Global Moran's I statistic was used to detect the extent of spatial clustering or dependency of hotel locations in the Shanghai metropolitan area, which is expressed as follows [67]:

$$Moran'sI = \frac{n\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3}$$

where $x_i$ and $x_j$ denote the observed values in this study and $\bar{x}$ is the mean value of $x$. $W_{ij}$ is the spatial weights matrix, measuring the connection structure of spatial units in the area. $n$ denotes the number of luxury hotels. A positive Moran's I statistic indicates positive spatial autocorrelation of hotel locations, while negative values indicate dispersed patterns of hotel locations.

For a closer look at the local structure of the spatial distributions of luxury hotels, local Moran's I statistics were also employed and the measure equation is as follows [68]:

$$Moran'sI = \frac{n(x_i - \bar{x})\sum_{j} w_{ij}(x_j - \bar{x})}{\sum_{j=1}^{n}(x_j - \bar{x})^2} \tag{4}$$

In Equation (4), $n$ denotes the number of luxury hotels, $x_i$ and $x_j$ denote the observed values in this study and $\overline{x}$ is the mean value of $x$. $W_{ij}$ is the spatial weights matrix.

The local spatial autocorrelation can be divided into the following four categories of clustering, corresponding to the spatial association between a subdistrict and its neighbors: ① the high-high (H-H) aggregation type denotes a subdistrict with a high value surrounded by subdistricts of high values; ② low-low (L-L) aggregation type denotes a subdistrict with a low value surrounded by subdistricts of low values; ③ high-low (H-L) aggregation type denotes a subdistrict with a high value surrounded by subdistricts of low values; ④ low-high (L-H) aggregation type denotes a subdistrict with a low value surrounded by subdistricts of high values. Therefore, based on the local spatial autocorrelation types, significant hotel location clusters can be visualized and identified.

#### 3.2.2. MGWR Model

The multiscale geographically weighted regression (MGWR) model can consider various bandwidths of different independent variables, and identify the scale effect affected by different variables. Therefore, this study uses the MGWR model to explore the spatial heterogeneity characteristics and scale effect of the influencing factors on the distribution of luxury hotels in Shanghai City. The calculation formula of MGWR model is as follows [69]:

$$y_i = \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \quad (5)$$

where the observation unit $i \in \{1|, 2|, \ldots, |n\}$, $y_i$ denotes the dependent variable, $x_{ij}$ denotes the $j$-th independent variable, $j \in \{1|, 2|, \ldots, |k\}$, $bwj$ denotes the bandwidth of estimating the $j$-th variable, $\beta_{bwj}$ denotes the estimator of the $j$-th parameter at the position ($u_i$, $v_i$), and $\varepsilon_i$ denotes the error term [70].

### *3.3. Data and Variables*

We obtained the data on the number of luxury hotels in each subdistrict from the Shanghai Statistical Yearbook (1996–2016) published by China Statistical Press, and a popular online travel service (www.ctrip.com/, accessed on 20 October 2017). In China, the national tourism administration and travel operators promoted the star classification system, which was quickly accepted as a regulatory system and as a general standard to discriminate between hotel quality levels [25]. Therefore, this study focuses on the luxury hotels that are rated as 4-star or 5-star according to the Standards for Tourist Hotels' Star-rating published by the China National Tourism Administration. The data for our explanatory variables at the sub-district level were obtained from the Shanghai Statistical Yearbook (1996–2016) and other data platforms. Figure 2 presents the spatial location of all luxury hotels in the Shanghai metropolitan area as of 2015. A general pattern was found, that is, most luxury hotels were located around the city center but within the outer ring of the city. The distribution of luxury hotels in Shanghai City also exhibits a clear geographical attenuation trend from the city center.

Our independent variables for explaining locational choices of luxury hotels are divided into several sets (Table 1). The first is transport accessibility, which is measured by the following two indicators: the number of subway stations in each subdistrict and the distance from a luxury hotel to the nearest airport. As Shanghai City is the top financial center in China, the proximity to the nearest financial center was calculated to reflect the impact of market demand on luxury hotel location choice. To capture the effect on hotel location choice of physical environment or natural amenities, we include in our model the number of parks in each subdistrict. In addition, distances of each hotel to the central business center (CBD) are also included in the model. In order to test the potential administrative institution influences on luxury hotel location choice, we also calculate the distances from each luxury hotel to the Shanghai municipal government site and include it our model. Previous studies have argued that the mega events have a significant impact

on local tourism and the local economy [49,50]. Shanghai City hosted the 2010 Expo with the Shanghai Expo Garden constructed along the Huangpu River. We expect that the Expo might have a positive impact on luxury hotel location decisions. Therefore, this paper takes the distance from the World Expo as one of the variables. The average price of hotel rooms may also have a certain impact on the distribution of hotels. Therefore, the average price of hotel rooms is included in the model as a variable.

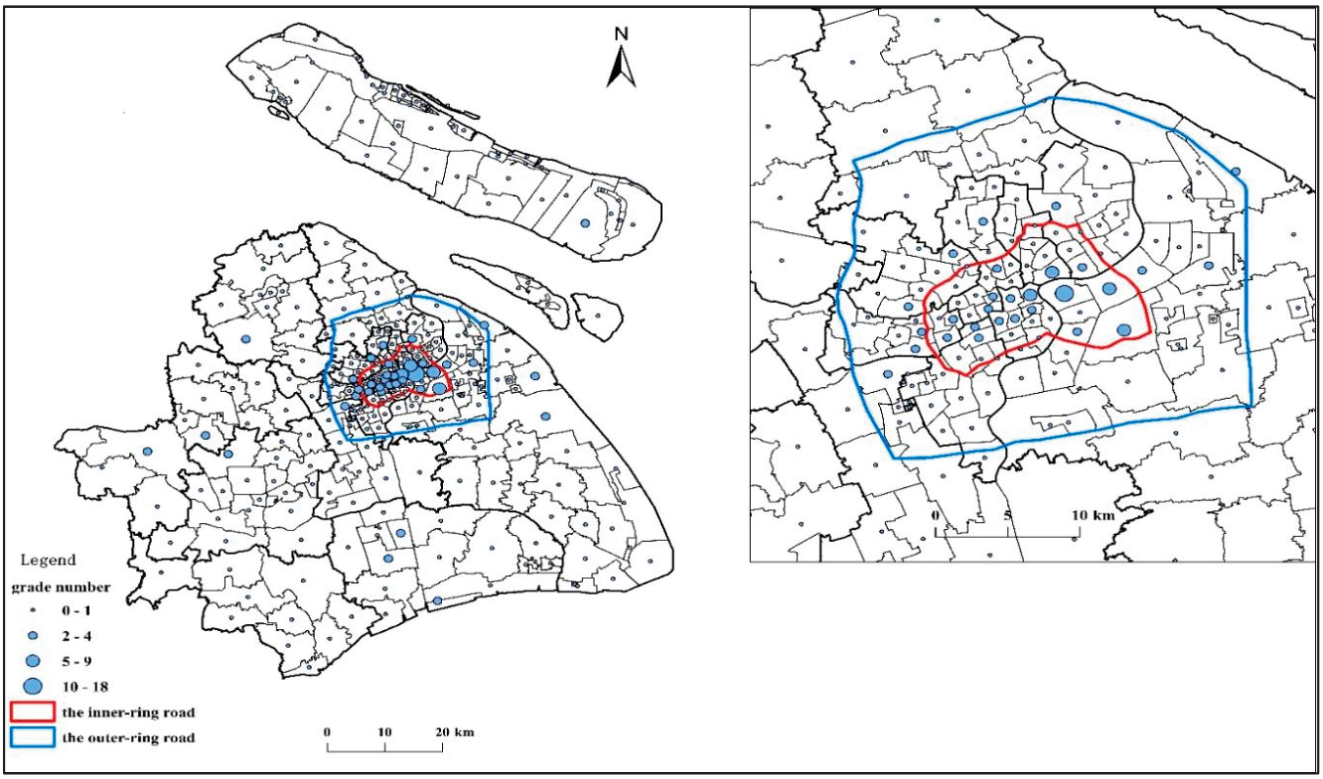


**Figure 2.** Quantitative description of luxury hotels location in Shanghai metropolitan area (2015).

**Table 1.** The descriptive statistics of model variables.

| Indicators | Measurement | Unite |
|---|---|---|
| Transportation accessibility | Number of subway stations in each zone (NS) | Number |
| | Distance to the nearest airport (DA) | Km |
| Market demand | Distance to the nearest financial center (DFC) | Km |
| Business environment | Distance to the nearest business center (CBD) | Km |
| | Room rate (RA) | Yuan |
| Institutional proximity | Distance to municipal government (DG) | Km |
| Green space | Number of parks in each zone (NP) | Number |
| Mega events | Distance to the World Expo (DE) | Km |

## 4. Results

### *4.1. Luxury Hotel Development Trend in Shanghai City*

According to the tourism statistics for the 1995 to 2015 period, the number of luxury hotels increased from 13 in 1995 to 160 in 2015 (Table 2) and the average annual growth rate was as high as 56.5%. The Lorenz curve approached the average line (line AC) during 1995–2015, indicating that the luxury hotels were gradually expanding into the surrounding districts in Shanghai City (Figure 3). This trend is related to the urban development strategy and mega events of Shanghai City; in particular, Shanghai City accelerated the development of its modern service industry and the construction of international financial centers during 2006–2010, and there was a period of rapid growth in the number of luxury hotels at this

time. During this period, the number of luxury hotels increased by 74, and by 32 in 2010 alone because of the 2010 Shanghai World Expo.

**Table 2.** Descriptive statistics of luxury hotels characteristics in Shanghai City.

| Year of Opening | Number of Luxury Hotels | Percent | Total Number of Rooms | Percent |
|---|---|---|---|---|
| Before 1995 | 13 | 8.13 | 4624 | 9.56 |
| 1995–2000 | 11 | 6.88 | 4660 | 9.64 |
| 2001–2005 | 19 | 11.87 | 7041 | 14.56 |
| 2006–2010 | 74 | 46.25 | 20,924 | 43.28 |
| 2010–2015 | 43 | 26.87 | 11,104 | 22.96 |

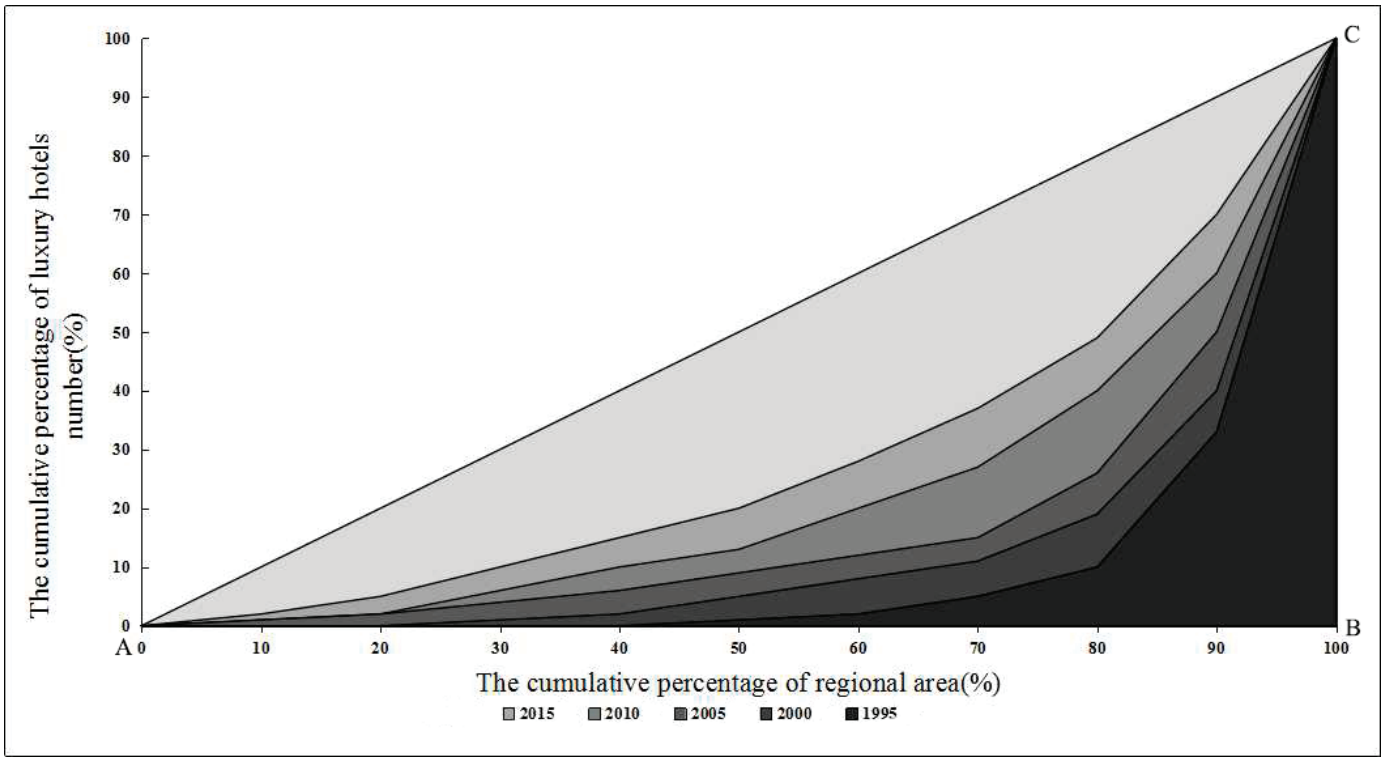


**Figure 3.** Lorenz curve of luxury hotel distribution in Shanghai City.

*4.2. Geo-Spatial Pattern Analysis*

To understand the spatial proximity of the luxury hotels and its dynamics in Shanghai City, the distances between each hotel and its nearest neighbor index were calculated. The nearest neighbor index of luxury hotels decreased from 1.01 to 0.47 during the period 1995–2015 (Table 3), indicating that luxury hotels gradually agglomerated in a particular space. In 1995, because of the low density of luxury hotels, the phenomenon of spatial agglomeration was not clear. In 2000, the nearest neighbor index was less than 1, and spatial clustering emerged at a marginal significance level of 10%. There was significant spatial agglomeration of hotels in 2005 (at the 5% significance level) and stronger agglomeration after 2010 (at a significance level of less than 1%). This suggests that the extent of agglomeration in the distribution of luxury hotels in Shanghai City becomes stronger with time.

**Table 3.** The nearest neighbor index (NNI) of luxury hotels.

| | Sample | Average Distance to the Nearest Neighbor (m) | Expect Distance to the Nearest Neighbor (m) | The Nearest Neighbor Index | Z-Test Value | Significance Level |
|---|---|---|---|---|---|---|
| 1995 | 13 | 97 | 103 | 1.01 | −0.37 | Non-significant |
| 2000 | 24 | 186 | 230 | 0.81 | −1.77 | 0.1 |
| 2005 | 43 | 321 | 443 | 0.72 | −3.45 | 0.05 |
| 2010 | 117 | 165 | 329 | 0.49 | −10.31 | 0.01 |
| 2015 | 160 | 171 | 341 | 0.47 | −12.38 | 0.01 |

Figure 4 depicts the spatial distribution of new hotel entrants in Shanghai City during the research period. In Figure 4a, the overall density of luxury hotels was relatively low, with few luxury hotels and no clear agglomeration pattern in 1995. The distribution density was highest in the Nanjing East Road and Huangpu District. In 2000, the initial development stage of luxury hotels in Shanghai City was reported. There was an increasing number of luxury hotels, and an agglomeration trend gradually emerged. In Figure 4b, it can be observed that the regions of highest density were concentrated in the Pudong New Area. This was mainly due to the implementation of the Pudong New Area Development Policy. All-round cooperation with foreign investment resulted in a rapid increase in the number of luxury hotels in Pudong New Area. At the same time, the location of luxury hotels was beginning to spread to suburban areas in Shanghai City. In 2005, the distribution density of luxury hotels increased greatly, and the agglomeration phenomenon was clear. In Figure 4c, it can be observed that the areas of highest density were in the Lujiazui zone (financial center of Shanghai). With the Expo 2010 held in Shanghai, a series of policies, including promotion of the development of the modern service industry and the construction of the Shanghai international financial center, were introduced. The luxury hotel industry entered a stage of rapid development. In Figure 4d, one can observe that the areas with a high density of luxury hotels were mainly concentrated around the city center and the Expo site. This result indicates that the location around the Shanghai Expo site was attractive for new luxury hotel entrants before the Expo. In 2015, the spatial distribution of luxury hotels in the suburbs of Shanghai City gradually became the mainstream distribution. Figure 4e shows that the number of luxury hotels located near the Expo site decreases, which might be a signal of excess hotel room supply in the area.

Figure 5 provides the maps of the barycenter and SDE of luxury hotels from 1995 to 2015. The barycenter of the new luxury hotel entrants' distribution gradually shifted to the north–east direction. In 1995, the barycenter of luxury hotels was located near the Nanjing West Road in the Jing'an District. With continuous development of the hotel industry, the barycenter elongated along the south–east direction to the vicinity of the Huangpu District in 2000. Then, the barycenter began to move towards the north–east direction in 2015. In addition, the SDEs of luxury hotels from 1995 to 2015 are different, suggesting that the centroid of hotel locations evolved significantly with time. Among them, the SDEs in 2015 were much larger than that in 1995, indicating that the agglomeration effect was significantly enhanced.

### *4.3. Spatial Autocorrelation Analysis*

The global Moran's I statistics for the luxury hotels in different years are all positive and statistically significant (Table 4). More importantly, Moran's I statistics increase from 0.268 in 1995 to 0.452 in 2015, indicating an increasing level of spatial clustering in the distribution of luxury hotels. The local spatial clustering patterns are revealed by using the LISA statistics, with local clustering maps of luxury hotels presented in Figure 6. The H-H clusters are mainly distributed in the Pudong New Area, the Nanjing East Road of the Huangpu District, and the Nanjing West Road of the Jing'an District. The H-H cluster reveals a hot-spot for hotel locations, suggesting a greater geographic concentration

of luxury hotels in these areas. Alternatively, the L-L clusters highlight the areas where there is a less-developed hotel industry. L-L clusters cover the areas in the Langxia zone, Jinshan District, and Chongming County. The H-L clusters suggest that the area with more luxury hotels is adjacent to areas with fewer luxury hotels and the H-L clusters are mainly distributed in the Jiading District. The L-H clusters highlight the fact that the areas with fewer luxury hotels are adjacent to areas with more luxury hotels. The distribution of L-H clusters is mainly attached to the surrounding areas of H-H clusters.

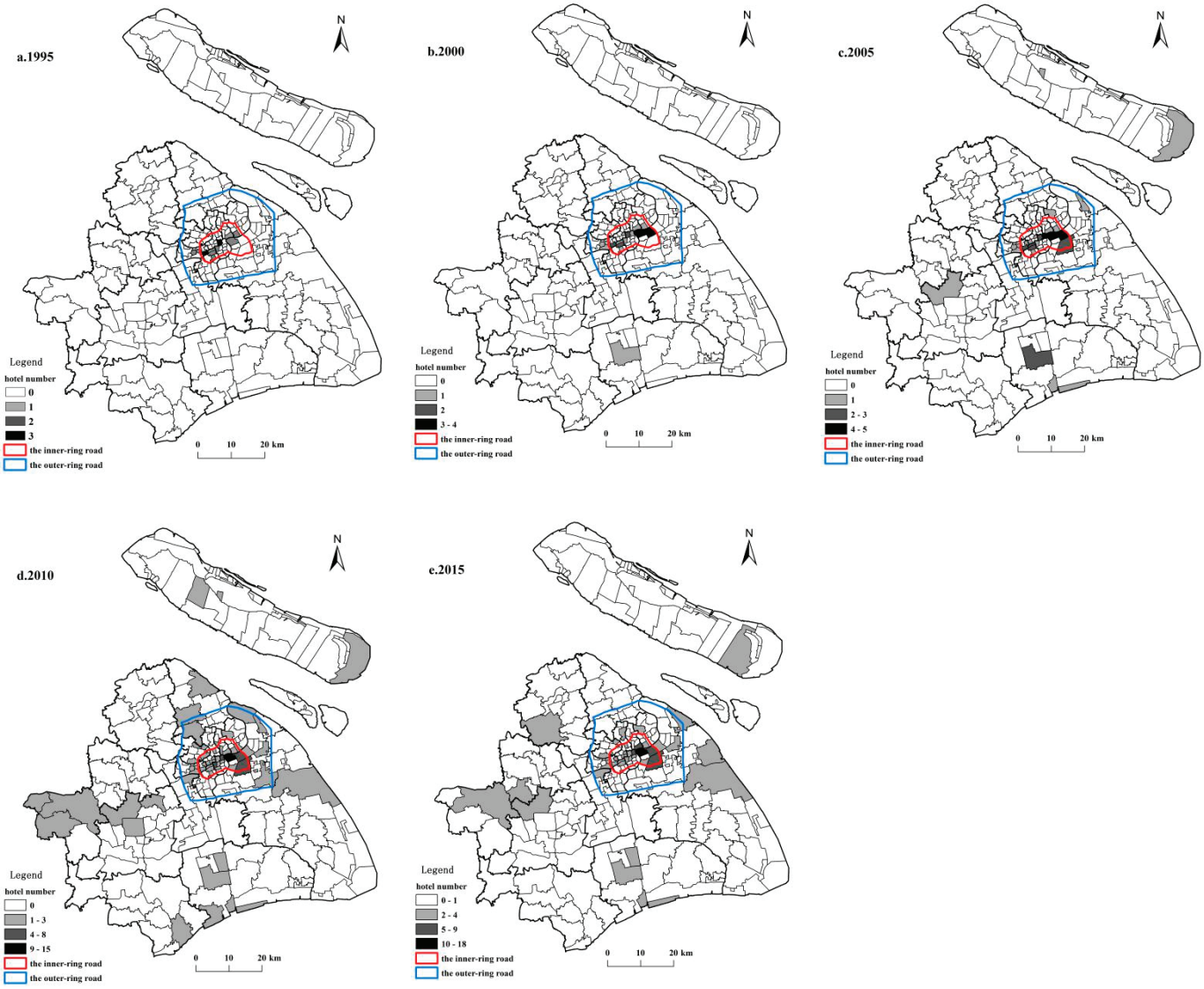


**Figure 4.** Spatial distribution of luxury hotels in Shanghai City.

**Table 4.** Moran's I index for luxury hotels in Shanghai.

| Year | Moran's I Value | *p*-Value | Z(I)-Score |
|---|---|---|---|
| 1995 | 0.268 | 0.001 | 7.775 |
| 2010 | 0.314 | 0.001 | 9.089 |
| 2015 | 0.452 | 0.001 | 12.76 |

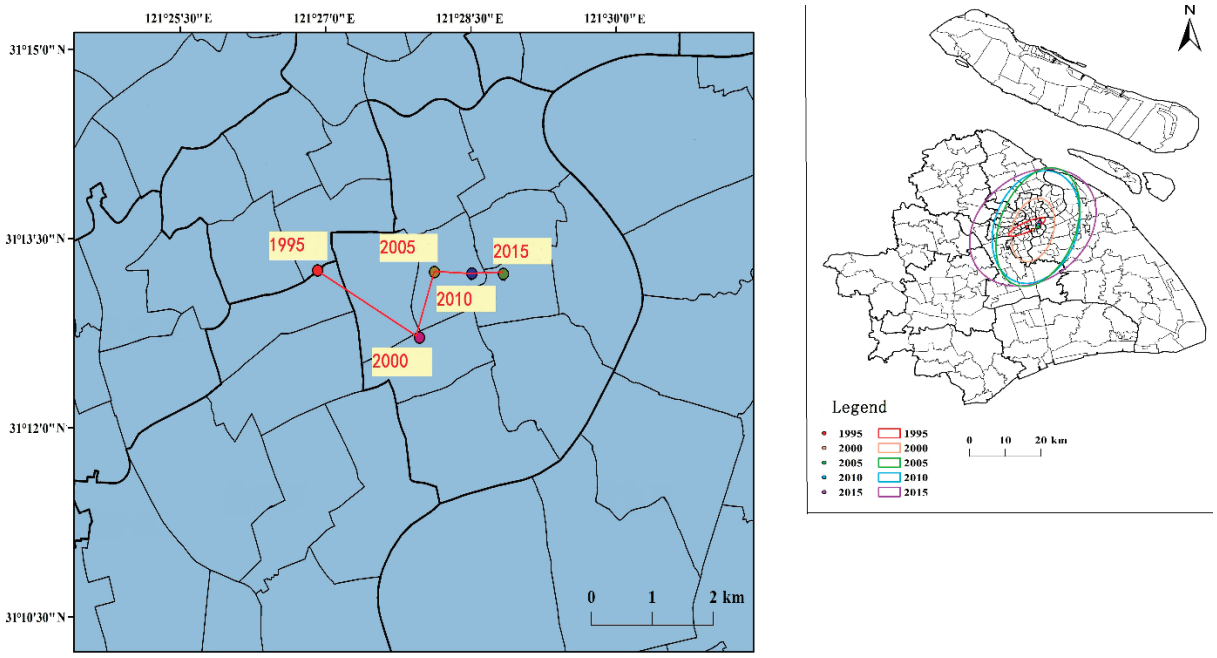


**Figure 5.** The barycenter distribution (**left**) and standard deviational ellipse (SDE) map (**right**) of luxury hotel locations from 1995 to 2015.

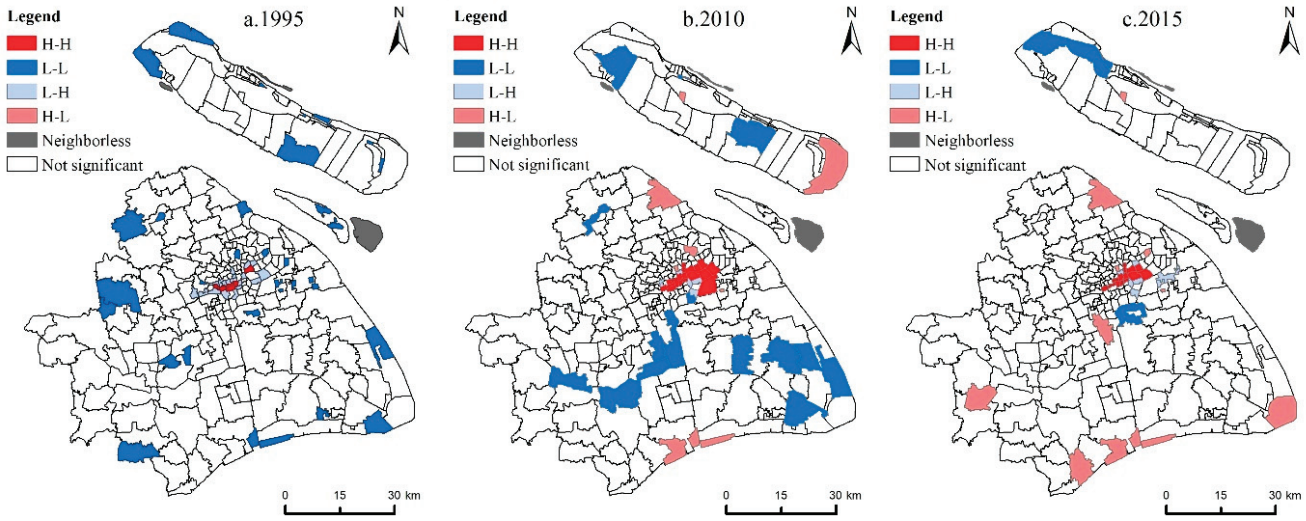


**Figure 6.** LISA spatial cluster map of all luxury hotels in Shanghai.

## 5. Factors of Luxury Hotel Location

In the analysis of influencing factors on the spatial distribution of luxury hotels in Shanghai City, this study constructs the following three regression models: the OLS model, GWR model and MGWR model. Before calculating the model results, we conducted a collinearity test on the independent variables and the results showed that the variance expansion factor is less than 7, indicating that there is no collinearity between each variable. By analyzing the results of these three models (Table 5), it is found that the $AIC_C$ values of OLS, GWR and MGWR are 194.085, 196.331 and 193.769, respectively. The $R^2$ value gradually increases in OLS, GWR and MGWR, and the maximum value is found in the MGWR model (0.551). Thus, the fitting effect of the MGWR model is the best among the three models. In addition, the MGWR model has various bandwidth choices for different influencing factors, so the MGWR model is more suitable for studying the influencing factors of luxury hotel distribution in Shanghai City.

**Table 5.** Model results of OLS, GWR, and MGWR.

| Variables | Model1: OLS | | Model2: GWR | | | Model3: MGWR | | |
|---|---|---|---|---|---|---|---|---|
| | $\beta$ | $T$ | $\beta$ | $T$ | Bandwidths | $\beta$ | $T$ | Bandwidths |
| Intercept | 0 | 0 | −0.027 | −0.263 | | −0.079 | −0.615 | |
| DFC | 0.058 | 0.178 | 0.328 | 0.653 | 75 | 0.215 | 0.456 | 75 |
| DA | 0.307 * | 1.422 | 0.277 | 1.224 | 75 | 0.238 | 1.072 | 75 |
| CBD | 0.003 | 0.008 | 0.000 | 0.004 | 75 | −0.052 | −0.138 | 75 |
| DG | −0.424 | −0.685 | −1.206 ** | −1.617 | 75 | −1.488 *** | −2.036 | 75 |
| NP | 0.14 * | 1.373 | 0.213 *** | 1.929 | 75 | 0.208 ** | 1.892 | 73 |
| NS | 0.09 | 0.788 | 0.087 | 0.753 | 75 | 0.087 | 0.777 | 73 |
| DE | −0.032 | −0.053 | 0.481 | 0.700 | 75 | 0.943 * | 1.382 | 75 |
| RA | 0.486 *** | 4.927 | 0.507 *** | 4.945 | 75 | 0.487 *** | 3.908 | 50 |
| AICc | 194.085 | | | 196.331 | | | 193.769 | |
| $R^2$ | 0.447 | | | 0.504 | | | 0.551 | |
| Adj.$R^2$ | 0.381 | | | 0.403 | | | 0.445 | |

Notes: $\beta$ represents the average estimates of variables. $T$ represents the average $t$ values of variables. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Firstly, the results of the MGWR model are analyzed. It can be found from the estimation results that the distance to the nearest financial center (DFC), distance to the nearest airport (DA), distance to the nearest business center (CBD), number of subway stations (NS) in each zone and other variables have no significant impact on the number of luxury hotels in Shanghai City. Distance to municipal government (DG) has a significant negative impact on the number of luxury hotels, indicating that the closer the area is to the municipal government, the fewer hotels there are. The number of parks in each zone (NP) has a significant positive impact on the number of luxury hotels. The more parks distributed in the subdistricts, the more luxury hotels there are. For distance to the World Expo (DE), the luxury hotels are closer to the Expo and the more hotels there are. Meanwhile, the room rate (RA) has a positive correlation with the distribution of luxury hotels. The average prices of hotel rooms are higher and the more luxury hotels are distributed in the subdistricts. It is worth mentioning that from the coefficient $\beta$ in absolute terms, distance to municipal government (DG) is the most dominant influence on the distribution of luxury hotels.

Secondly, this study uses ArcGIS 10.2.2 software to visualize the regression coefficients of variables with significant influencing factors, as shown in Figure 7. Different variables have significant spatial differences in the number of luxury hotels in different subdistricts of Shanghai City. There is a negative correlation between distance to municipal government and the distribution of luxury hotels. The higher negative value mainly appears in the north subdistricts of the city, mainly in the Baoshan District and Chongming District. The number of parks in each zone (NP) has a positive correlation with the number of luxury hotels in the subdistricts of Shanghai City. The high values of the regression coefficient are mainly distributed in the eastern zones of the city, such as Pudong New Area and Huangpu District. The low value areas are mainly distributed in the subdistricts of the Jiading District, Qingpu District and Songjiang District. This shows that the number of parks in each zone (NP) has a greater impact on the distribution of luxury hotels in the eastern part of Shanghai City, and a smaller impact on the distribution of luxury hotels in the western part of the city. The distance to the World Expo (DE) has a positive correlation with the number of luxury hotels in the subdistricts. The high value areas of the regression coefficient are mainly distributed in the subdistricts of the Qingpu District, Songjiang District, Pudong New Area and Jinshan District, while the low value areas of the regression coefficient are mainly distributed in the subdistricts of Baoshan District, Jiading District and Songming District in the north of the city; this shows that distance to the World Expo has a relatively small impact on the spatial distribution of luxury hotels in these subdistricts. On the whole, the impact of distance to the World Expo on the distribution of luxury hotels gradually decreases from the south to the north in Shanghai City. The room rate (RA) also shows a positive correlation with the number of luxury hotels in the subdistricts, and its regression coefficient gradually

decreases from the northeast to the southwest of Shanghai City, which indicates that room rate has small impact on the number of luxury hotels in the Qingpu District, Songjiang District and Jinshan District, but it has a significant impact on the number of luxury hotels in Pudong New Area, Baoshan District and Chongming District.

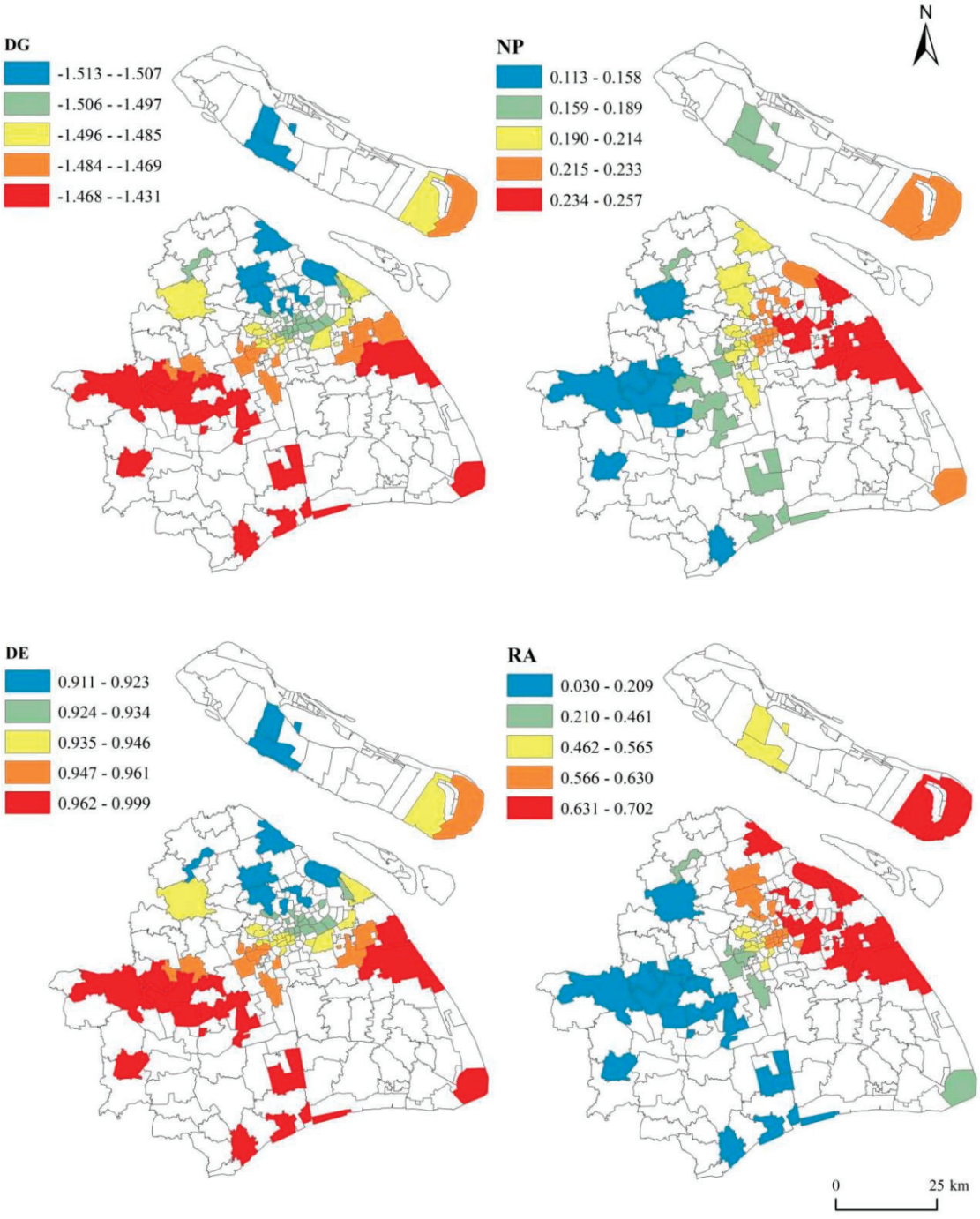


**Figure 7.** Spatial patterns of estimators of variables.

Finally, according to the influencing factors of the distribution of luxury hotels in Shanghai City, this study further carried out the analysis of their scale effects. Figure 8 shows the different bandwidths of each variable in the MGWR model, that is, different variables have an appropriate bandwidth to reflect the scale effect. This can explain the spatial change degree of the factors that affect the distribution of luxury hotels. However, it is only the average bandwidths of each variable in the GWR model, and the scale difference

of influencing factors that are not reflected. Among the significant independent variables, the bandwidth of these factors from small to large includes room rate (RA), number of parks in each zone (NP), distance to municipal government (DG) and distance to the World Expo (DE). The bandwidth value of room rate is 50, indicating that the effect of room rate on the distribution of luxury hotels is limited to 51 subdistricts, and its effect shows significant spatial heterogeneity outside the subdistricts. The bandwidth value of the number of parks in each zone is 73 and it shows that the impact on the distribution of luxury hotels has increased to 73 subdistricts. Therefore, these two variables have significant spatial non-stationarity and scale effects. In addition, the bandwidth values of distance to the World Expo and distance to municipal government are the largest (75), indicating that these two variables act on a global scale, and there is no obvious spatial difference in their effects.

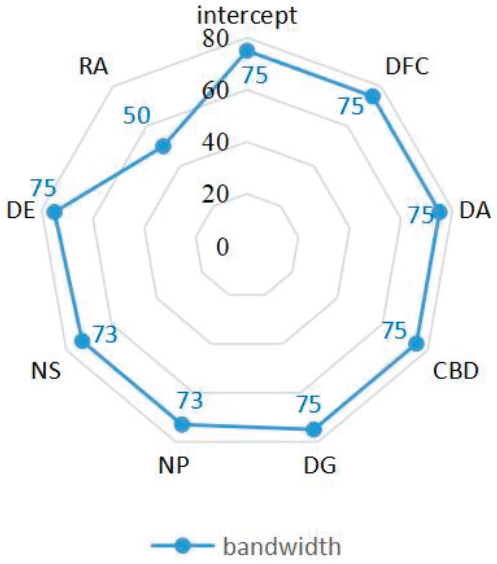


**Figure 8.** Bandwidths for influencing factors in the MGWR model.

Other variables are not significant and will not be discussed here.

## 6. Conclusions and Discussion

This study analyses the spatial-temporal distributions of luxury hotels and identifies underlying factors of the distributional dynamics by using a range of spatial statistical tools and the MGWR model. We found that the distribution of luxury hotels in Shanghai City is mainly concentrated in the central city within the inner ring road, which has formed a mono-central cluster pattern in the metropolitan area. This finding is consistent with the observation made by Egan and Nield [14] that luxury hotels prefer a central location because their higher room rates that target affluent guests are likely to cover the higher land values associated with a central location. Overall, the spatial locations of luxury hotels in Shanghai City spread gradually from the city center to suburban areas during the research period. Shanghai's luxury hotels developed quickly and presented an overall agglomeration from 2000, and the luxury hotels are characterized by high-concentration development, which became increasingly obvious in the research period.

Institutional proximity, green space, mega events, and room rate are the primary factors in influencing the locational choices of luxury hotels in Shanghai City. Institutional proximity has a negative impact on the distribution of the number of luxury hotels. For Shanghai City, the municipal government is mostly located in the central area of the city. The high land price and serious traffic congestion problems in this area not only increase the operating cost of luxury hotels, but also may limit their future development opportunity. Therefore, from the distribution of luxury hotels, the location around the municipal government is not a suitable area. The finding that regional green environments are paramount to hotel location also supports previous research [40]. A perfect urban landscape is more likely to result in the

higher satisfaction of hotel guests, and in turn, they may revisit. This study also unveiled that the Expo 2010 Shanghai had a significant impact on luxury hotel's location decisions. Luxury hotels with a higher land rent affordability were likely to be located around the Expo core area. This result reinforces the previous findings from Zhang et al. [51] that the relationship between mega-events and hotel location choices was important in China. Generally, the room rate is related to the service quality of the hotel and the results show that the location sites of luxury hotels associated with advantages of green environments, and service quality are assumed to be endowed with higher demand for business travelers and more developed public infrastructure systems. This finding supports the common notion that with attractive green environments and high-quality service, the region becomes increasingly welcoming for clients who stay at luxury hotels [25]. In summary, the spatial pattern of formation and evolution of the luxury hotels corresponded with the urban spatial development pattern and the urban function structure evolution. Various elements, such as institutional proximity, regional green landscape, and mega events, and the room rate of hotels, effectively promote the agglomeration and decentralization of the luxury hotel through mutually influenced comprehensive mechanisms.

This research has several policy implications in the following aspects. On the one hand, when new luxury hotel entrants choose a location in metropolitan settings, it is essential for them to identify the most important regional factors in choosing an attractive destination to expand to. On the other hand, the result is useful in assisting luxury hotel investor's assessment in identifying a potential location in Shanghai City. The spatial distribution of luxury hotels in Shanghai City is very imbalanced and we anticipate that some peripheral areas in Shanghai City have potential for future luxury investment. Meanwhile, mega-event zones (the Expo site) have experienced market saturation and a decline in occupancy rate and it is necessary for hotel investors to think about the long term for luxury hotel development and expansion. In addition, the level of regional green environments can effectively improve the hotel service quality, and the room rate is a direct reflection of the hotel service quality. Therefore, luxury hotels with excellent green environments and high room rates may be the first choice for investors.

This study is also of interest to urban planners and based on the analytical results, various exogenous factors of luxury hotel location provide useful suggestions for urban planning. Green environments and construction conditions are significant variables, so urban planners need to consider these factors to boost their chances of attracting luxury hotels. Increasing the construction of park green landscapes is a necessary measure to promote the development of the hotel service industry. Since luxury hotel location selection in Shanghai City is influenced by several dimensions of regional factors, there is a need for a holistic understanding of the hotel industry and the regional economy by the urban planners. As the regional factors that influence a luxury hotel's location are now known, it is possible for urban planners to project future spatial growth patterns of luxury hotels and identify areas of strengths and weaknesses to attract luxury hotels in the future.

Finally, several limitations may hinder the applicability of our findings that need to be addressed in future research. First, due to data unavailability, there are exogenous factors that are not taken into consideration in this paper. For example, during certain periods of time, the Chinese government played a dominant role in the selection of hotel location [20], and policy issues are complex and vary across regions [51]. Therefore, the variables tested in the study's models need to consider more sophisticated factors, such as regional policy, institutions, land-use changes and FDI projects. Second, we cannot consider any of the hotel's characteristics in the current study, such as number of rooms, revenues, and profit; if these data could have been obtained and examined in this research, the results would be more convincing to shed light on the choice of luxury hotel location. Finally, we also acknowledge that performance and development strategies affect the location selection of luxury hotels in a way that the empirical model was not able to consider, owing to the limitation of the data source. With regard to future work, it is possible to analyze hotel location choice at the company level. As the era of big data is approaching, the integrated

application of big data and spatial information technology is becoming mainstream and the use of these methods to analyze hotel location selection in a more meticulous manner is the direction of future studies.

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# Accommodation and Avoidance: Functional Conflict Theory (FCT)-Based Governance Logic of Resettled Community Conflict in China

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**Abstract:** The resettled community is a special type of transitional community in China where the residents are urbanized peasants who lost their lands during urbanization development. However, resettled community conflicts (RCCs) are barriers to sustainable community transformation. Focusing on functional conflict, this study identified the conflicts in the resettled community and proposed feasible governance logic for RCCs. The research in this article has a significant theoretical foundation in functional conflict theory. By examining a large sample of cases, seven RCC types were identified (e.g., inner discontent of residents, mass incidents), of which three have positive functions and four have negative impacts. Furthermore, three RCC causes were identified: right-based, interest-based, and value-based conflicts. Their mechanisms for the conflict function are, respectively, the contextual dual-functional, destructive one-way, and structural dual-functional paths. Considering these findings, we propose a dual governance logic of RCC: accommodation and avoidance. Within the dual logic, specific governance strategies are proposed for the different RCC causes and their functional formation paths. This research serves as an important reference for proper policy measures to govern RCCs and promote the sustainable transformation of resettled communities. The methodology adopted can be extended to the study of RCC in broader global contexts.

**Keywords:** resettled community conflict; functional conflict theory; sustainable community transformation; landless peasants; conflict governance

## 1. Introduction

The resettled community for landless peasants is a kind of transitional community occasioned by urbanization in China, which has features of both urban and rural communities. Since 1978, China has experienced rapid and unprecedented urbanization, causing more than 120 million landless peasants to be moved into resettled communities from rural communities as of the end of 2020 [1]. According to the Ministry of Civil Affairs, up to 35,000 resettlement communities were built over the last decade, and the population of this kind of community will continue to increase along with China's rising urbanization rate. The sustainable transformation of a resettled community to an urban community is crucial to the 'citizenisation' of landless peasants and has become a core mission in the process of new-type urbanization in China. However, habitual rural life behaviors, for example, the private occupation of public space, competition for parking space, holding wedding and funeral ceremonies in open spaces, growing vegetables by destroying green belts, burning ghost money in corridors, and noise pollution [2–4], are quite common in these communities. These behaviors, related to space competition, have caused a large

number of conflicts among community residents [5], and severe conflicts challenge the sustainable transformation of resettled communities.

Academia has gradually come to recognize the significance of conflict governance to the sustainable transformation of resettled communities during the urbanization process [6–8]. Several studies have investigated resettled community conflicts (RCCs) from the perspectives of concepts, causes, and functions. Most of these studies have focused on cause analysis and proposed governance strategies, usually based on the root causes of conflicts identified in the study. Existing studies have proposed several conflict governance strategies from the perspectives of community planning and construction [2,5,9], resident rights protection [10], cultural transformation [8,11], social capital reconstruction [7,12], and urban adaptation [3]. Meanwhile, numerous studies on governance strategies for conflicts in other kinds of resettled communities, such as slums and refugee communities, can be found worldwide. Similar to the studies on RCC governance strategies, these studies primarily introduce solutions and suggestions for suppressing community conflicts based on the analysis of influencing factors [13–15]. In summary, current studies of conflict governance strategies in resettled communities have taken the perspective of conflict suppression and do not explore functional conflict. Furthermore, previous research on RCC has only investigated individual cases.

Community conflict cannot disappear, but it can be properly governed. Thus, the good governance of RCC contributes to a healthy new-type urbanization. With a focus on functional conflict, this paper aims to first identify the conflicts in the resettled community and then propose a feasible governance logic for RCCs. Functional conflict theory constitutes an important basis for the research in this article. To fill the gaps in the current research methodology, we examined a large sample of cases. This study not only extends the research perspective on RCC functional conflicts but also provides decision-makers with important references for introducing a proper policy to RCC governance. The methodology adopted here can be generalized to the study of RCC in a broader global context.

This paper is structured as follows. Section 2 reviews conceptualizations of resettled community conflict, its causes, and debates over its functions. Section 3 describes the adopted methodology. Section 4 explores the functions of RCC. In this part, the types and causes of RCC are identified by content analysis and then their functions are examined based on functional conflict theory (FCT). Lastly, the relationships between RCC functions and causes are presented. Based on the research findings, Section 5 proposes the formation mechanism of RCC functions and then further explores RCC dual governance logic.

## 2. Literature Review

### *2.1. Conceptualizing RCC*

Coleman [16] proposed the concept of community conflict; that is, conflicts driven by different interests and goals among residents or between residents and organizations inside a community. Sanders [17] then posited three core factors of community conflict: opposite relationships, distribution of different powers, and intense emotions of community residents. Community conflict emphasizes the spatial elements on a community scale and is concerned more with realistic and direct interests within the community. Community conflict has the general characteristics of social conflict since it derives from the study of social conflict. Conflict is the contradictory behavior and psychological opposition caused by different actor orientations, which are reflected in the divergent ways they deal with specific objects. The former is mainly manifested as actors' behavioral opposition while the latter is mainly as psychological contradictions within individuals [18]. From the perspective of conflict elements, actors can be an organization, group, or individual [19,20] while the objects of conflict can be interests, power, resources, goals, methods, opinions, values, feelings, procedures, information, relations, etc. [21,22]. Regarding conflict forms, conflict is a dynamic process that develops from the interactions among individuals, individuals and groups, individuals and organizations, groups and groups, and organizations and organizations [23,24]. According to the five-stage conflict model proposed by Rubin and

Pruitt [25], each stage has different forms of conflict, and the change in forms of conflict along with the stage presents a trend of escalation. Some scholars have elaborated on this model. For example, Glasl [26] classified conflict into nine stages obeying the logic of conflict escalation.

Compared with conflicts in other types of urban communities, RCC has its own exclusive characteristics closely related to the community formation context and community features [3,7]. The resettled community is a production of government-led spatial reconstruction during the urbanization process in which community conflict is connected to space competition [8]. Using a case study, several researchers have investigated the space competition phenomenon in resettled communities and found that after landless farmers moved in, space gradually underwent fragmentation, diversification, and functional shifts [2]. In the meantime, numerous researchers have discovered that space competition is related to RCC, where poor housing quality and space occupancy are frequent drivers of conflicts. These conflicts also attract multiple parties. Housing quality problems are typical in resettled communities, and they frequently trigger inter-group conflicts among residents, governments, developers, and other community actors [27,28]. Simultaneously, many conflicts have resulted from the occupation of public space. The behaviors of community space reconstruction frequently occur, leading to serious conflicts between landless peasants and other community groups (e.g., property management companies, community managers, and other residents).

### *2.2. Causes of RCC*

The causes of RCC are complex because it is a realistic reaction to various contradictions and disputes on the economy, politics, and actor values in the resettled community [8]. Scholars generally analyze the causes of RCC based on negative impacts in the aspect of the social, physical, environmental, and economic realms brought about by demolition and resettlement, such as space transformation, social relationship reconstruction, and cultural adaption [3,4,8]. From the perspective of spatial transformation, numerous scholars have conducted case studies that have noted the prevalence of spatial re-creation in resettled communities. They have also emphasized the disputes that emerge between landless peasants and community managers within the communities due to the competition for space. Some researchers feel that the inadequacy of these community spaces is the cause of the spatial transformation that leads to conflict [5], whereas others believe that conventional lifestyles are to blame [2]. In recent years, scholars have paid increasing attention to the spatial viewpoint of RCC formation [2,4–6]. From the perspective of residents' rights and interests, several researchers have utilized questionnaires to explore the causes of RCC, through which the problem of effectively protecting the rights of migrants was examined. For instance, some scholars have argued that the existing migration system fails to sufficiently preserve the land rights of rural residents and the migratory and adaptation benefits derived from those rights [3]. The lack or abuse of public space exceeds 10% among the causes of RCC while the growing recognition of rights has sparked fierce community conflict [24]. From the perspective of social relations, researchers have found that residents in such communities still have a high degree of interaction with their former neighbors, friends, and village cadres. Social interaction allows them to maintain rural traditions through spatial transformation, which thus causes conflicts [7]. From the perspective of cultural adaptation, it illustrates the psychological dilemmas and cultural barriers experienced by relocated residents during the process of spatial transition. Through interviews and questionnaires, scholars have discovered the connection between cultural adaptability and RCC among landless farmers. The source of RCC is the residents' retention of the cognitive patterns and behaviors learned in rural life [7]. Institutional and spatial-territorial barriers faced by landless peasants in China have long kept them in a marginalized economic and social position, making their resettlement and adaptation process similar to the experience of international migrants [29]. Thus, RCC in China has a high degree of similarity with the conflict in other kinds of resettled communities worldwide. Cross-cultural issues faced

by resettled migrants due to resettlement [30,31], employment and education [32], social services [33], living environment [34,35], and community support [28] are important factors in the formation of such community conflicts. Numerous studies of conflict in immigrant communities have highlighted the themes of cultural shift and psychological adaptation. Through case studies of typical communities, researchers have reported that the origins of immigrant community conflicts are psychological adaption difficulties, stress accumulation, and a lack of coping mechanisms [15,30]. Additionally, place attachment also plays an important role in the formation of RCC [36].

### *2.3. Debate over the Functions of RCC*

The functions of conflict and the harmful nature of conflict were widely recognized by researchers before the concept of the functions of social conflict was proposed by Coser [37]. According to the functional conflict theory (FCT), conflict has both positive and negative functions. For example, conflicts between groups can promote cohesion and integration among the members of each group. Therefore, conflict is not only a destructive force for social stability and order but also a driving force of social development. Regarding the definition of positive conflict functions, Deutsch [38] argued that conflicts are constructive to the extent that participants consider that they gained more benefits than costs overall.

Scholars of organization studies have discussed the positive effects of conflict. Conflict has been linked to learning, higher levels of cooperation [23], the promotion of decision-making [39], and an overall increase in team effectiveness [40]. Some have located these positive effects in the conflict issues, with task-related issues (e.g., what is the best strategy for the organization) generating more positive consequences than relationship-related and person-related issues (e.g., disagreements about values, distrust of other people). Others have located these positive effects in the way conflict situations are perceived and managed. Perceived cooperative goals and ensuing constructive controversy create more positive outcomes than perceived competitive goals and a lack of constructive controversy [41]. The conflict management method also generates positive effects. On the one hand, many studies have argued that open-minded discussions of anger can be very useful for strengthening relationships and restoring respect between persons [39,42]. On the other hand, some scholars have indicated that cooperative conflict management can be very useful for teamwork and alliance partners in China. Indeed, experimental and field studies have found that collectivist, compared to individualistic, values promote cooperative, positive conflict [43].

However, scholars have primarily argued the negative effects of the functions of resettled community conflicts. Interracial conflicts are common in resettled communities, which bring racial tensions and violence. Its negative effects have raised concerns [13,44]. Other adverse psychological impacts in resettled communities were noted as well. Conflicts caused by displacement as multi-dimensional stress and major disruptions [14] and some residents' dissatisfaction with the government [2] have frequently occurred.

All these studies offer a perspective to understand conflicts since they provide relevant knowledge, such as space competition related to RCC [4,8] and the negative and positive functions of conflict [37,45]. However, there are some obvious limitations in previous studies, which can be summarized as follows: (1) RCC is related to space competition, but the relationship between behaviors of space competition and RCC has not been deeply explored; (2) the causes of RCC are diverse but no consensus exists, and a holistic view of RCC analysis is lacking since previous studies mainly focused on individual cases; and (3) the positive functions of RCC have been neglected, and most previous studies developed community conflict governance strategies from the perspective of conflict mitigation. To fill these research gaps, this study identified both the functions and causes of different RCC types by examining a large sample of cases. The relationship between RCC functions and causes is presented, which serves as a reference for identifying the formation mechanism of different causes of RCC and developing an RCC dual governance logic and specific strategies.

## 3. Methodology

### *3.1. Theoretical Framework*

Based on FCT, we propose a connection between conflict causes, conflict functions, and conflict governance strategy (Figure 1). Conflict causes can have indirect effects on conflict functions, and then conflict governance strategies can be customized to certain conflict functions. Conflict types directly determine conflict functions, such that realistic conflicts have a positive function and non-realistic conflicts a negative one. This theoretical framework suggests that the most important relationship is that conflict causes influence conflict functions indirectly, primarily via the role of the conflict type to be achieved.

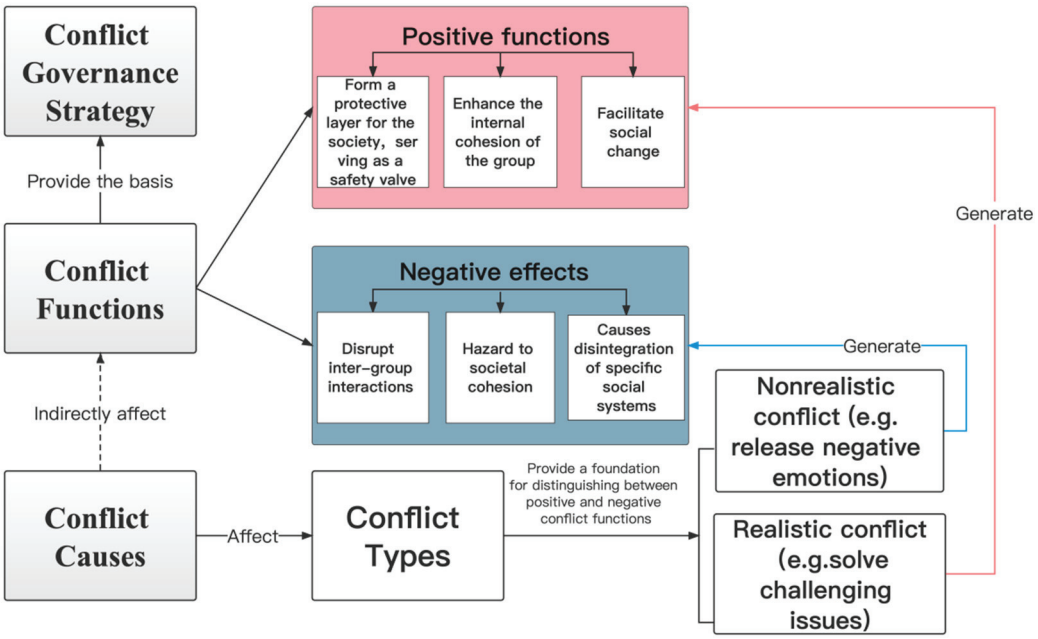


**Figure 1.** A framework based on FCT. Source: Authors.

FCT posits that conflict performs both positive and negative functions (see Figure 1). Typically, social conflict is viewed as a harmful phenomenon manifesting in three forms [37]: first, social conflict leads to the disruption of inter-group interactions, hence increasing the instability of group relations. This destructiveness cannot be ignored, as it brings about inter- and intra-group provocations, quarrels, violence, etc. Then, conflict is detrimental to social cohesion. People gradually lose faith in society as a whole. The glue that holds the entire civilization together is lacking. Third, conflict causes the disintegration of specific social systems. This societal transformation typically occurs rapidly and violently.

FCT recognizes the destructive character of social conflicts but focuses on the positive functions that social conflict serves in society and communities as a whole, which emerge in three ways [37]: first, loosely structured groups and open societies allow conflict to exist, thus forming a protective layer that can reduce the threat of disagreement, which may at a minimum undermine the core values of society, and thus serve as a safety valve. Second, the functions of conflict or tension are closely associated with social change. Conflict results in social restructuring, increases its adaptability, and can facilitate or at least benefit social transformation. Last, social conflict with external groups increases internal cohesion. In particular, conflict determines the group's internal identity and identification and strengthens the group's solidarity and cohesion.

Based on the conflict types proposed by FCT, we present criteria for determining the positive and negative functions of conflicts. FCT argues that under different conflict circumstances, conflicts not only have negative effects but also positive ones [23,37]. Coser [37] defined realistic and non-realistic conflicts. Realistic conflict serves to achieve one's desire, under which the conflict is a tool but not a goal. Non-realistic conflict is the release of

negative emotions by conflict actors. In this situation, conflict in itself is the goal, not a tool. Current studies have demonstrated a relationship between conflict types and conflict functions. For instance, Van and Doherty [45] argued that task conflicts of communities belong to realistic conflict, whose goals contribute to decision-making. Such realistic conflict has positive functions. However, relationship conflicts belong to non-realistic conflict, whose goal is to release negative emotions. Ultimately, this has a negative impact. This study held that realistic conflict has positive functions and non-realistic conflict has negative effects (see Figure 1).

### *3.2. Methods*

The research methods designed to achieve the defined research objectives are shown in Figure 2. First, a web crawler was adopted to collect news related to RCC online. News reports focus on hot events, offering the advantages of strong timeliness and high credibility. Therefore, news reports form an important data source for RCC. Web crawler technology automatically collects the required information from one or more pages based on a specific strategy and can access network resources using a simulated browser [46]. This is an essential method to make effective use of network resources related to RCC. Next, content analysis was applied to extract key information from the news. The content analysis includes the domain of qualitative methods, focusing on both manifest and latent content [47]. Typically, textual data are coded into different categories at various levels, such as words, phrases, sentences, paragraphs, or themes. The coding categories represent different characteristics of interest according to the research objective. Qualitative analysis was utilized to identify RCC types and causes. Additionally, we investigated the functions of RCC on the basis of FCT. The relationship between RCC causes and types was then analyzed using co-occurrence analysis, which is commonly employed in bibliometrics to explore collaborative structures between keywords, authors, institutions, terminology, etc. It is a method for quantifying co-occurrence data in multiple information carriers. Through co-occurrence analysis, one can find the close and distant correlations between research objects and investigate implicit or possibly valuable information and understanding [48]. This article uses co-occurrence analysis to explore and quantitatively present the link between RCC causes and types. Finally, RCC governance logic is proposed based on its positive functions and negative effects.

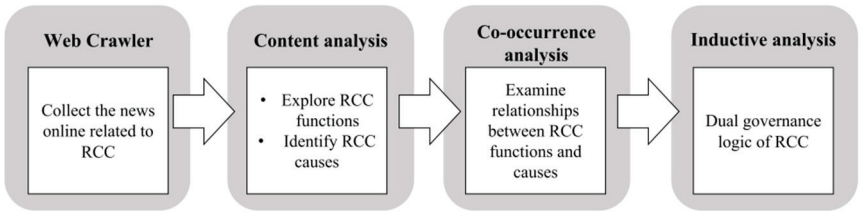


**Figure 2.** The research framework.

#### 3.2.1. Data Collection

Since Baidu is the largest search engine in China, Baidu News reports information about specific events in a comprehensive and representative manner. Using the Baidu News search engine (http://news.baidu.com/), this study adopted Python codes to add the word 'conflicts in resettled community' as a keyword to perform searches. A total of 3800 news items were collected on 10 April 2022, and after screening and deletion, 890 news reports strongly related to RCC remained. These included conflict news items from all provinces in China (Figure 3). To ensure the comprehensiveness and accuracy of the analysis, this study captured the title, time, and full text of news items, yielding about 1,297,000 words of text. The earliest of the 890 news reports on RCC collected appeared in 2007, and the number of news reports has increased annually (see Figure 4). This demonstrates that the issue of RCC is increasing and attracting people's attention, and RCC news reports may become more abundant.

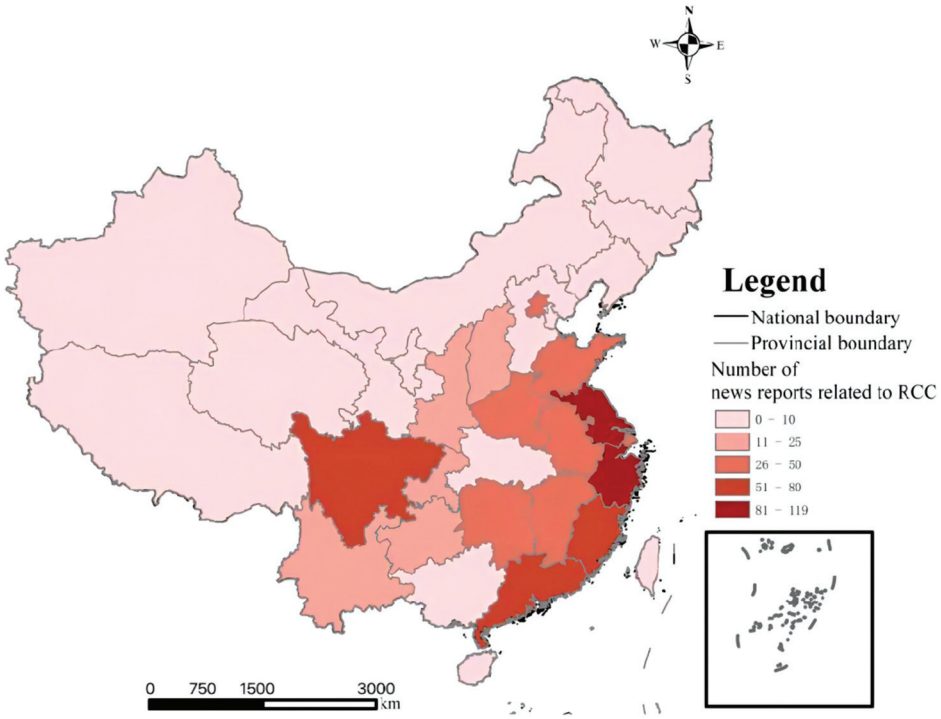


**Figure 3.** The distribution of RCCs in China.

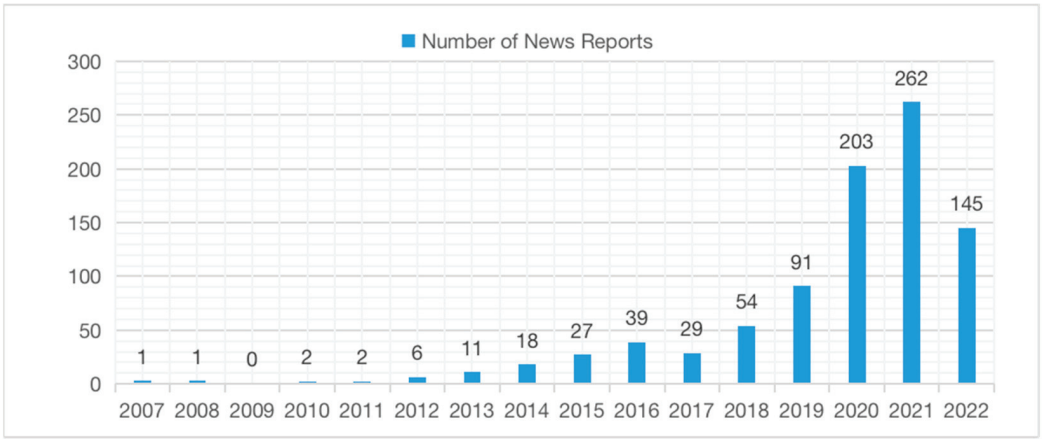


**Figure 4.** The number of news reports on RCC in China (2007–2022).

### 3.2.2. Data Analysis

First, content analysis was applied to identify RCC types and causes; based on the steps proposed by Elo and Kyngas [49], we used a simple three-phase process of preparation, organizing, and reporting to obtain them. Preparation involves the design, identification of the units of analysis, and representative sampling. The organization phase involves the analytical process of category coding and identification. The final phase is the presentation of the results linking the findings to previous knowledge. We next analyzed the functions separately for each type, according to FCT.

In the second step, this study used co-occurrence analysis to obtain the relationship between types and causes. Adopting co-occurrence analysis, the main cause of RCC was

identified in each news item; however, each news item corresponded to multiple types of RCC. Therefore, the co-occurrence matrix of RCC causes and type was obtained as follows:

$$O = \begin{pmatrix} C_1T_1 & C_1T_2 & \cdots & C_1T_n \\ C_2T_1 & C_2T_2 & \cdots & C_2T_n \\ \cdots & \cdots & \cdots & \cdots \\ C_mT_1 & C_mT_2 & \cdots & C_mT_n \end{pmatrix} \quad (1)$$

In the formula, $C_m$ is the cause of RCC in the $m$th news items, $m = 1, 2, 3, \cdots, 890$; $T_n$ indicates the types of RCC in news, $n = 1, 2, 3, \cdots$; $C_mT_n \in \{0, 1\}$.

Finally, based on FCT, we calculated the conflict function values of the different types, more specifically classifying the positive and negative functions of the different types. If the conflict has a positive function, it is assigned the value +1; if the conflict has negative effects, it is assigned $-1$. Then, the conflict function value was calculated based on the co-occurrence matrix of causes and types of RCC ($V_{T_n}$):

$$V_{T_n} = \begin{cases} \sum_{m=1}^{890} C_m T_n, \text{when } T_n \text{ has positive functions} \\ -\sum_{m=1}^{890} C_m T_n, \text{when } T_n \text{ has negative effects} \end{cases} \quad (2)$$

where $V_{T_n}$ refers to the conflict value corresponding to the $n$th type of RCC. When $T_n$ has a positive function, the larger its value, the stronger its positive function; when $T_n$ has negative effects, the larger its value, the stronger its negative effects.

## 4. Results

### *4.1. RCC Function Analysis*

#### 4.1.1. RCC Classification

From the content analysis of 890 news items, we found that RCC may undergo escalation. Conflict escalation is reflected in two aspects: the scope of the conflict's negative impact is expanded, and more people become involved in the conflict events [24,50]. We explored how RCC escalation is accompanied by diffusion from within to outside the community and how additional actors become involved in conflict events. In addition, RCC destructiveness gradually increases (Figure 5). Seven RCC types are identified: (1) inner discontent of residents; (2) verbal clash between residents; (3) intervention of a property management company; (4) intervention of a neighborhood committee; (5) intervention of local government; (6) intervention of media; and (7) mass incidents (see Table 1). Because of the complexity of RCC, each news item may include more than one conflict type. Regarding frequency, 'inner discontent of residents' appeared 890 times, which means that all news items included this type. 'Intervention of local government' and 'intervention of property management company' numbered over 200, followed by 'intervention of media', 'verbal clash between residents', and 'intervention of neighborhood committee'. The remaining RCC types occurred less commonly, with 'mass incidents' occurring 40 times. In percentages, 'inner discontent of residents' accounted for over 50 percent, followed by 'intervention of local government' (13.96%) and 'intervention of property management company' (11.49%). Other RCC types only accounted for less than 10 percent.

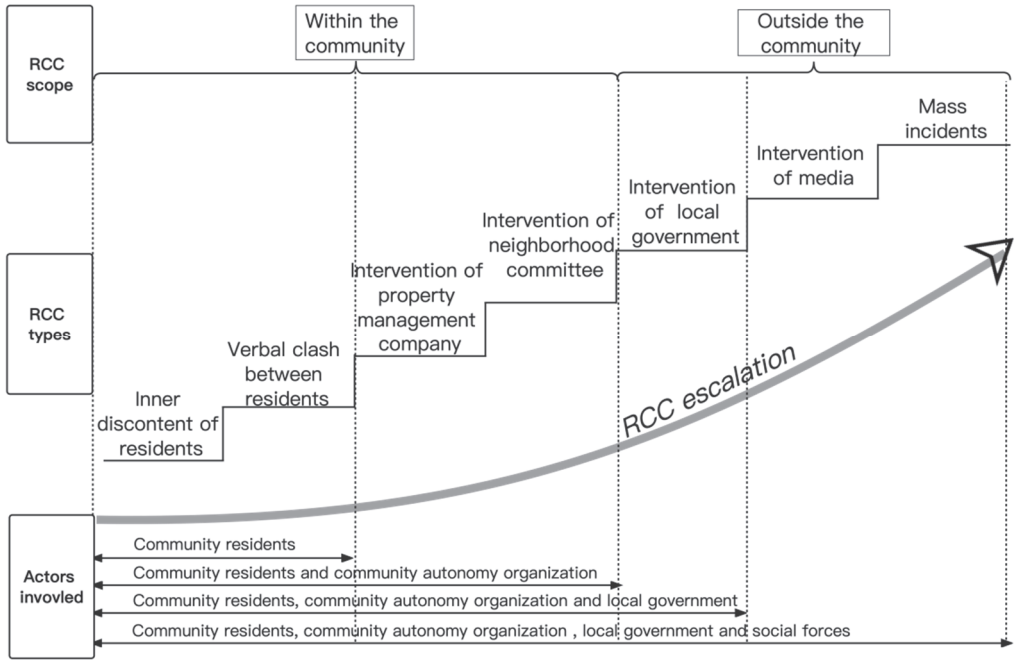


**Figure 5.** The distribution characteristics of RCC based on RCC escalation. Source: Authors.

**Table 1.** The distribution characteristic of RCC types.

| ID | RCC Types | Features | Frequency | Percentage |
|---|---|---|---|---|
| CT1 | Inner discontent of residents | Residents' feeling cheated, worried, disturbed, and afraid | 890 | 50.11% |
| CT2 | Verbal clash between residents | Debate, critique, quarrels between residents | 130 | 7.32% |
| CT3 | Intervention of property management company | Ask the property management company to intervene in solving problems | 204 | 11.49% |
| CT4 | Intervention of neighborhood committee | Ask the neighborhood committee to intervene in solving problems | 104 | 5.86% |
| CT5 | Intervention of local government | Leave a message on government affair platform, Complaint call | 248 | 13.96% |
| CT6 | Intervention of media | Call the media hotline, leave a message on the Internet | 160 | 9.01% |
| CT7 | Mass incidents | Group fighting, violent rights protection behaviors, illegal rights protection behaviors | 40 | 2.25% |

'Inner discontent of residents' remains in the stage of emotional perception, which might provide a fertile ground for positive confrontation. Starting from 'verbal clash between residents', RCC began to move towards a positive confrontation. 'Intervention of property management company' is a powerful means of reflecting on problems and expressing residents' needs. However, because of the transitional characteristics of the resettled community, the governance of such communities is less effective. Property management companies often have problems such as poor service quality and slow response time [8]. When the 'intervention of property management company' fails to solve a conflict, 'intervention of neighborhood committee' is an essential way to express residents' demands. Landless peasants in resettled communities have a habitual reliance on administrative power. They used to look to village committees when they encountered problems; thus, they now turn to neighborhood committees for help [8]. However, because of the formation of such communities, RCC closely relates to the government; when the neighborhood committees fail to fulfil their function, the government intervenes to regulate the conflict. With the awakening regarding residents' rights and the popularization and facilitation of government complaint channels in recent years [50], 'intervention of local government'

has become an important RCC type. 'Intervention of media' usually refers to community residents seeking attention regarding the community conflict by calling a hotline and leaving messages on the Internet. Finally, conflicts may be resolved by increasing exposure and leading public opinion. 'Mass incidents' is important to release negative emotions and incur destructive social impact through group fighting and violent and illegal rights protection behaviors.

#### 4.1.2. RCC Function Analysis Based on RCC Classification

According to the theoretical framework given in this study, realistic conflict serves a positive role while non-realistic conflict serves a negative function. This has led to the functional classification of different RCC types (see Table 2). 'Inner discontent of residents' belongs to non-realistic conflict, whose goal is the conflict itself. As it results in the accumulation of negative emotions [50], this study regarded its conflict function as negative (−). 'Verbal clash between residents' is interpersonal conflict, mostly for the purpose of releasing negative emotions. It is a non-realistic conflict that leads to damage to neighborly relationships and personal emotions. Therefore, this study regarded its conflict function as negative (−). 'Intervention of a property management company' is a realistic conflict that promotes resolution of the problem, so this study regarded its conflict function as positive (+). 'Intervention of neighborhood committee' is an essential method for community residents to seek help [8], and it ultimately promotes the resolution of realistic problems. It is a realistic conflict and was classified as having a positive function (+). 'Intervention of local government' is a conflict method with Chinese characteristics. It is a necessary method for residents to express their own ideas and seek help [51]. Therefore, this realistic conflict was regarded as having a as positive (+) conflict function. As a realistic conflict, 'intervention of media' is also the method of solving problems. This study regarded its conflict function as positive (+). 'Mass incidents' relates to sudden events with a wide influence. It primarily expresses emotions and releases hostilities through group fighting and other violent behaviors, and its consequences are to destroy social stability. It belongs to non-realistic conflicts, so we regarded its conflict function as negative (−).

**Table 2.** Conflict functions based on different types of RCC.

| RCC Types | RCC Functions (+, −) | Basis for Determining RCC Functions |
|---|---|---|
| Inner discontent of residents | − | Non-realistic conflict |
| Verbal clash between residents | − | Non-realistic conflict |
| Intervention of the property management company | + | Realistic conflict |
| Intervention of the neighborhood committee | + | Realistic conflict |
| Intervention of the grassroots government | + | Realistic conflict |
| Intervention of the other government department | + | Realistic conflict |
| Intervention of the media | + | Realistic conflict |
| Mass incidents | − | Non-realistic conflict |

### *4.2. RCC Cause Identification*

The 890 news items were read and coded as the raw data and units of analysis. These were read and information related to space competition behaviors was identified (meaning units). The coding process entailed the identification of descriptive terms for the relevant areas. After coding 890 news pieces, 19 kinds of space competition behaviors were identified (see Table 3). 'Fight for parking space' is the most common behavior, whose frequency was over 100, far greater than the next space competition behavior, 'water leakage' (79), followed by 'construct privately' (64) and 'throw objects from high-rise buildings' (62). 'Gather together for chatting' (14) seldom happens in the resettled communities.

**Table 3.** The distribution characteristic of RCC causes.

| Code | Sub-Category | Category | Frequency | Percentage |
|---|---|---|---|---|
| Reconstruct houses with group-oriented leasing | Conflicts of right to survival (C11) | Right-based conflicts (C1) | 33 | 3.71% |
| Construct privately | | | 64 | 7.19% |
| Subtotal | | | 97 | 10.90% |
| Occupy the road for business activities | Conflicts of right to development (C12) | | 36 | 4.04% |
| Open a store privately | | | 21 | 2.36% |
| Subtotal | | | 47 | 6.40% |
| Water leakage | Conflicts of immediate interests (C21) | Interest-based conflicts (C2) | 79 | 8.88% |
| Poor sound insulation | | | 48 | 5.39% |
| Peeling walls | | | 31 | 3.48% |
| Insufficient lighting | | | 29 | 3.26% |
| Subtotal | | | 187 | 21.01% |
| Stockpile sundries | Conflicts of secondary benefits (C22) | | 51 | 5.73% |
| Disturb residents by square dancing | | | 38 | 4.27% |
| Gambling noise | | | 29 | 3.26% |
| Subtotal | | | 118 | 13.26% |
| Grow vegetables by destroying the green belt | Conflicts of habitus (C31) | Value-based conflicts (C3) | 54 | 6.07% |
| Gather together for chatting | | | 14 | 1.57% |
| Celebrate positive events and funerals | | | 43 | 4.83% |
| Subtotal | | | 111 | 12.47% |
| Fight for parking space | Conflicts of public awareness (C32) | | 112 | 12.58% |
| Occupy space for drying | | | 36 | 4.04% |
| Destroy public facilities | | | 49 | 5.50% |
| Throw objects from high-rise buildings | | | 62 | 6.97% |
| Drop litter carelessly | | | 61 | 6.85% |
| Subtotal | | | 320 | 35.96% |

Sub-categories were then identified from the codes. 'Conflicts of public awareness' (35.96%), 'conflicts of immediate interests' (21.01%), and 'conflicts of secondary benefits' (13.26%) are the top three most represented sub-categories. 'Conflicts of right to development' (6.40%) is under-represented, making up less than 10%.

According to the social conflict literature, the object of conflict can be interests, power, resources, goals, methods, opinions, values, feelings, procedures, information, relations, etc. [21,22]. We reviewed the forms of conflict objects in the literature and compared their definitions. Concurrently, based on the content analysis of the sub-category of RCC and definitions of conflict objects, we developed three types of RCC causes: right-based, interest-based, and value-based conflicts (see Table 3). 'Value-based conflicts' (48.43%) have the largest proportion, accounting for almost half of the causes. 'Interest-based conflicts' (34.27%) rank second, whereas 'right-based conflicts' (17.30%) have the lowest percentage.

#### 4.2.1. Right-Based Conflicts

Lefebvre posited the theory of right to the city, and many researchers argued that citizens have aspects of city rights [52]. With the awakening of residents' rights awareness, conflicts over rights protection occur frequently [24,53]. The right-based conflicts in resettled communities also closely relate to the context of demolition and resettlement. (1) Conflicts of right to survival: landless peasants, who have lost their survival tools, have difficulties in retaining their right to survival. Most also rely on rental income from

relocated houses [8]. Therefore, 'reconstruct houses with group-orientated leasing' is a method for landless peasants to struggle to survive. In addition, there is insufficient space in the resettled community to meet the needs of landless peasants [5]. Therefore, 'construct privately' acts as a complement to space use. (2) Conflicts of right to development: landless peasants have high expectations for development and a better life in the community after demolition. However, there is a large gap between the positive expectations regarding relocation and the actual life of landless peasants [8]. For positive development and to meet their expectations, landless peasants choose to occupy roads for business activities and open stores privately to achieve their rights to development.

#### 4.2.2. Interest-Based Conflicts

Because of extensive interests and motivations in the use of space, there are contradictions between different actors [54]. Specifically, because of the limitations on their resources, social status, and powers [55], different actors strive to maximize self-interest, especially marginalized landless peasants, in such communities. (1) Conflicts of immediate interests: because the resettlement policy has economic benefits as the main goal [56], the construction of a large number of relocated houses only meets minimum standards. This has frequently led to quality problems such as water leakage, poor sound insulation, and insufficient lighting, which cause landless farmers to strive to protect their immediate interests through conflict. (2) Conflicts over secondary benefits: this kind of conflict arises from the negative externalities affecting others generated by individual activities. How to use public space is becoming an important source of conflict [5]. At present, the issue of noise pollution, such as noise from gambling and disturbance of residents by square dancing, has become an important manifestation of the conflict of secondary benefits. In addition, stockpiling sundries is quite common in resettled communities, which is a form of interest competition among community residents for the use of corridor space.

#### 4.2.3. Value-Based Conflicts

Value-based conflicts generally refer to distinct differences in values [57]. Landless peasants in the resettled communities experienced the transition from the countryside to the city, which means the transformation from agricultural to industrial civilization. This process is accompanied by opposition and inconsistency in values [7], leading to value-based conflicts. (1) Conflicts of habitus: rapid urbanization leads to great changes in such a community's physical and communication environments, leaving little time for the adaptation of landless peasants. In this case, inner psychological perceptions, such as emotions related to the land, nostalgia for rural living environments, and a vague cognition of identity, make it inevitable that landless peasants continue their rural living habitus [58]. However, other residents living in such communities resist behaviors associated with retaining habitus. Different attitudes towards rural habitus stem from the gap between different groups' perceptions of traditional rural customs [5,6]. The conflict of habitus is therefore a highly characteristic value-based conflict in resettled communities for landless peasants. (2) Conflicts of public awareness: public awareness refers to caring more about public interests than individual benefits. Researchers have shown that there is a significant gap between the public awareness of landless peasants and the public spirit and ethics required by urban communities [8]. Landless peasants focus more on their own benefits than on maintaining public interests. Thus, conflicts of public awareness are an important part of the value-based conflicts in the context of resettled communities. According to current studies of RCC related to space competition [3–6,8,56,58], three aspects are correlated with conflicts of public awareness, namely, fight for public space, destruction of public facilities, and destruction of sanitary conditions. Based on these aspects, our spatial competition behaviors corresponding to them are, respectively, 'fight for parking space' and 'occupy space for drying'; 'destroy public facilities'; and 'throw objects from high-rise buildings' and 'drop litter carelessly'.

### *4.3. Relationships between RCC Functions and Causes*

#### 4.3.1. Comparison of RCC Dual Functions by Cause

The results show that RCC not only has positive functions but also negative effects (see Figure 6). In addition, the negative effects of RCC in general outweigh the positive functions. Interestingly, different causes of RCC have different functions. In the first group of causes, the positive effects of RCC are close to its negative effects. Under C11, the difference between the value of positive effects and negative effects is 3 while under C12, the difference is 25. In the second group of causes, the negative effects of RCC slightly outweigh the positive effects. Under C21, the value of negative effects exceeds the value of positive effects by 59, and under C22 by 82. In the third group of causes, the negative effects greatly outweigh the positive effects. Under the influence of C32, the value of negative effects exceeds positive effects by 264. In the fourth group of causes, the positive effects exceed the negative effects. Notably, the fact that certain types of RCC causes can have positive effects is identified for the first time in this study.

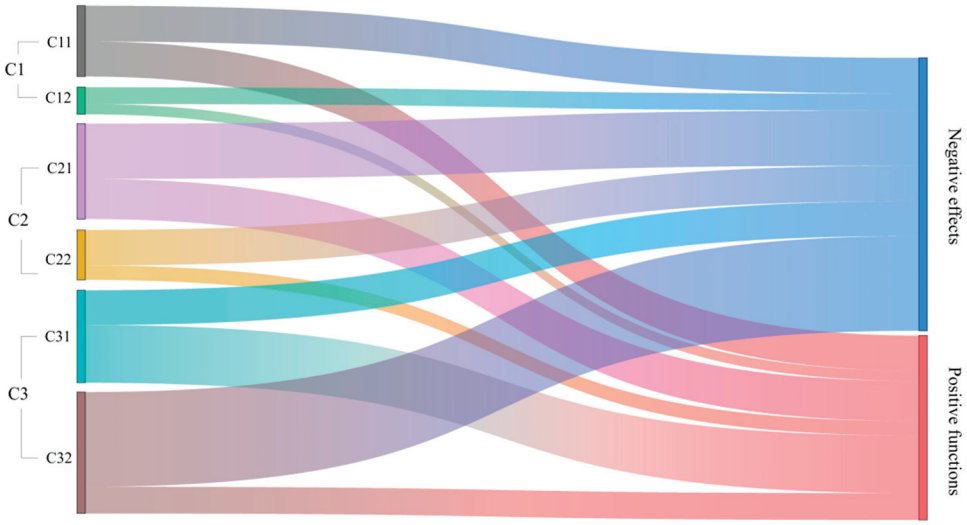


**Figure 6.** Dual functions based on causes. Source: Authors.

#### 4.3.2. Distribution Characteristics of Positive RCC Functions

Four types of RCC having positive functions play different respective roles by cause (see Figure 7). Under C1, CT5(+68) is the most essential form while CT4(+20) is less important. It can be concluded that when facing right-based conflicts, residents more readily turn to the government for help than to the neighborhood committee. Previous studies have pointed out the importance of government and the neighborhood committee in the resettled community [8,24], but we explain this point based on the priority of the government in the settlement of right-based conflicts. Under C2, we find similar results: CT5(+72) ranks first and CT4(+20) ranks last. Therefore, the government is the most essential actor in interest-based conflicts while the neighborhood committee plays a marginalized role. This finding is consistent with previous studies emphasizing the importance of the government when residents face interest-based conflicts. Under C3, the results are different. CT3(+100) has the largest score while CT6(+56) has the smallest. The property management company is the most important party in managing value-based conflicts, whereas the government plays a relatively small role. Some studies have mentioned value-based conflicts between community residents and property management companies [5], but we point out that the property management company has a major role in such conflicts having positive effects.

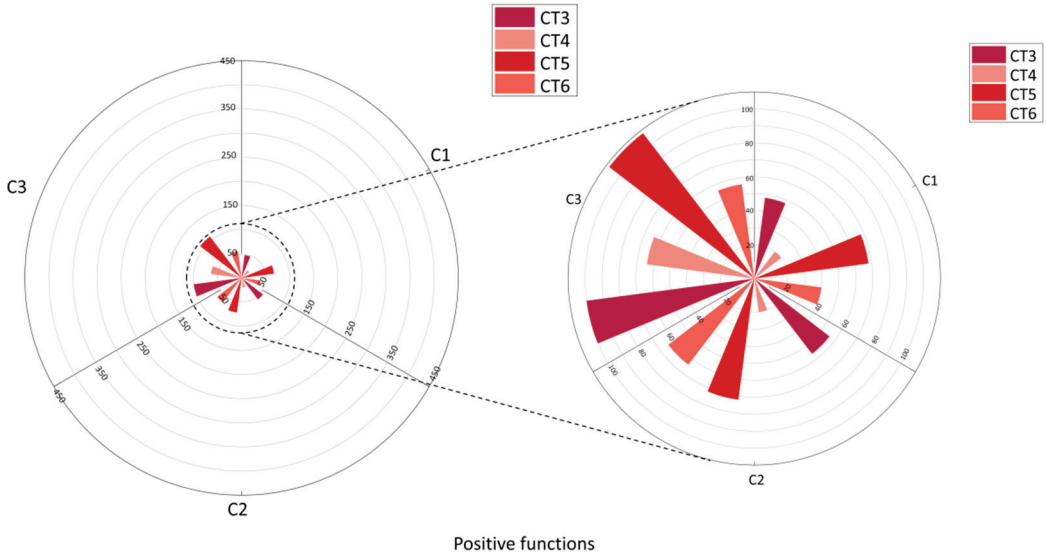


**Figure 7.** Distribution of the characteristics of positive RCC functions by cause. Source: Authors.

4.3.3. Distribution Characteristics of Negative RCC Effects

Three types of RCC that bring negative effects play different roles by cause (see Figure 8), but there is no obvious difference in RCC forms by cause. Under C1, C2, and C3, CT1 always has a decisive role. We can thus conclude that residents' inner discontent is common in resettled communities when facing issues of interests, rights, and values. This finding is consistent with previous studies [3,9]. Apart from CT1, CT2 and CT7 are also important forms. RCC with negative effects is closely related to interpersonal conflicts, such as verbal clashes. This may be because RCC mostly occurs among community residents [8]. Second, mass incidents are also an essential RCC form, but they occur infrequently; in contrast to social conflicts, the destructiveness of RCC is kept to a relatively modest level.

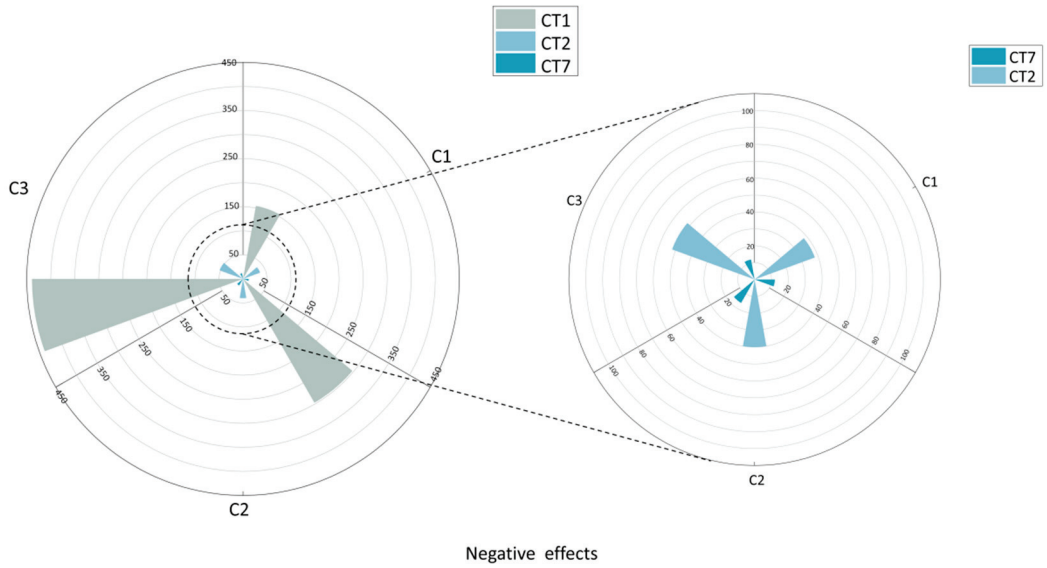


**Figure 8.** Distribution of the characteristics of negative RCC functions by cause. Source: Authors.

## 5. Discussion

### *5.1. Formation Mechanism of RCC Functions*

5.1.1. Right-Based Conflict: Contextual Dual-Functional Path

The magnitude of positive functions of conflicts regarding the right to survival and conflicts of right to development are close to that of negative effects (see Figure 6). These positive effects of conflicts are proposed here for the first time, contrary to the results of

previous studies analyzing right-based conflicts from the perspective of negative effects [4]. This article further discovered how these right-based conflicts have positive and negative functions based on FCT. Regarding positive functions, FCT holds that the functions of conflict or tension are closely associated with social change in the community [37]. We argue that right-based conflicts can promote resettled community development. Conflicts of survival guide the government and community managers to pay attention to the survival needs of landless peasants, such as leasing their houses to earn a living [8]. In the demolition and resettlement process, ways to protect the survival right of landless peasants are a crucial issue that deserves greater attention. In addition, development conflicts increase the community's economic vitality. All this ultimately promotes community development. Negative and positive functions occur simultaneously in right-based conflicts. Regarding negative effects, FCT holds that conflict causes the disintegration of specific social systems. In the context of resettled communities, we found that these conflicts destroy resettled communities' physical environment. Space competition behaviors, such as reconstructing houses with group-oriented leasing, constructing privately, occupying roads for business activities, and opening stores privately not only destroy the quality and structure of private physical space but also encroach on public space. We call this equal positive and negative function of right-based conflicts a contextual dual-functional path, which is similar to the concept of contextual ambidexterity [59]. Notably, the positive and negative functions of a right-based conflict are regarded as a whole and are synergistic.

#### 5.1.2. Interest-Based Conflict: Destructive One-Way Path

Conflicts of immediate interests and conflicts of secondary benefits both have more negative than positive effects (see Figure 7). These negative effects of interest-based conflicts are consistent with the findings of previous research [6,28]. This study further discovered how these interest-based conflicts bring about negative effects based on FCT. As FCT points out, social conflicts have negative outcomes as they disrupt social relations. From the analysis of Figure 8, the negative effects of interest-based conflicts are primarily felt by community residents, which has a significant negative impact on neighborhood relations. Different groups within the resettled community have distinguishable differences in their living habits, community awareness, and values. Therefore, it is easy for contradictions to arise during communication [8]. These interest-based conflicts will encourage a preference for inter-group communication, which soon leads to isolation from and mutual hostility with other groups (tenants and urban residents), negatively affecting harmonious neighborhood ties. Moreover, interest-based disputes can result in multiple mass incidents with horrifyingly damaging consequences for the community and society [24,50]. This is because both sub-categories of interest-based conflicts are dominated by negative effects and negatively impact neighborhoods. We consequently refer to the mechanism of interest-based conflicts as a destructive one-way path.

#### 5.1.3. Value-Based Conflict: Structural Dual-Functional Path

Conflicts of habitus have more positive functions than negative effects while conflicts of public awareness have more negative effects than positive functions (see Figure 6). Even though numerous studies have revealed the harmful consequences of public awareness conflicts [5,7], this study highlights the good functions of habitus conflicts. We analyzed the function of value conflict formation mechanisms on the basis of the FCT. According to FCT, the adverse consequences of social conflict are reflected in its damage to social cohesion. In the context of resettled communities of landless peasants, conflicts of public awareness aggravate the social exclusion of landless peasants, which is equally damaging to social cohesion. Social exclusion has been widely mentioned in previous studies [60–62] but not fully addressed. Within the context of China, landless peasants are regarded as outsiders in terms of location, culture, psychology, and relationship network [60]. Based on the theory of territorial stigmatization proposed by Wacquant [63], we found that the resettled community is labeled with undesirable characteristics (e.g., poor sanitary

conditions), which makes these locations inferior to others. However, the conflicts of public consciousness have undoubtedly exacerbated the stigmatization of community residents, and the group of landless peasants is regarded as inferior.

The formation mechanism of positive functions can be attributed to the following three factors based on FCT. First, FCT argues that loosely structured groups and open societies allow conflict to exist, thus forming a protective layer that can reduce the threat of disagreement, which may at a minimum undermine the core values of society [37]. RCC can effectively identify landless peasants' value orientations that bring positive effects, thus preventing the generation of core value conflicts and embracing a greater number of values. Second, FCT holds that the functions of conflict or tension are closely associated with social change in the community [37]. Conflicts of habitus can promote updating of the physical space of such a community. After conflicts end, the property management company will take action and update the physical space. Through the reconstruction of the physical environment, habitus needs can be met, and the quality of the physical space may be improved. Lastly, FCT posits that conflict with external groups increases internal cohesion. Group boundaries between landless peasants and urban residents are established through conflicts. Conflicts thus strengthen the internal cohesion of the landless peasants' group.

We regard the existence of positive functions of these conflicts and the negative effects of public awareness in value-based conflicts as a structural dual-functional path, which is similar to the concept of structural ambidexterity [64]. The structural dual-functional path emphasizes that value-based conflict separates positive functions from negative effects. By establishing dual structures, the separated conflict causes both positive and negative functions.

### *5.2. Dual Governance Logic of RCC*

From the formation mechanism of RCC functions, we conclude that RCC's positive functions help form a protective layer for the community while RCC's negative effects hinder the community's sustainable transformation. Based on the Thomas–Kilmann Conflict Mode Instrument (TKI) positing five styles of conflict management (competing, compromising, avoiding, collaborating, and accommodating), we propose RCC's dual governance logic: when faced with conflicts that have positive functions, 'accommodation' should be adopted; when facing negative-effect conflicts, 'avoidance' may be applied. RCC governance will then be more effective, thus promoting the resettled community's sustainable transformation (see Figure 9).

#### 5.2.1. Accommodation: Governance Logic Based on Positive Functions of RCC

Strategies should be proposed to achieve accommodation, which contributes to the transformation of landless peasants' resettled communities. RCC accommodation strategies are embodied in two dimensions. One is retaining beneficial habitus to enhance cultural integration; the other is to respect the needs of landless peasants and foster diversity and inclusion in cities. Regarding conflicts of habitus belonging to value-based conflicts, cultural integration is an essential issue. This means that society must adhere to modern urban culture and embrace traditional village culture. Previous studies of the governance of resettled communities for landless peasants mostly argued that they should follow urban community rules and that rural behaviors should be eliminated, gradually enhancing citizenship [3,5,7,29]. However, this study shows that traditional Chinese village culture, characterized by emphases on unity, cooperation, and emotional sharing between individuals, should be fully utilized. The habitus of landless peasants should be respected as well. Hence, we should make efforts to promote beneficial values and habitus. As RCC is closely related to space competition, we propose specific strategies for physical space and social spaces to make use of beneficial habitus. Scholars have found that physical space transformation can contribute to migrants' adaption to the resettled community [7,36]. Therefore, the planning and construction of resettled communities' physical space should help retain the habitus of landless peasants. Some such practices have been implemented,

such as 'shared vegetable gardens'. Public spaces should be systematically redesigned and constructed to satisfy the needs of habitus conservation. Regarding social space, many scholars have argued that the advantages of the semi-acquaintance society could be used to promote the reconstruction of neighborhood relationships [8]. We analyze how to realize this. The landless peasants' reservation of habitus can be utilized to increase the frequency and depth of communication between residents, strengthening internal cohesion. Regarding respect for the needs of landless peasants, this method of settling rights conflicts is crucial because behind the struggle for rights is the expression of the needs of landless farmers. The model of urban communities cannot be rigidly applied to resettled communities. Landless farmers' needs should be respected, not neglected. This illustrates the need for inclusive and varied cities. The suggested governance strategy drew heavily on this as inspiration.

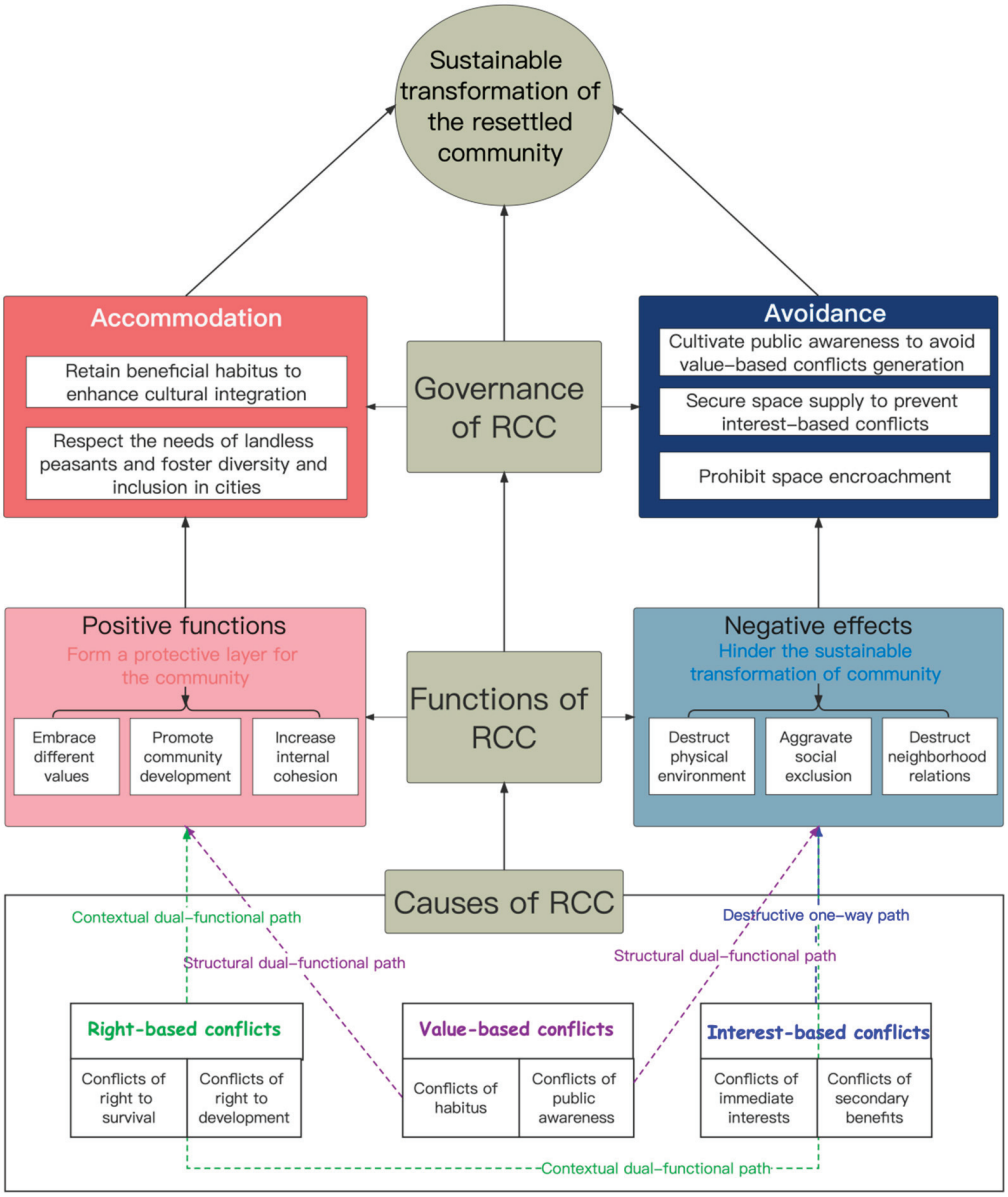


**Figure 9.** A framework for dual governance logic of RCC. Source: Authors.

5.2.2. Avoidance: Governance Logic Based on the Negative Effects of RCC

Strategies should be formulated to avoid conflicts, which would promote a smooth transition in the resettled community. RCC avoidance strategies can be applied in the following three respects. First, public awareness of landless peasants needs to be cultivated to

cultivate landless peasants' sense of belonging and enhance community responsibility [8]. Simultaneously, their identities require nurturing. This ultimately contributes to the cultivation of public awareness. Then, strategies should be formulated to secure the space supply to prevent interest-based conflicts. The quality of private space and public spaces should be improved. Previous studies have shown that it is necessary to fully guarantee construction standards in such communities and improve space quality [5,7]. We found that the built community should be renovated to optimize the layout of spatial functions and improve the utilization rate of community spaces. Interest-based conflicts can thus be avoided. Lastly, the behaviors of space encroachment should be prohibited to protect the physical environment of the community. For example, the reconstruction of houses for group-oriented leasing should be prohibited. However, resettlement policies can be introduced to reduce this kind of behavior; for instance, resettlement houses are currently of a small size.

## 6. Conclusions

The resettled community for landless peasants is a kind of transitional community with both rural and urban features, which causes serious community conflicts. Previous research has only taken conflict functions into consideration, which makes it difficult to provide guidance for proper governance of RCC. Taking a holistic view instead of considering individual cases, this study proposes a dual governance logic for RCC based on FCT. First, 890 RCC case reports were collected using the Baidu search engine. The functions of seven RCC types and three RCC causes were identified using content analysis. Using co-occurrence analysis, the relationship between RCC functions and causes was presented. Finally, the formation mechanism of RCC functions and dual governance logic was proposed.

Results show that there are seven RCC types: inner discontent of residents, verbal clashes between residents, mass incidents, and interventions of property management companies, neighborhood committees, local governments, and media. Based on FCT, three RCC types have positive functions and four have negative effects. We next identified three causes of RCC (right-based, interest-based, and value-based conflicts), with six sub-categories of causes. Regarding the relationship between RCC functions and causes, we conclude that RCC not only has positive functions but also negative effects. In addition, the negative effects of RCC in general outweigh its positive functions. Different RCC causes lead to different functions as follows: the negative effects of interest-based conflicts outweigh positive functions; the positive functions of right-based conflicts are close to the negative effects; the positive functions of habitus conflicts (a sub-category of value-based conflict) exceed the negative effects while the negative effects of public-awareness conflicts (another sub-category of value-based conflict) far outweigh the positive functions. We explored these RCC formation mechanism functions, which constitute a destructive one-way path, a contextual dual-functional path, and a structural dual-functional path, respectively.

Based on RCC function formation mechanisms, this study proposes a dual governance logic for RCC. When facing conflicts with positive functions, 'accommodation' should be adopted; when facing negative-effect conflicts, 'avoidance' should be applied. Accommodation includes two aspects. One is to retain beneficial habitus to enhance cultural integration; the other is to respect the needs of landless peasants and foster diversity and inclusion in cities. Avoidance also has three aspects: public awareness of landless peasants needs to be cultivated; strategies should be formulated to secure space supply to prevent interest-based conflicts; and behaviors of space encroachment should be prohibited to protect the community's physical environment.

This research also has some limitations regarding specific strategies in different conflict scenarios. This requires the proposal of a governance framework for different conflict scenarios to provide more specific references for RCC governance and to promote the sustainable transformation of resettled communities.

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land

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*Review*

# Review of Urban Land Management Based on Bibliometrics

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**Abstract:** As the carrier of global urbanization, urban land is the basic means of productivity and life of urban residents. Urban land management is of great significance to global climate change mitigation, improving ecological quality, promoting economic development, and ensuring sustainable urban development. At present, although studies on urban land management have accumulated at the global level, the differences in research methods, objectives, and perspectives have led to the fragmentation and confusion of research conclusions. Therefore, it is necessary to review the literature of urban land management, clarify the research contexts, grasp the research progress, and predict the research trends. Bibliometrics, as a quantitative analysis method of literature review analysis, is more comprehensive and objective than relying only on a literature review. It is of great value to grasp the topics and trends of the research field from an overall perspective. In this paper, the Bibliometrix R software package was used to conduct an econometric literature analysis on urban land management from 1979 to 2021, using the Web of Science database. The results showed that: (1) the annual scientific research output and citation frequency in the field of urban land management has generally increased. Combined with the annual change trend of scientific research output, urban land management research can be divided into three stages: the budding period, from 1979 to 1989, the development period, from 1990 to 2008, and the high-yield period, from 2009 to 2021. (2) The 129 countries/regions reviewed differed in their research output, and developed countries showed strong research. The United States, China, and Australia were the top three countries in terms of solo publications and cooperation publications. In addition, among the 16,270 authors, the top three authors were Pradhan, Zhao, and Li. (3) The top three keywords in the field of urban land management were "Management", "City/Cities" and "Land Use". The research topics can be divided into three stages. The first stage covers studies with topics of "Management", "Urbanization" and "GIS", from 1979 to 2013. From 2014 to 2018, the research topics were gradually enriched by "Urbanization", "Impact", "System", "GIS", "Management", "Policy", "Conservation" and "land", with a trend towards multidisciplinary and multi-perspective comprehensive analyses. From 2019 to 2021, "Management" and "Climate Change" were the main topics.

**Keywords:** literature review; urban land management; Web of Science; Bibliometrix R

## 1. Introduction

With the advance of global urbanization, urban land has spread and expanded accordingly, and urban land management has become an important issue, gradually becoming of wide concern to various experts, scholars and governments [1]. Urban land is the most important spatial carrier of urbanization [2]. At a global scale, cities account for 3% of the global land area, but carry 55% of the population [3]. In the future, global urban areas are expected to further expand, and, by 2030, more than 60% of the world's population is expected to live in urban areas [4]. By 2050, this proportion is expected to reach 68% [5]. The growth of urban population will inevitably bring about the expansion of urban land, and the speed of urban expansion is significantly higher than the population growth rate,

indicating that the urban land area will exceed the area needed to maintain population growth [6]. At the same time, the rapid expansion of urban land has resulted on the one hand, in large areas that are not adequately used [7–9], whereas, on the other hand, it has also caused prominent social and ecological problems, such as global warming, urban water pollution, an extensive food crisis, a decline in biodiversity and the need for extensive residential land use efficiency, [10–16]. In the future, global urbanization is expected to advance further, with massive challenges for urban land management. On the one hand, urban land management is highly dependent on the political and economic levels as well as on the degree of scientific and technological development and the methods of urban land management differ largely among different countries [17]. On the other hand, different countries differ in climate, hydrology, geology, topography, and other natural environmental conditions, resulting in differences in national policies on urban land management [18,19].

In urban land management, the monitoring, systematic evaluation, and standardized management of urban land are important issues of urban planning, geography, and land resource management [20–22], with practical significance in restraining the unreasonable expansion of urban land and realizing sustainable land use [23]. In the field of urban planning, urban land management should strengthen government supervision, formulate strong policy systems, improve institutions and market operation tools, support effective land market operation, and form a top–down governance system. At the same time, it should give full play to the enthusiasm of citizens to participate in public programs, promote openness and transparency of policies, systems, and projects, and form a bottom–up supervision system [24]. The formation of top–down and bottom–up joint efforts should be used to achieve the efficient and intensive use of urban land [25]. Quantitative analysis of data and models commonly used in the field of geography, as well as the simulation, analysis, and prediction of urban land use, can provide references for decision makers to achieve sustainable land use and the science-based management of urban land [26,27]. Studies on land resource management emphasize the rational allocation of urban land resources from the perspective of management. Through public intervention in urban land management (land ownership, land use, land marketing, and land taxation), as well as tripartite control of legal, fiscal, and governmental aspects, the efficiency and fairness of urban land use allocation could be improved [28,29]. In this context, urban land can be regarded as the carrier of economic, social, and cultural activities as well as ecological civilization, and it is difficult to solve all issues in the field of urban land management by relying on a single discipline and specific technical means. This makes it important to solve the problems in the field of urban land management of the future via the integration of multiple disciplines, the complementarity of multiple technologies, and the intersection of multiple information sources, with the aim of obtaining a comprehensive understanding of the progress of urban land management.

Reviews collect, analyze, and summarize literature to gain a deeper understanding of a certain research field, and conducting a review is an important method to comprehensively grasp past research. There are numerous reviews in the field of urban land and land management. For example, in terms of urban land, scholars such as Youjung Kim reviewed the literature on LCM (Land Change Modeling) in urban land and identified drivers, scenarios, and themes, enabling planners to model future land changes through scenarios to provide more certain conditions [30]. Wagner compared the results obtained by using cellular automata (CA), artificial intelligence (AI), and operations research (OR) to solve urban planning and urban land management issues through review and analysis [31]. Regarding land management, Biratu proposed the importance of managing resources and improving ecosystems in agricultural landscapes to enhance environmental sustainability from the perspective of land management [32], whereas Hanaček studied the impact of land management changes on culture, agro-ecosystem services, and environmental conflicts [33]. Although these studies contributed to an understanding of urban land and land management, the studies were limited to specific countries/regions and specific

disciplines, lacking a global perspective and a comprehensive perspective of all disciplines, and a review of urban land management using bibliometrics was not involved. Therefore, it is of great significance to comprehensively analyze global urban land management by using bibliometric analysis methods, with the aim of developing a deeper understanding of the progress and future trends of urban land management at the global scale.

Scientific research platform databases can be used to obtain high-quality scientific results. Databases such as Web of Science, Scopus, Emerald, and CNKI are widely used all over the world, with the advantages of fast literature retrieval and effective tracking of academic frontiers [34]. Of these, Scopus is a new navigation tool, focusing on prospective scientific, technological, and medical literature worldwide [35]. Emerald was founded in 1967 by scholars from Bradford University Management Center, one of the world's top 100 business schools, publishing journals in management, library science, engineering, and other professional fields [36], whereas CNKI focuses on industry, agriculture, medicine and health, economy, and education, mainly targeting Chinese users [37]. Web of Science is an internationally recognized large-scale comprehensive, multidisciplinary, and core journal citation index database. It enjoys a good reputation in the scientific, technological, and educational circles around the world, with citation index databases, such as SCIE and SSCI, JCR Journal Citation Reports, and ESI Basic Scientific Indicators [38]. The Web of Science core collection database contains more than 8700 global authoritative and high-impact academic journals, covering natural sciences, engineering technology, biomedicine, social sciences, arts and humanities, and other fields [39]. Its powerful analysis function can help researchers better grasp relevant topics and seek research breakthroughs and innovations because it offers quick identification of high-impact papers, and facilitates the discovery of the research directions being considered by domestic and foreign peer authorities, revealing the development trend of the topic, and it selects appropriate journals for submission. An innovative research platform of "retrieval—analysis—management—writing" has been established for researchers [40]. The Web of Science database, therefore, has more advantages than Scopus, Emerald, CNKI, and other databases, due to its wide collection range and complete data sources.

Bibliometrics is a quantitative analysis method that measures the interrelationships and impacts [41] of publications in specific research fields through mathematical and statistical tools. It enables researchers to map out complex knowledge maps, represent knowledge structures in the research field, and study its properties [42–44] through statistical and mathematical methods. Serving as a powerful tool to analyze the field of knowledge and reveal its knowledge structure [45], it provides a macro-overview of academic research and reliably identifies influential authors, journals, organizations, and nations [46]. Among the software packages for measuring and analyzing scientific literature data, CiteSpace, VOSviewer, and Bibexcel have been widely used in the field of global information science due to their scientific and effective advantages in practical applications [47–49]. Regarding the application of such software in literature reviews, CiteSpace has the advantages of rich drawings and of visualizing the key development of a certain field. The VOSviewer software is mainly based on literature co-citation, and, especially when there is a large number of literature keyword co-occurrence, its analysis ability is strong. The BibExcel software specializes in analyzing data that does not include visualization in the results. However, the operation of these software packages in bibliometric analysis is complex, and the function of specific modules is prominent, which cannot assist researchers in building a complete workflow for literature analysis [50]. The Bibliometrix and Biblioshiny software packages compensate for this drawback. Of these, the Bibliometrix R software package provides a set of tools for sociometric quantitative research. Benefiting from the strongest qualities of the R language, compared to other languages in scientific computing, it has the advantages of statistical calculation and quick visualization in bibliometric analysis [51], making it more flexible than other bibliometric tools [52]. Moreover, the software integrates the network analysis and visualization functions of various bibliometric tools, enabling an entire scientific literature analysis and data flow. This not only prevents researchers

from performing tedious multi-step operations but also improves work efficiency and reduces the probability of error. The software is better suited to handle high-volume, highly repetitive, and multi-step computing tasks, and the one-stop handling of problems does not require cross-platform development. Due to these advantages, the Bibliometrix and Biblioshiny software packages have been widely used in different fields [53–55].

Several scholars have reviewed studies on urban land and land management [30–33] and performed bibliometric analyses of land use, land consolidation, land cover, and other related research by using large-scale data sets and bibliometric methods [56–58], with valuable results. However, so far, relevant studies on urban land management are scarce, and most studies in the field of land management have focused on rural land, specific countries or regions, or a single disciplinary perspective [59–61]. Therefore, based on the Web of Science database, and using the Bibliometrix and Biblioshiny packages in R tools, we systematically combed 6318 urban land management studies from 1979 to 2021 and determined the annual numbers of urban land management publications, the major countries/regions, and the main authors and topics, with the aim of providing a reference for future global urban land management research. Specifically, the research objectives of this paper were as follows: (1) to reveal the main research areas and keywords of urban land management in the past 42 years; (2) to assess the research status of the urban land management field; (3) to explore the focus and research direction of future urban land management.

## 2. Data Sources and Methods

### *2.1. Research Data*

Web of Science is one of the largest and most disciplinary comprehensive academic information resource databases in the world [62], including more than 8700 core academic journals [57] in the fields of natural sciences, engineering, biomedicine, social sciences, arts, and humanities. This paper is based on the Web of Science database, using its core collection as the data source. The search scope was selected as "topic", and the search term entered was "urban land management (Urban land management, land management in urban, Management of Urban Land, urban land administration, city land management, land management of city, land management in the city, management of city land, land administration in the city, administration of city land, metropolitan land management, management of the metropolitan land, land management in metropolitan, land administration of metropolitan, land administration in metropolitan, metropolitan land administration, land management of the metropolis, metropolis land management, land management in the metropolis)". To ensure accuracy, the study limited the literature types to "articles", "conference articles", "conference papers", "review papers", "online publications", "data papers" and "brief reports". The search language was set to all languages, with a retrieval period of 1970–2021 (1970 was the first year obtained after the retrieval by subject). After preprocessing, such as deduplication and removal of irrelevant data, 6318 papers in the field of urban land management were obtained, and the time period was finalized as 1979–2021. The downloaded data were saved in plain text format.

### *2.2. Research Methods*

Bibliometrics provides a more objective and reliable literature analysis [63]. Through quantitative analysis, it offers a comprehensive overview, analysis, and presentation of a large number of scattered research papers and objectively identifies past and present research topics and future research trends [64]. Literature review using bibliometrics can not only synthesize past research results, but also plays a key role in effectively using the existing knowledge base, advancing the research direction, and maintaining professional judgment and evidence-based insights regarding professional knowledge practice.

The Bibliometrix R package provides a set of tools for quantitative studies [65]. It was written in the R language, and the mode of operation is composed of code commands [56]. The R language is an open-source environmental analysis tool with functions for efficient

statistical analysis and visualization of large amounts of data. The advantages of statistical computing and rapid visualization of graphics may be the strongest qualities of the R language over other languages in scientific computing [46]. Biblioshiny is a secondary development of Bibliometrix in R by Massimo Aria, who encapsulated the coding of Bibliometrix and created a Web-based online data analysis framework. Users can conduct the relevant scientific measurements and visual analyses using the interactive Web interface, reducing the user's use threshold and information input strength [66].

A literature review using the Bibliometrix and Biblioshiny installation packages in the R tool can be divided into the following two steps. The first step includes selecting topics for the review, sorting and combining different definitions of keywords, searching in the Web of Science, primary selection and detailed screening of data, and downloading and compressing the filtered data. It should be pointed out that "or" is used between different search terms of the same interpretation. The preliminary screening limited the time period as up to 2021, with the earliest research as the initial time, and the search scope was "subject". Detailed screening included the type of literature and the category of the journal. The second step was the use of the metrology software for bibliometric analysis, including data set import, data visualization analysis, and plotting. The specific procedures and methods are shown in Figure 1.

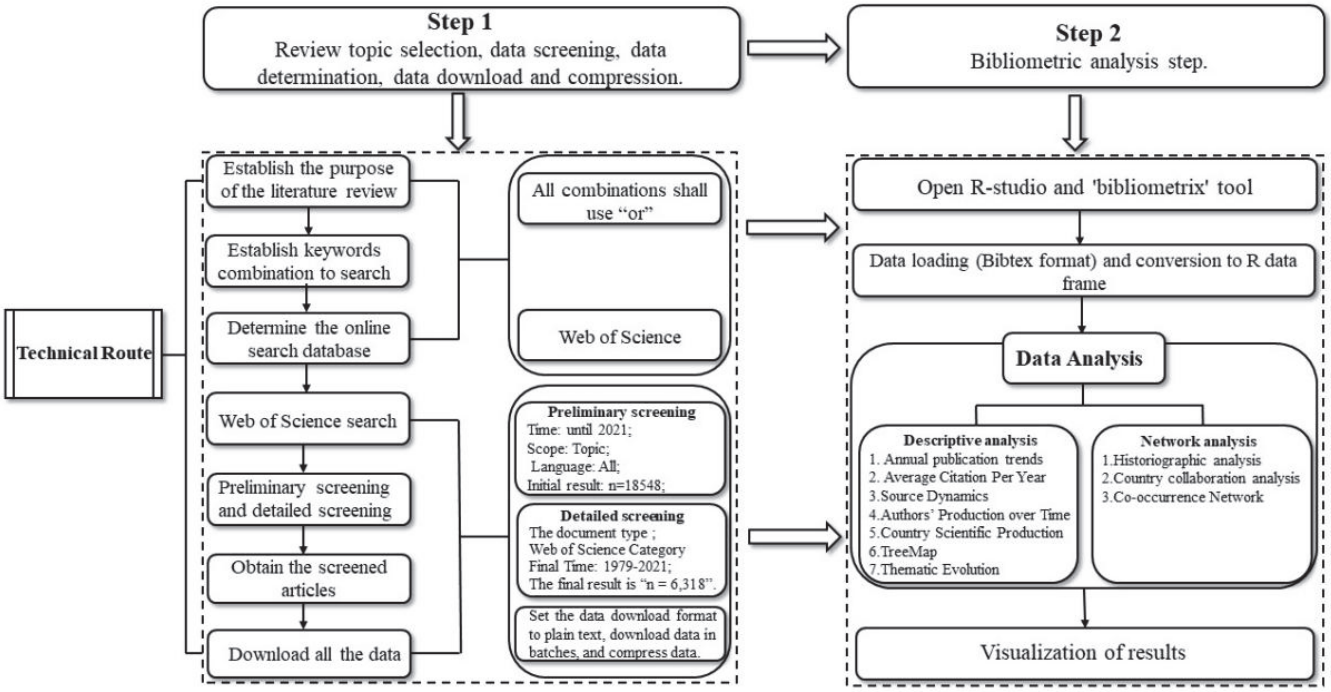


**Figure 1.** Technical Route of the Urban Land Management Review.

## 3. Results

### *3.1. Literature Time Sequence Analysis*

#### 3.1.1. Analysis of the Annual Publication Volume

The distribution of publications from the time series analysis can reflect the study trend [67]. From 1979 to 2021, the number of published research reports in urban land management areas generally increased (Figure 2). Combined with the changing trend, urban land management research was divided into three stages: 1979–1989, 1990–2008, and 2009–2021. The period from 1979 to 1989 was the embryonic period of urban land management research, with a very low number of annual publications, and, in some years, no relevant studies were published. The period from 1990 to 2008 was the development period, in which the number of published papers increased steadily, indicating that urban land management had gradually attracted the attention of the academic community. For

example, the Second United Nations Conference on Human Settlement (HABITAT II), focusing on "Adequate Shelter for All" and "Building Viable Human Settlements and Achieving Full Urbanization in a Changing world", was held in Istanbul, Turkey, in 1996. During the meeting, it was pointed out that in the face of rapid urban population growth and the gathering of large numbers of people in cities, employment, housing, infrastructure, and environmental security issues would become challenges for cities. In this context, how to scientifically and effectively carry out urban planning and urban land management was one of the key elements to achieve sustainable socio-economic development, especially in developing countries [68,69]. The period from 2009–2021 was a high-yield period, with a significant growth in the number of relevant studies.

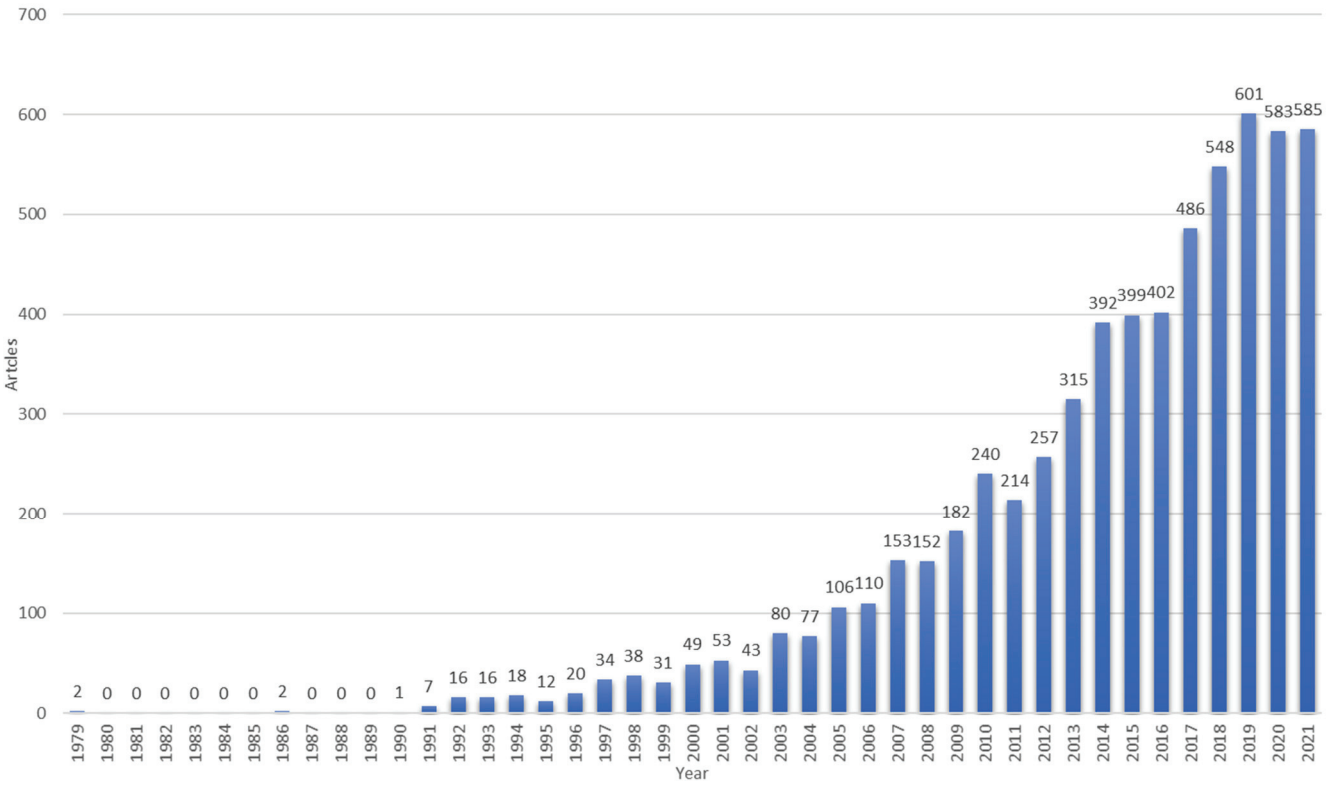


**Figure 2.** Annual output of urban land management studies in Web of Science from 1979 to 2021.

The 2016 United Nations Conference on Housing and Sustainable Urban Development (Habitat III), held in Quito, Ecuador, noted that the continuous growth of the urban population is accompanied by the unplanned expansion of cities, and the problem of slums in developing countries is difficult to solve, with increasing poverty and a greater vulnerable population. How to solve urban social problems, restrain urban sprawl, coordinate the relationship between humans and the land, and make cities places with diversity, inclusiveness, and innovation were important topics [70–72]. The conference also formally adopted a landmark outcome document, the New Urban Agenda, which was part of the United Nations' 2030 Sustainable Development Goals and set global standards for sustainable urban development in the future, which helped in rethinking how we should build and manage urban land and live in cities [73–76].

### 3.1.2. Analysis of Annual Average References

The number of studies can reflect the communication and interaction characterizing academia, and a high number mirrors the high popularity and influence of a specific research field. According to the average citation distribution of the annual papers (Figure 3), the citation rates were very low from 1979 to 1989. In 1979, the reference frequency was only 0.3, indicating that the research relevance was low. The average citation rates from 1990 to

2008 and 2009 to 2021 were 1.81 and 2.98, respectively, showing that the field was constantly developing and that its influence was constantly increasing. In 2005, 2012, and 2020, the citation rates were 3.4, 3.2, and 3.9, respectively. To some extent, the citation frequency was closely related to the development stage of the research field itself. However, 106 papers were published in 2005, 257 in 2012, and 583 in 2020 (Figure 2). From 2009 to 2021 (high-yield period), the number of papers increased, but the quality decreased. Overall, the citation frequency of papers from 1979 to 2021 increased, with some fluctuations, indicating that the overall influence of urban land management-related research increased.

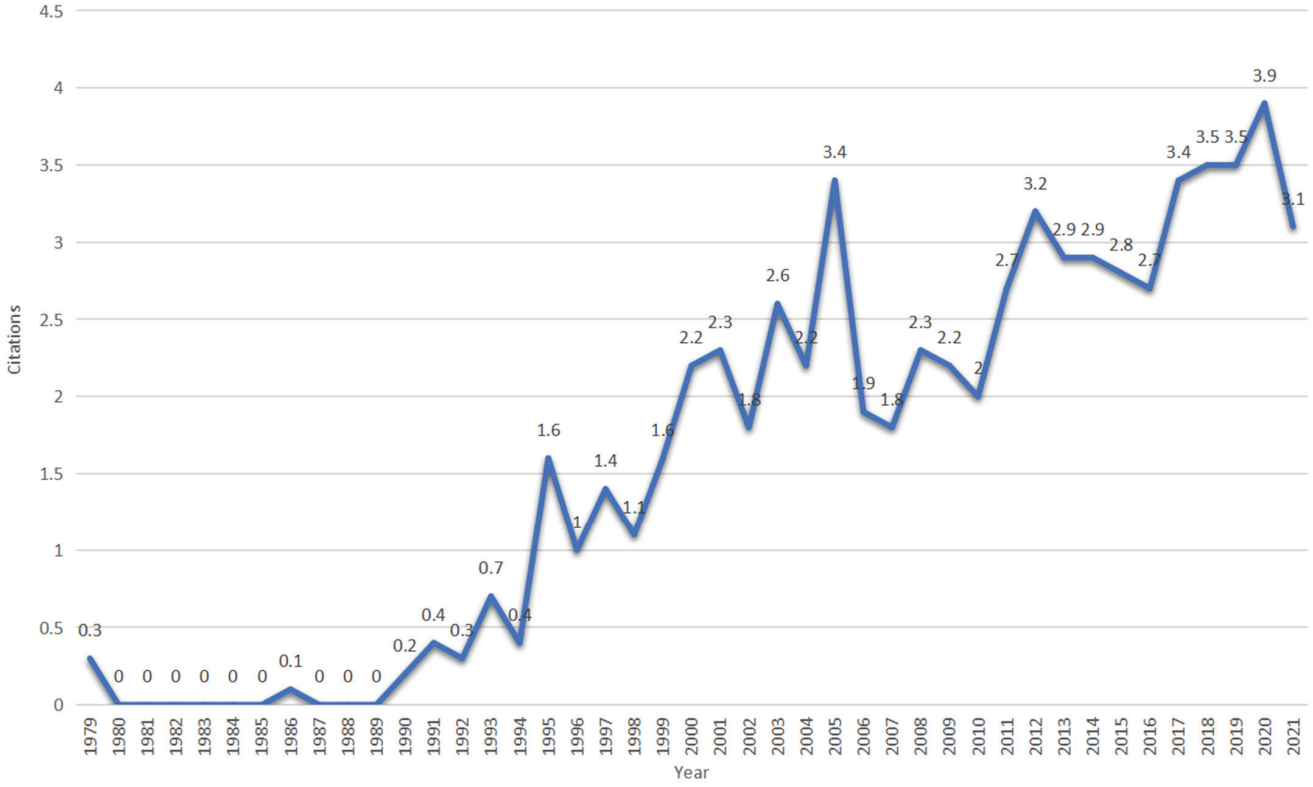


**Figure 3.** Annual citations of papers published by Web of Science from 1979 to 2021.

From 2009 to 2021, the average citation volume fluctuated and increased. During this period, scholars not only focused on the impacts of macro-factors, such as policies and management mechanisms, on urban land management, but also considered the impacts of other single factors on urban land management. For example, in 2015, Michael Eduful et al. studied and analyzed the situation of water body degradation during urban land management in Kumasi, Ghana [77]. The authors pointed out that previous studies tended to focus on policies and regulations as well as the causes, processes, and challenges of urban transformation, calling attention to the impact of urban land use change on water bodies in the field of urban land management, as well as increasing public participation.

### 3.1.3. Analysis of the Dynamic Change of the Published Journals

From 1979 to 2021, 6318 selected articles were published in 1434 different journals and books. An analysis of the scientific output of each journal indicated that annual publications increased for all journals (Figure 4). The top five journals published in Web of Science publications were Landscape and Urban Planning, Remote Sensing, Journal of Hydrology, Habitat International, and Urban Forestry & Urban Greening. Among these, the number of papers in Landscape and Urban Planning and Remote Sensing increased significantly. The number of articles in Landscape and Urban Planning increased from 1 in 1991 to 360 in 2021, followed by Remote Sensing, which grew from 3 articles in 2011 to 211 in 2021.

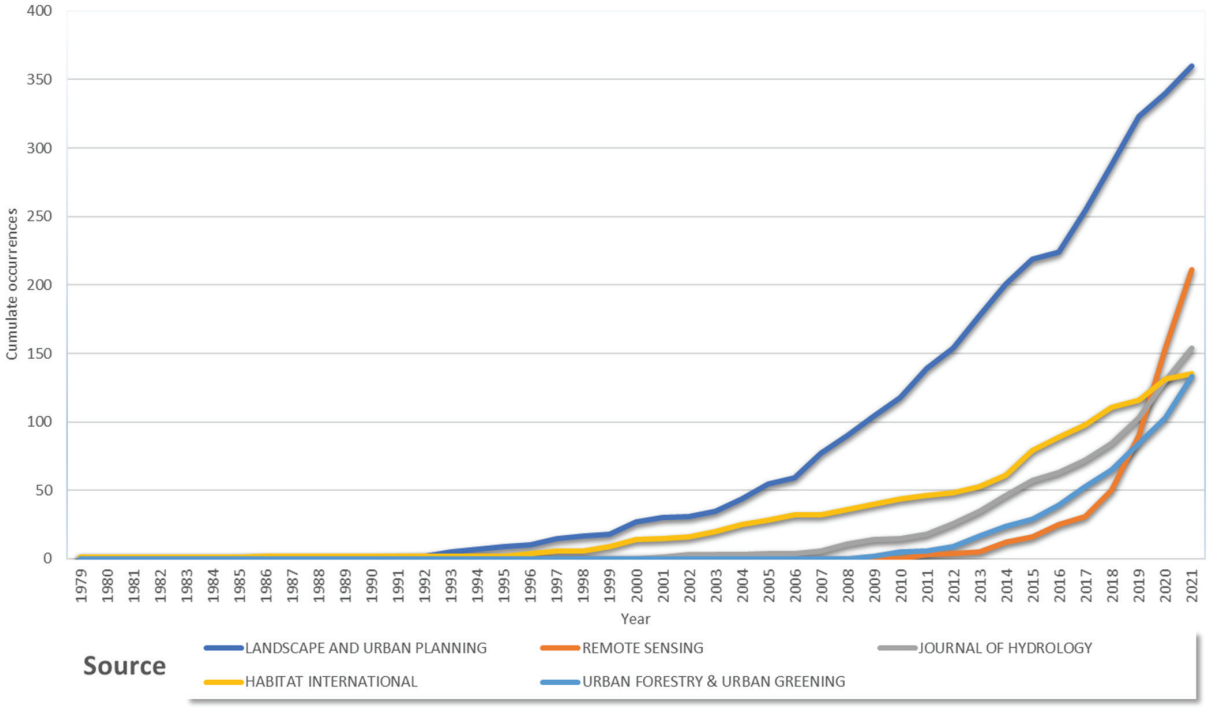


**Figure 4.** Trends in annual publications of different journals in Web of Science from 1979 to 2021 (Top Five).

Based on the main information of the five journals (Table 1), Landscape and Urban Planning started publishing studies on urban land management in 1991 and is still the most influential journal today. Among all journals, the h-index was 70, the g-index was 112, the m-index was 2.118, and the total citations (hereinafter referred to as "TC") were 17,080.

**Table 1.** Journals with the highest numbers of published papers in the field of urban land management in Web of Science (Top Five).

| Journal | h-Index | g-Index | m-Index | TC | NP | PY-Start |
|---|---|---|---|---|---|---|
| Landscape and Urban Planning | 70 | 112 | 2.118 | 17,080 | 356 | 1991 |
| Remote Sensing | 27 | 40 | 2.250 | 2947 | 211 | 2011 |
| Journal of Hydrology | 35 | 64 | 1.591 | 5052 | 154 | 2001 |
| Habitat International | 33 | 58 | 0.750 | 4269 | 136 | 1979 |
| Remote Sensing of Environment | 33 | 51 | 1.269 | 5705 | 51 | 1997 |

Note: h-Index represents the importance and the influence of the accumulated research; the g-Index represents the derivative index of the h-Index; m-Index = h/n; n represents the age when the author published in the field; TC stands for total citations; NP represents the number of publications; PY-Start represents the start of the publication year.

### *3.2. Analysis of Major Countries/Regions and Researchers*

#### 3.2.1. Analysis of Major Countries/Regions

The papers published in different countries partly reflect the importance and influence of a given country in the field of urban land management. From 1979 to 2021, a total of 129 countries or regions published papers on urban land management. Among the top 10 countries, there were two Asian countries (China, India), two North American countries (USA, Canada), one South American country (Brazil), four European countries (Britain, Italy, Germany, Spain), and one Oceanian country (Australia) (Figure 5). The top three countries with the largest numbers of publications, excepting China, were developed countries, mainly in Europe, indicating that developed countries were strong in urban land management research. Theoretically, this was related to the high level of urbanization,

the early development of urban planning work, and the relatively mature urban land management modes in developed countries.

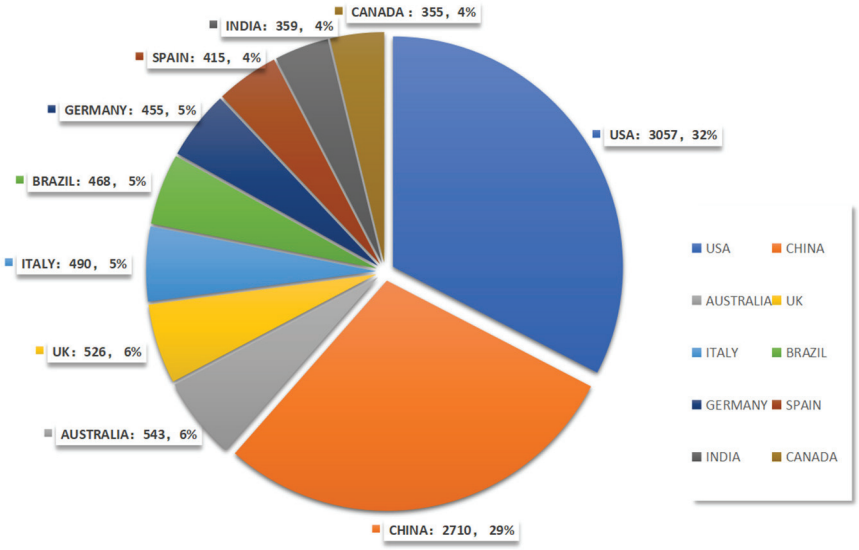


**Figure 5.** Research output by country in the field of urban land management in Web of Science from 1979 to 2021.

3.2.2. Cooperation Analysis of Major Countries

Regarding the cooperation among major countries around the world (Figure 6), each country had different degrees of cooperation, forming two core-edge clusters. In the field of urban land management, cooperation and exchanges among scholars from the United States, China, and Australia deepened. For example, the American scholars, Wolch and Newell, in collaboration with Australian scholar, Byrne, published "Urban Green Space, Public Health, and Environmental Justice: The Challenge of Making Cities 'Just Green Enough'" in Landscape and Urban Planning in 2014. The article "Just Green Enough" reviews UK and US research on the role of urban green space in shaping public health and environmental justice and compared the efforts of China and the United States in urban greening, concluding that improving the spatial distribution of urban green space can help achieve environmental and spatial justice, as well as class equality [78]. Articles by the American scholars, Wolch and Newell, and the Australian scholar, Jason Byrne, demonstrated that access to urban park resources varied by class and racial dimensions and required intervention [78]. In addition, the authors proposed a "Just Green Enough" urban green space strategy, calling on urban planners, designers, and ecologists to protect social, ecological, and land use sustainability and to strengthen urban land management [78].

The number of publications and citations of scientific papers is an important indicator to measure a country's scientific research strength. From 1979 to 2021, the statistical results of national collaborative papers in Web of Science, by nationality of the corresponding authors, showed that the number of papers published by corresponding authors and the total citations placed the United States, China, and Australia in the top three (Table 2), indicating the strong academic influence of these three countries. Among the developed countries, the United States had 1244 corresponding authors and 39,715 citations, ranking first in the world, indicating the highest academic level in the field of urban land management. Among them, the single-country publications (SCPs) were 1085, and the multiple-country publications (MCPs) were 159. In developing countries, 1091 articles on urban land management were published in China, which became one of the most important countries in the field. However, the average article citations of Chinese papers were relatively low, with only 18.22, indicating that the quality of Chinese papers needed to be further improved. In China, the number of SCPs was 835, and that of MCPs was 256, suggesting that Chinese scholars paid more attention to international collaborations.

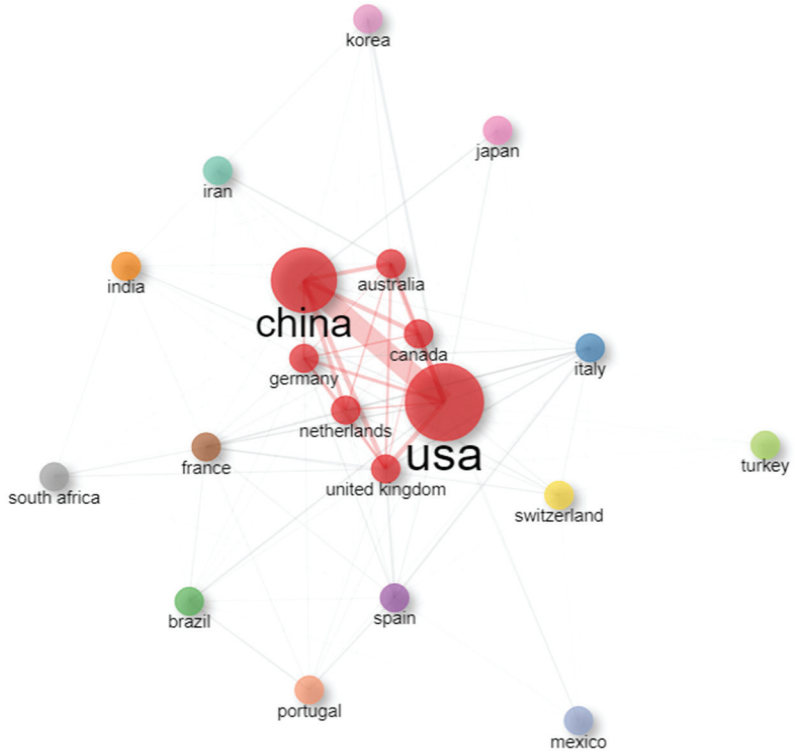


**Figure 6.** Top 20 national collaborative networks in the field of urban land management in Web of Science in terms of scientific research output from 1979 to 2021. Note: The 20 circles generated represent cooperative maps of 20 countries. The size of the circle represents the scientific research output. The connection lines among countries indicate the state of cooperation among these countries, and the thickness of the lines indicates the cooperation strength.

**Table 2.** Statistics of national cooperative papers in Web of Science from 1979 to 2021 by nationality of the corresponding authors (Top Ten).

| Country | Articles | SCP | MCP | Total Citations | Average Article Citations |
|---|---|---|---|---|---|
| USA | 1244 | 1085 | 159 | 39,715 | 31.93 |
| China | 1091 | 835 | 256 | 19,878 | 18.22 |
| Australia | 274 | 207 | 67 | 7428 | 27.11 |
| Italy | 244 | 193 | 51 | 4212 | 17.26 |
| United Kingdom | 234 | 166 | 68 | 6464 | 27.62 |
| Spain | 208 | 169 | 39 | 2958 | 14.22 |
| Brazil | 205 | 177 | 28 | 763 | 3.72 |
| India | 183 | 162 | 21 | 2640 | 14.43 |
| Germany | 180 | 117 | 63 | 4200 | 23.33 |
| Canada | 167 | 131 | 36 | 3093 | 18.52 |

Note: SCP, single-country publications; MCP, multiple-country publications.

Further analysis showed that countries at different development levels faced different urban land management issues and differed in their concerns regarding urban land management. For example, developed countries proposed the concept of "Smart Growth", managing urban land by demarcating urban growth boundaries, encouraging mixed land use, and protecting farmland and open space, with widespread impacts [79]. Many of the states in the United States, including Florida, Maryland, and New Jersey, managed urban land [80] through legislation to support the compact development of urban centers. Many European countries (such as the United Kingdom, the Netherlands, Germany, Norway, Poland, Spain, and Italy) started from increasing density, improving land use efficiency, and reusing vacant land to curb cities and manage urban sprawl [81], whereas developing countries were mostly interested in unmanaged urban land expansion and unplanned and

decentralized urban redevelopment models [82]. Moreover, the existence and potential impact of vacant land in developing countries were largely ignored [83], and some developing countries were in the transition period from sprawling development to the quantitative management of urban land using technological means [84].

3.2.3. Analysis of the Main Authors

Highly cited scholars represent the guidance of researchers in this field, reflecting the commanding heights of national or regional knowledge innovation. Highly cited papers mean that the authors' research results were, at least for some time, widely recognized, inherited, and further developed by other researchers. In view of this, this paper selected high-citation authors and studied their published high-citation papers to understand their research scope. A total of 16,270 authors contributed to the field of urban land management during the studied period, with Pradhan, Pengjun, and Xiang being the first three authors, publishing 20, 14, and 19 papers, respectively (Table 3). The h-index was commonly used to measure the importance of authors and the influence of cumulative research contributions [57,85]. To prevent the uncertainty caused by the comparison of the h-index, and to compare the influence of the authors in the field during different periods, both the g-index and the m-index were introduced in the software, using the following equation:m=h/n.

**Table 3.** The 10 most influential authors in the field of urban land management in Web of Science from 1979 to 2021.

| Author | h-Index | g-Index | m-Index | TC | NP | PY-Start |
|---|---|---|---|---|---|---|
| PRADHAN B | 13 | 20 | 1.300 | 758 | 20 | 2013 |
| ZHAO PJ | 13 | 14 | 0.929 | 728 | 14 | 2009 |
| LI X | 11 | 19 | 0.440 | 900 | 19 | 1998 |
| LIU YX | 11 | 12 | 1.100 | 516 | 12 | 2013 |
| SALVATI L | 11 | 17 | 1.000 | 713 | 17 | 2012 |
| ZHOU WQ | 11 | 17 | 1.000 | 1209 | 17 | 2012 |
| JIM CY | 10 | 16 | 0.385 | 345 | 16 | 1997 |
| WANG J | 10 | 23 | 0.667 | 566 | 25 | 2008 |
| YANG J | 10 | 15 | 0.714 | 566 | 15 | 2009 |
| FLETCHER TD | 9 | 9 | 0.900 | 499 | 9 | 2013 |

Note: h-Index represents the importance and the influence of the accumulated research; the g-Index represents the derivative index of the h-index; m-Index = h/n; n represents the age when the author published in the field; TC stands for total citations; NP represents the number of publications; PY-Start represents the start of the publication year.

Where n represents the age of the author when publishing in the field [86], and the g-index is the derivative index of the h-index, mainly to compensate for the defect that the h-index does not respond well to reflect highly cited papers. In this field, Pradhan published the largest number of papers, with an h-index of 13, a g-index of 20, and a total citation number of 758, indicating that the papers of this author were of high quality and highly influential.

Further analysis revealed that Pradhan's most frequently cited paper appeared in 2019 (the darkest color in Figure 7), being cited 60 times. This was because in 2019, Pradhan's "Urban Flood Risk Mapping Using the GARP and QUEST Models: A Comparative Study of Machine Learning Techniques", published in the "Journal of Hydrology", proposed using the genetic algorithm rule-set production (GARP) model to draw urban flood risk maps, with the aim of strengthening urban flood risk management and improving urban land use efficiency, thereby better serving urban planning and urban land management [87].

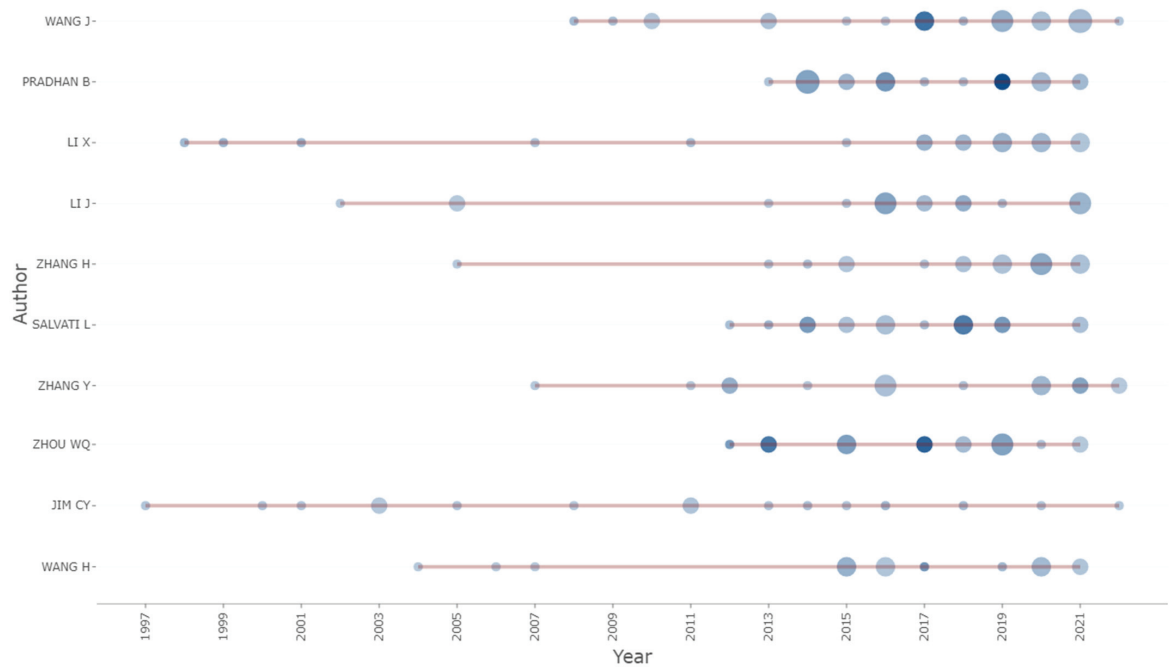


**Figure 7.** Long-term outcomes of highly cited authors in Web of Science in urban land management.

3.2.4. Historical Citation Analysis of the Main Authors

This paper used the local citation store (LCS) and global citation store (GCS) indicators, as well as historical citation visualization, to analyze the research methods and the contents of classical publications. The LCS refers to reference citations in the downloaded dissertation dataset, whereas GSC refers to reference citations in the Web of Science core collection database. The historical reference visualization selected the top 24 cited nodes, with the node content set to the author and the year of publication, revealing pioneering work and some classical research in the field (Figure 8). Among the first 24 cited papers in urban land management, the earliest node was an article published in Landscape and Urban Planning by Nowak in 1996 (Figure 8), titled "Measuring and analyzing urban tree cover" [88]. The paper pointed out that by revealing the characteristics of the entire urban vegetation, measuring urban tree cover can facilitate urban vegetation planning, management, and research.

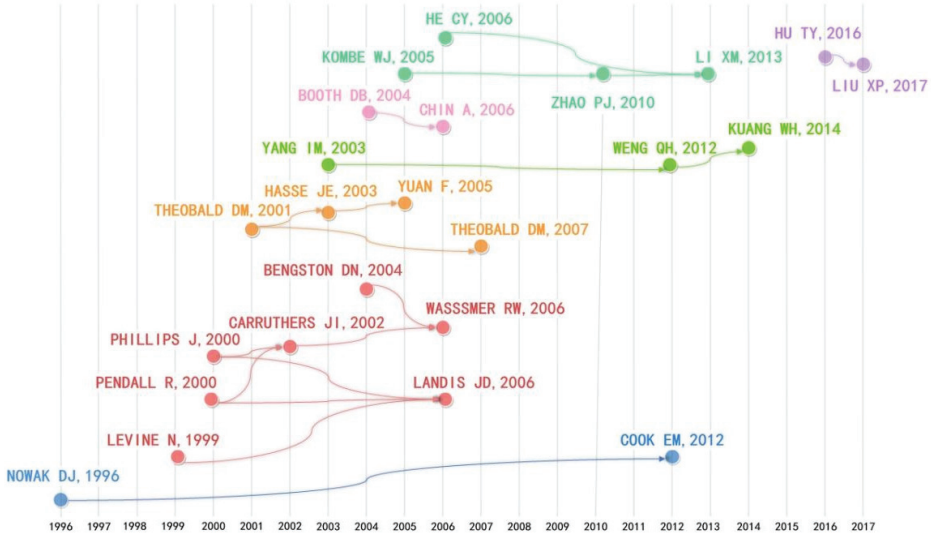


**Figure 8.** Historical direct citation network of authors of the top 24 most cited papers in urban land management from 1979 to 2021.

Several classical articles appeared between 1996 and 2017, clearly showing the historical citation relationships among the top 10 authors in the field of urban land management (Figure 8). For example, in 2000, Phillips published an article in Contemporary Economic Policy, titled "Growth management and housing prices: the case of Portland, Oregon", with two different reference chains (Figure 8), with an LCS of 31 (Table 4) and a joint fifth place in the LCS in that time interval (1979–2021). Taking Portland, Oregon, as an example, this article used econometric analysis to conclude that the urban growth boundary (UGB) had less impact on land and housing prices. It pointed out that the UGB was a compact form of zoning, aiming to control urban sprawl and facilitating urban land management [89].

**Table 4.** Top 10 LCS publications in urban land management from 1979 to 2021.

| Publications | DOI | Year | LCS | GCS |
|---|---|---|---|---|
| WENG QH, 2012, REMOTE SENS ENVIRON | 10.1016/j.rse.2011.02.030 | 2012 | 55 | 660 |
| YUAN F, 2005, REMOTE SENS ENVIRON | 10.1016/j.rse.2005.08.006 | 2005 | 50 | 628 |
| BENGSTON DN, 2004, LANDSCAPE URBAN PLAN | 10.1016/j.landurbplan.2003.08.007 | 2004 | 38 | 341 |
| HU TY, 2016, REMOTE SENS-BASEL | 10.3390/rs8020151 | 2016 | 34 | 224 |
| COOK EM, 2012, URBAN ECOSYST | 10.1007/s11252-011-0197-0 | 2012 | 31 | 253 |
| PHILLIPS J, 2000, CONTEMP ECON POLICY | 10.1093/cep/18.3.334 | 2000 | 31 | 105 |
| HASSE JE, 2003, APPL GEOGR | 10.1016/j.apgeog.2003.08.002 | 2003 | 30 | 283 |
| CARRUTHERS JI, 2002, URBAN STUD | 10.1080/0042098022000011317 | 2002 | 30 | 101 |
| PENDALL R, 2000, J AM PLANN ASSOC | 10.1080/01944360008976094 | 2000 | 29 | 210 |
| NOWAK DJ, 1996, LANDSCAPE URBAN PLAN | 10.1016/S0169-2046(96)00324-6 | 1996 | 27 | 225 |

Note: LCS (local citation score) refers to the citations in the downloaded paper dataset, and GSC (global citation score) refers to the citations in the Web of Science core collection database.

Similarly, the article published by Theobald in 2001 also developed two citation chains (Figure 8), and two articles in one of the citation chains ranked in the top 10 in LCS and GCS (Tables 4 and 5), indicating that these two publications are classical papers in the field of urban land management, with strong relations to other disciplines. These two publications are "Land resource impact indicators of urban sprawl", published by Hasse in "Applied Geography" in 2003, and "Land cover classification and change analysis of the twin cities (Minnesota) metropolitan area by multitemporal Landsat remote sensing", published by Yuan in "Remote Sensing of Environment" in 2005 [90,91]. Hasse quantified changes in land resources using land cover/land use change datasets compiled by the State of New Jersey, as well as the U.S. Census and other environmental data, allowing policymakers and researchers to better understand current issues and scientifically manage urban land [90]. Yuan's article cited the above, both of which pointed out that using data to map, monitor, and analyze changes in land cover over time in the face of rapidly growing metropolitan areas can provide an accurate and effective reference for urban land management and policy decisions [90,91].

**Table 5.** Top 10 GCS-ranked publications in the field of urban land management from 1979 to 2021.

| Publications | DOI | Year | LCS | GCS |
|---|---|---|---|---|
| WENG QH, 2012, REMOTE SENS ENVIRON | 10.1016/j.rse.2011.02.030 | 2012 | 55 | 660 |
| YUAN F, 2005, REMOTE SENS ENVIRON | 10.1016/j.rse.2005.08.006 | 2005 | 50 | 628 |
| BENGSTON DN, 2004, LANDSCAPE URBAN PLAN | 10.1016/j.landurbplan.2003.08.007 | 2004 | 38 | 341 |
| YANG LM, 2003, CAN J REMOTE SENS | 10.5589/m02-098 | 2003 | 18 | 337 |
| HASSE JE, 2003, APPL GEOGR | 10.1016/j.apgeog.2003.08.002 | 2003 | 30 | 283 |
| THEOBALD DM, 2007, LANDSCAPE URBAN PLAN | 10.1016/j.landurbplan.2007.06.002 | 2007 | 23 | 278 |
| THEOBALD DM, 2001, GEOGR REV | 10.2307/3594740 | 2001 | 23 | 257 |
| COOK EM, 2012, URBAN ECOSYST | 10.1007/s11252-011-0197-0 | 2012 | 31 | 253 |
| CHIN A, 2006, GEOMORPHOLOGY | 10.1016/j.geomorph.2006.06.033 | 2006 | 21 | 248 |
| ZHAO PJ, 2010, HABITAT INT | 10.1016/j.habitatint.2009.09.008 | 2010 | 18 | 239 |

Note: LCS (global citation score) refers to the citations in the downloaded paper dataset, and GCS (global citation score) refers to the citations in the Web of Science core collection database.

Qihao published "Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends" in Remote Sensing of Environment in 2012 [92]. The GCS of this paper was as high as 660, with an LCS of 55 (Tables 4 and 5). There was only one citation chain (Figure 8), indicating that this paper focused on urban land management. Digital remote sensing was used to extract and study the impervious surface in urban areas, which is also of great significance to urban planning, as well as environmental, land, and resource management.

### *3.3. Keywords Analysis*

#### 3.3.1. High-Frequency Keywords Analysis

The top 10 keywords in the field of urban land management were Management, City/Cities, Land Use, Impact/Impacts, Urbanization, Model, Climate Change, Urban, Classification, and Dynamics (Figure 9). Thus, Management, Urbanization, Classification, and Model were the research hotspots in the field of urban land management. By using model quantitative analysis, we can accurately analyze, predict, and guide the changes in urban land use and manage urban land based on scientific rationales. For example, the article "Quantitative decision making in land banking: A Monte Carlo simulation for China's real estate developers", published in the "International Journal of Strategic Property Management" in 2012, by Bao et al., was concerned with facing the shortage of urban development land in China and other developing countries, and developing a land reserve decision model for real estate development companies to strengthen the management of urban land. It also supported real estate enterprises in making rational and dynamic decisions [93] in the current dynamic real estate market. Back then, urban planning was a complex, systematic, and dynamic work field, and it was a new trend to use novel technologies to extract, identify, and classify land during urbanization. For example, Li et al. adopted a clustering method in the article "Understanding the diversity of urban-rural fringe development in a fast urbanizing region of China" in "Remote Sensing" in 2021. Multi-dimensional urbanization indicators were included to understand the temporal and spatial changes in the development of urban and rural fringes (areas between urban and rural areas) in China's Yangtze River Delta urban agglomeration [94]. By analyzing the diversity of rural–urban margins in rapidly urbanizing regions, the authors of this paper filled a gap in previous research and provided insights for reorienting rural–urban interfaces and land use management.

Keywords such as Land-cover, Climate, and Ecology did not rank at the top of the statistical table of high-frequency keywords (Table 6). In the paper, "Effects of land use and land cover change on carbon sequestration and adaptive management in Shanghai, China", in Physics and Chemistry of the Earth, Zhang et al. analyzed the mechanism between carbon sequestration and land use and land cover change in Shanghai. It was pointed out that strengthening urban land management work and enhancing the carbon fixation capacity of urban ecosystems can help alleviate climate change in the process of urbanization and achieve the goal of sustainable development [95]. Topics closely related to "Climate" and "Urban land management" are "Climate Change Adaptation". In our database, there were 119 papers related to "Climate Change Adaptation" (compared to 6318 in the database), but "Climate Change Adaptation" did not appear in the high-frequency keyword statistics table because the software could not count the combined vocabulary (Table 6), but "Climate Change Adaptation" is the research hotspot in the field of urban land management. Governments around the world have felt the huge negative impact of natural disasters caused by extreme climate change on production and livelihoods, such as extreme heat and urban waterlogging. Related to urban land management, climate change requires urban land management departments and urban planners to allocate urban construction land more rationally, to improve the efficiency of urban carbon sinks, to reduce carbon dioxide emissions, to mitigate extreme natural disasters caused by climate change, and to reduce property losses. For example, in order to cope with climate change in Germany, the planning and management department incorporated climate change into spatial planning

research, converted abandoned land in cities into green and open spaces, and improved the carbon sink efficiency of urban land. At the same time, more emphasis was placed on public participation, providing citizens with measures to perceive and evaluate the urban climate environment, and, thereby, improving the efficiency of urban land management [96].

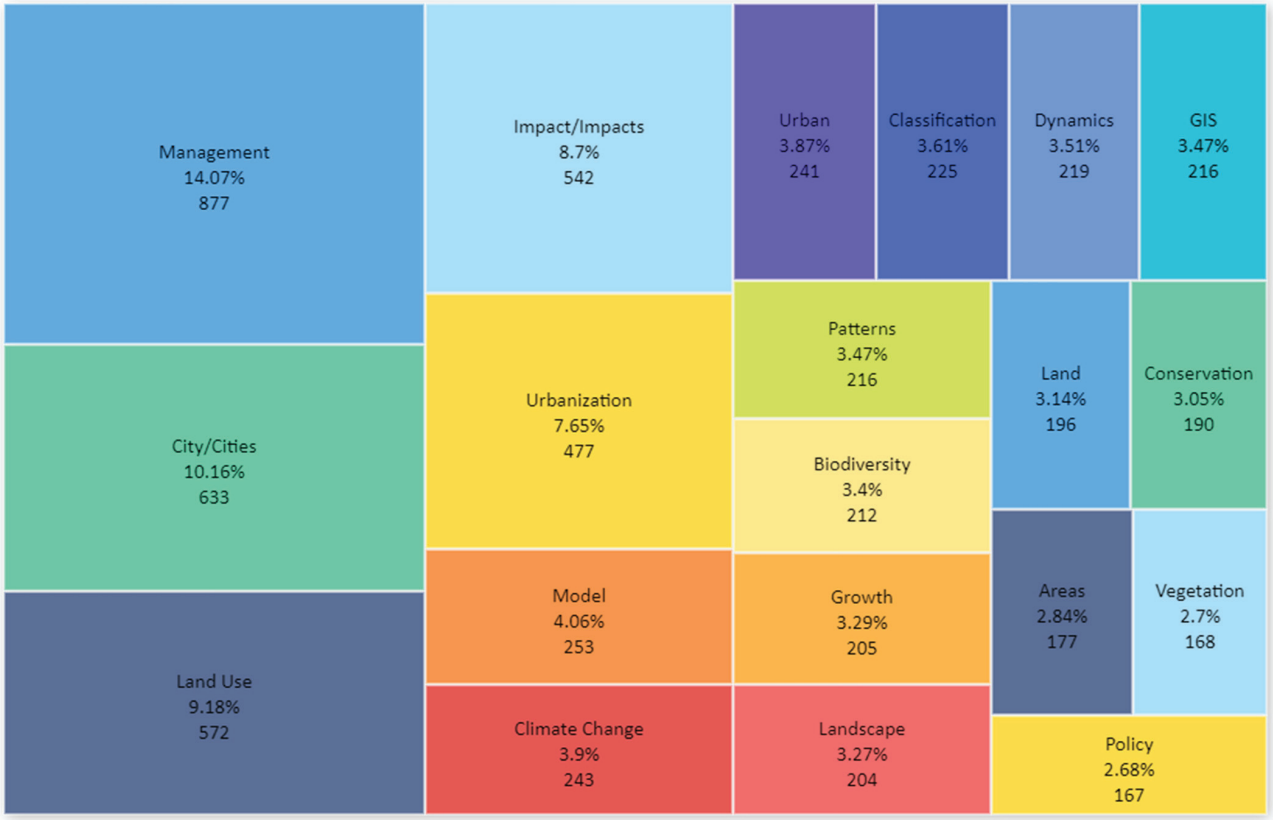


**Figure 9.** Tree map of high-frequency keywords in the field of urban land management in Web of Science from 1979 to 2021 (Top 20).

**Table 6.** High-frequency keywords and frequency of occurrence in the field of urban land management (Top 40).

| Keywords | Frequency | Keywords | Frequency |
|---|---|---|---|
| Management | 877 | Area | 160 |
| City/Cities | 633 | Ecosystem Services | 160 |
| Land Use | 572 | China | 157 |
| Impact/Impacts | 542 | Land Use Change | 140 |
| Urbanization | 477 | Sprawl | 140 |
| Model | 253 | Cover | 128 |
| Climate Change | 243 | Water | 123 |
| Urban | 241 | Quality | 118 |
| Classification | 225 | Framework | 116 |
| Dynamics | 219 | Governance | 113 |
| GIS | 216 | Climate | 111 |
| Patterns | 216 | Forest | 109 |
| Biodiversity | 212 | Expansion | 108 |
| Growth | 205 | United States | 107 |
| Landscape | 204 | Land Cover | 105 |
| Land | 196 | Ecology | 104 |
| Conservation | 190 | Region | 101 |
| Areas | 177 | Scale | 99 |
| Vegetation | 168 | Systems | 98 |
| Policy | 167 | Runoff | 96 |

3.3.2. Co-Occurrence Network Analysis of High-Frequency Keywords

The purpose of co-word analysis is to identify word co-occurrence, create networks, and cluster keywords from selected articles. Keyword co-occurrence is studied using normalized association methods, pointing out a general conceptual framework of the research field. Co-word analysis is the only analysis that uses the true nature of an article and that can be applied to the full text, abstract, and keywords [46,97]. Limiting the number of keywords to 30 generated a network of keyword co-occurrences (Figure 10). The keyword co-occurrence network in this study described two clusters. When two keywords occurred simultaneously in one or more articles, they were likely to be grouped in one cluster. The size of the simultaneous circle indicated the number of file appearances. Collaborative strength was demonstrated by the distance between circles in individual pairs, the density of lines between circles, and the width of the lines. The earlier the keyword appeared, the lighter the ring color was.

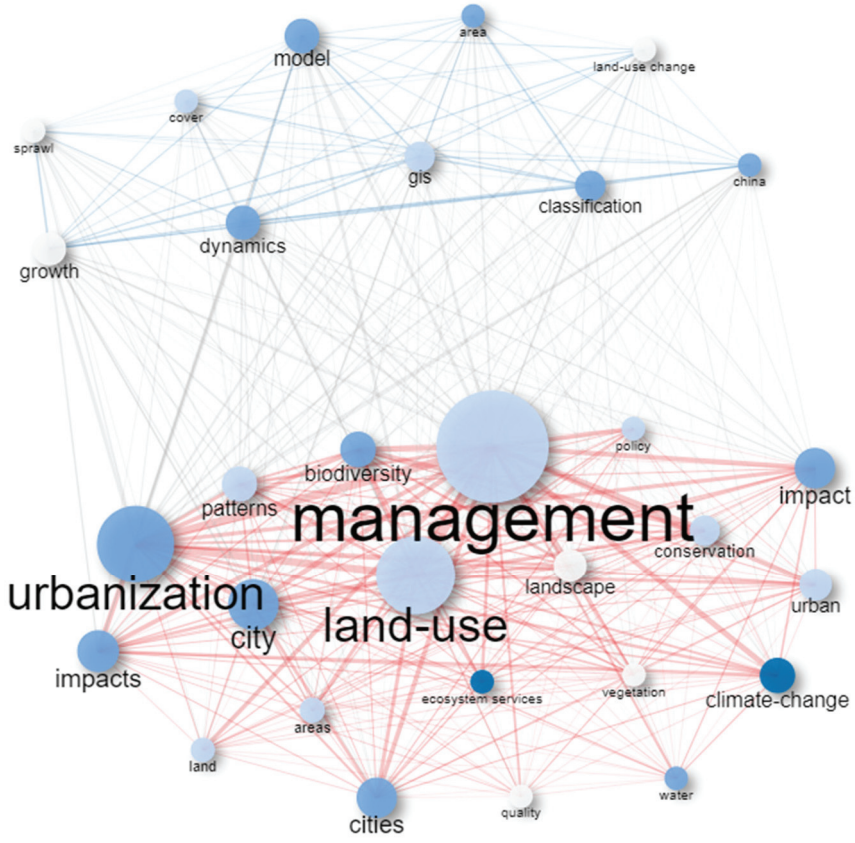


**Figure 10.** Keyword Co-occurrence Network Analysis (Top 30).

Further analysis showed that "Management", "Urbanization", "Land Use", and "Climate Change" were closely linked (Figure 10). For example, Kazak published "The use of a decision support system for sustainable urbanization and thermal comfort in adaptation to climate change actions—the case of the Wrocław larger urban zone (Poland)" in Sustainability. The paper proposed that, to better adapt to the potential impacts of future climate change, land use modeling could realize the rational use and management of urban land in the future, and, by creating a more sustainable urban structure, it could better adapt to climate change and environmental extremes [98].

3.3.3. Analysis of the Thematic Evolution

The Sankey diagram is highly important for studying the topic and topic evolution in a certain field [99]. This diagram, also known as the Sankey energy shunt diagram, mainly describes the flow of different nodes in the network and is frequently used to analyze

the flow of energy or matter. The arrows or direction lines of the Sankey plot are used to represent these flows, and the thickness of the arrow or direction is proportional to the flow size. These charts are commonly used in industrial ecology to describe product lifecycle assessments and to rapidly visualize energy efficiency [100] in engineering. Sankey diagrams, which emphasize the magnitude and direction of traffic within a system, have also been used in geography, urban planning, and environmental science because of their widespread utility [41,101,102].

Based on the Sankey diagram, this paper intuitively presents the changes of urban land management topics over time, indicating that the research topics related to urban land management change over time (Figure 11). Among them, in the first stage (1979–2013), urban land management research was in the embryonic stage, and scholars began to explore this topic from the perspectives of "Management", "Urbanization", and "GIS". The second stage (2014–2018) showed a gradually enriched research content of urban land management, mainly related to "Urbanization", "Impact", "System", "GIS", "Management", "Policy", "Conservation", and "Land Subsidence", with a multidisciplinary and multi-perspective comprehensive development. The third phase (2019–2022) mainly focused on two aspects, namely "Management" and "Climate Change". In this phase, the research in the field of urban land management was deeper, with more diversified perspectives, more mature technologies, and more attention to human needs and environmental friendliness. In general, from 1979 to 2021, in the field of urban land management, "Management" was always one of the core themes in the field of urban land management, and the overall research themes were first diversified and then focused.

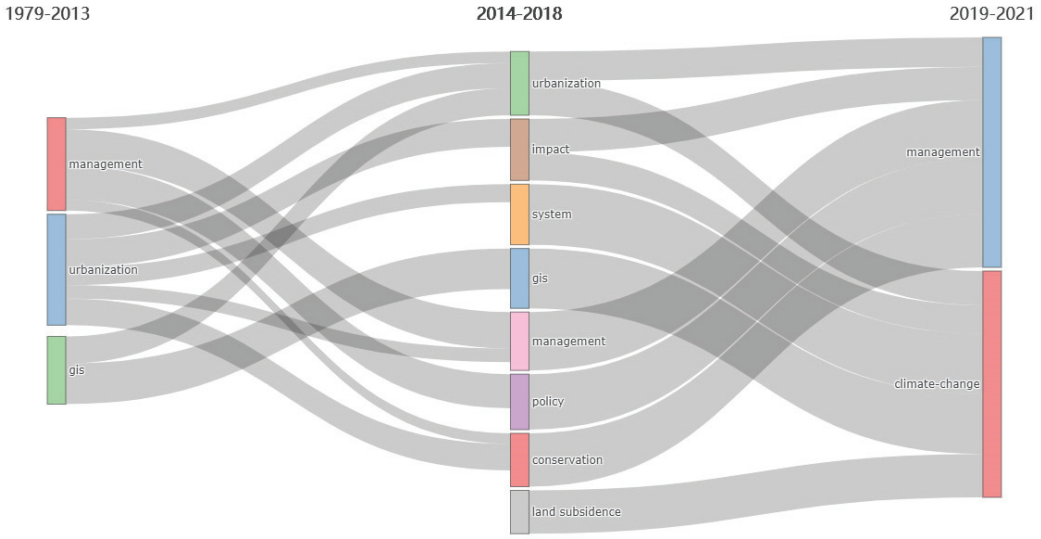


**Figure 11.** Thematic evolution in the field of urban land management (1979–2021).

## 4. Discussion

### *4.1. Analysis of the Research Trend of Urban Land Management*

Research work on urban land management and development policy provides the guidance and guarantee of urban land management. "Management", as one of the main themes in the field of urban land, has been subject to laws and policies to protect the sustainable use of urban land. Urban land management is affected by time and space, and the research focus, direction, and contents of different countries/regions in different periods are also different. Therefore, studying the development of different countries is conducive to the formulation of relevant policies and urban land management. For example, in the temporal dimension, China changed from aggressive development in the period of the reform and opening up to delineating the boundaries of urban development in the context of today's land and space to activate the stock, leave a margin, and grow shrewdly [103]. Israel was strongly influenced by top–down land use policies, with planning principles and policies

developed at the national level and issued as laws and directives for implementation at the local level. The period from the 1950s to the 1970s was marked by an urgent need to establish and protect borders, due to agricultural land conservation and land use policies. Therefore, the creation of small agricultural communities and new towns on the geographical edge of the country limited the urban spread and the growth of urban land to some extent. In the 1980s, when restrictions on urban development were loosened, the policy still focused on protecting farmland. The 1990s and 2000s fall into the era of planning shocks and urban growth management, and the policy of urban growth management was established in Israel's land use planning. The policies established over the past few years encourage higher-density development and slow the loss of open space, setting targets for benign urban growth management [104]. In terms of space, the urbanization work in developed countries, such as those in Europe and the United States, was carried out earlier and urbanization occurred earlier, while the current urbanization rate tends to be stable, and urban planning and urban land management work have gradually reached a policy-oriented management stage. The US public sector developed a broad range of policy tools (public land acquisitions, regulatory approaches, and incentive-based approaches) to manage urban growth and protect open space, with the aim of stemming the tide of urban sprawl in the US. The US managed urban land, protected open space, and limited urban growth through the transmission and implementation of government departments at all levels [105]. South Korea proposed national policies and strategies for low-carbon and green growth. Transportation-oriented compact development was implemented in urban structure and land use, providing standards and guidelines for integrated urban planning and land management [106]. However, urban land in developing countries was still in an incremental stage, and urban land management was in an immature stage of development [107]. As can be seen, issues related to urban land or urban land management vary from politics to governments, and, therefore, localized research examples tend to be more effective than broad policy recommendations, which can provide broad guidance, but little depth. To ensure urban land management based on scientific rationale, we must seek the commonality from the individuality, and on the basis of absorbing extensive experience, we must adopt measures according to the local conditions and the time.

The study of urban land management in urbanization is an important basis for grasping the mechanism of urban land evolution and all stages of urban land management. "Urbanization" and "Urban Land Management" are two inseparable topics. Cities are the main places for social, economic, and political activities, and urban land is the carrier of urbanization. The policies, as well as the economic, social, and ecological environments of different countries, have different impacts on urban land, which can be reflected in urban land changes. For example, urban expansion is one of the main pressures affecting the Mediterranean coastal region. Faced with the problems arising with urbanization in the Mediterranean coastal areas, France has formulated coastal management policies to assist in spatial planning, to study urbanization and to determine the characteristics of the evolution of coastal built-up areas, to monitor urban land changes, and to effectively manage urban land [108]. As a factor in land management, the land–atmosphere interaction maintains air quality and improves ecosystem functions. Therefore, it is necessary to monitor, analyze, and evaluate land use change in a temporal and spatial context and to quantify the impact of land use change on the global and even regional climate models so as to formulate scientific and effective land management measures [109].

The emergence of spatial analysis tools, such as GIS and ENVI, has expanded the research in the field of urban land management. In particular, the integration of GIS and urban land management has promoted the production of research results and publications in the field of urban land management. The trend chart of the annual publication volume (Figure 4) and the topic evolution chart in the field of urban land management (Figure 11) support this view. In the first stage (1979–2013), the research on urban land management was in its infancy (Figure 11), with a small number of publications published on Remote Sensing (Figure 4). In the second stage (2014–2018), the research topics of urban land

management were gradually enriched, showing a trend of comprehensive development from multiple disciplines and perspectives (Figure 11). The number of publications on Remote Sensing increased rapidly (Figure 4). With the development and maturity of GIS, the application of GIS in urban land management has become a scientific supplement to the research of urban land management under the guidance of policies. The ability of "GIS" to collect, manage, analyze, and output urban spatial information has provided strong support to urban land management. As it is necessary for urban planners and governments to consider the land use status, timely and adequate urban land use information undoubtedly promotes the sustainable development of urban areas. At this time, the application of geographic information technology and big data can accurately and effectively draw the urban land use map, facilitating the scientific, quantitative, and dynamic management of urban land. For example, Luxembourg managed urban land by using data from typical municipalities and its implementation in GIS to plan, monitor, or forecast land consumption [110]. By integrating remote sensing and social media data, we point out that urban land use information has played an important role in urban management, government decision making, and population activity monitoring [111].

### *4.2. Analysis of Urban Land Management Practice*

Urban land management ensures the orderly zoning of urban functions. Rapid urbanization not only leads to sprawl and disorderly development of urban land, but also causes chaotic conditions in areas such as public services, commerce, housing, and greening. Therefore, reasonable urban land management contributes to the balance of public service facilities among regions, the agglomeration of economic development scale, the enhancement of the livability level of residential areas, the improvement of urban greening quality, and the realization of spatial justice. For example, Japan proposed the Integrated Station-City Development (ISCD) strategy on the basis of drawing lessons from the TOD theory of Europe and America. The ISCD is a highly complex mode of urban development, community construction, use, and agglomeration, centered on railway hubs. This model makes the railway hub area become an urban comprehensive center with highly intensive land use, highly compound urban functions, orderly functional zoning, and a good landscape environment. The planning and design of the railway hub section should be incorporated into the overall urban planning to make it highly integrated with urban functions, facilities, land use, and landscape [112]. It is worth noting that realization of the intensive and efficient use of urban land by means of planning and design is not only the responsibility of the planning industry but often requires the participation of multiple parties. It is more convenient for the implementation of urban land management to change the top–down government-led urban planning policy, implement urban planning work combining top–down and bottom–up, improve the intensity of public participation, and form a multi-governance pattern of "government–market–citizen" participation. Promoting the coordination of all departments horizontally can achieve the requirements of data unification, base map unification, and goal unification. To promote the formation of urban functionally clear zoning, a healthy and orderly development of spatial patterns is necessary.

With the advancement of urbanization, various countries have encountered social and economic problems, such as lack of vitality in the inner city, decline of the central area, and substantial differences in the quality of residential areas, which aggravate the fragmentation and inefficiency of urban land use. To cope with these issues, different countries have combined the existing problems of urban land management from different aspects of exploration. For example, the United States takes the revitalization of the inner city as an economic strategy, aiming to give full play to the potential advantages of the location of the inner city, to build on the basis of existing companies, to establish viable enterprises, to provide employment opportunities, and to create a favorable environment for business to enhance the vitality of the inner city and re-empower the land in the inner city [113]. Heinrich took Weissenfels and Bernburg, in Germany, as examples and pointed

out that urban renewal should be used to control the decline of urban central areas. The author proposed specific frameworks, governance models, and optimization strategies to maximize the economic and social benefits of urban land [114]. Zhang et al. point out that megacities in China urgently need to be developed to realize the current situation of intensive use of urban land, the need to build a concrete knowledge framework for megacities reconstruction, and, at the same time, place more emphasis on local background and policy dynamics, as well as the importance of public participation [115]. Campbell advocated the concept of green urban planning to guide urban land management, proposed the concept of "Planner's Triangle", and pointed out three key elements to coordinate urban land efficiency, in terms of environmental protection, economic development, and social equity, with the aim of achieving the goal of building a green city and realizing the coordination of the urban man–land relationship, spatial justice, and sustainable development of urban land management [116]. Durand-Lasserve and Royston looked at land in poor urban areas and used cities with different social, legal, and economic constraints as case studies to study how urban stakeholders can find solutions to secure urban land ownership and to meet the needs of most residents in shanty towns and informal settlements, and to provide experience for urban land management in developing countries, such as those in Africa, Asia, and Latin America [117]. Similarly, Mulherin, from the perspective of sociology and economics, pointed out that the supply of affordable housing could not only alleviate poverty in urban areas and promote social harmony but could also effectively save urban land and avoid the pressure brought by the massive development and construction of residential areas [118].

### *4.3. Comparative Analysis of Related Studies*

Comparing the work of different scholars in the same field can help to find differences, make up for shortcomings, and enrich research results. This paper studied the urban land management publications of various countries and regions in the world. Based on the results, this research field is gaining increased attention. From 2019 onward, "Management" and "Climate Change" dominated the research. Scholz conducted a review on the theme of sustainable multifunctional land and urban management in Europe, emphasizing the importance of integrating environmental policies into other policy sectors. The focus was on large-scale European projects that have had a major impact due to policy changes, thereby making significant contributions to new policy developments [119]. This work has certain practical implications and can be used as a case supplement to this review. Wagner reviewed the "Decision Support Methods for Urban Development and Land Management", horizontally discussing the differences in the monitoring and simulation results of urban land by different technologies. Finally, the results obtained by using technical means could provide certain policy suggestions for governments and urban planners to manage urban land and formulate laws and regulations related to urban land management [31]. Through comparison, it was found that although scholars such as Wagner did not use metrology software to analyze and review the results in this field, the keywords and opinions in the paper all appeared in Chapter 3.3 of this paper, namely the "keyword analysis" column, which also showed the reliability of the research results.

### *4.4. Limitations of the Study and Future Research Directions*

This paper used the core collection in the Web of Science database as the data source. To ensure the coherence of the research, the starting point was the year 1979, when the first studies on urban land management appeared. To exclude the interference of the nonwhole year to the study results, studies published until 31 December 2021, were included in this review. To ensure the integrity of the study, different definitions of "urban land management" were searched in the scope of "subject". To ensure the accuracy of the study, experts in the field were invited to screen literature types and journal categories, as well as other processes, such as manual deduplication and deleting irrelevant data. To prevent data omission, the data exported from the Web of Science were saved in batches in plain text

format and imported into the Bibliometrix as a compressed package. However, there were still some errors and omissions in the study. First, only the Web of Science database was used, neglecting Scopus, American Periodicals, British Periodicals, and CNKI databases. Second, because of the manual data selection and screening, the data sources still had a certain subjectivity. Finally, we only analyzed the impacts of policies on urban land management in Section 4. However, in practice, urban land management is affected by economic, policy, social, and other factors. However, in this study, economic and social factors were not specifically analyzed. In addition, in the field of urban land management, localized research examples are often more targeted than global reviews. However, we only analyzed typical cases of individual countries/regions. In the future, we will seek a set of universal urban land management systems based on the current discussion content.

## 5. Conclusions

From 1979 to 2021, based on relevant research on urban land management, the number of publications and the average annual number of citations increased, along with the number of major journals publishing these papers. Overall, 129 countries/regions around the world contributed to the field of urban land management. Among them, China published the most outstanding research results in Asia, the United States in North America, Brazil in South America, Australia in Oceania, and Italy in Europe. In terms of national cooperation, the United States, China, and Australia were the three countries most in cooperation with other countries.

From 1979 to 2021, the research topics in the field of urban land management were divided into three stages. The number of research topics first increased and then decreased. Management was the main topic throughout the entire period. Urban land management evolved into "Management" and "Climate Change", which shows that land management and tackling climate change are at the core of urban land management work. Land is the most precious resource in all countries, and urban land is particularly important. However, urban land management should not only consider the land itself but must also take into account the combined influence of multiple factors. Since urban land management is composed of social, economic, ecological, policy, and transportation elements, future research should focus on "how to develop appropriate policies from the dual dimension of time and space", "how to improve the laws and regulations", and "how to consider multiple elements", with the overall aim of achieving social, land, economic, ecological, policy, and transportation element coordination and to ensure the sustainable use of urban land.

**Author Contributions:** S.S.: Methodology, Software, Data curation, Writing—original draft; W.S.: Conceptualization, funding acquisition; S.S. and W.S. Writing—review & editing; H.L. and L.N.: investigation, validation; S.S.,W.S., H.L. and L.N.: proofreading. All authors have read and agreed to the published version of the manuscript.

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*Review*

# Review of Research on Non-Conforming Urban Expansion: Measurement, Interpretation, and Governance

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**Abstract:** Spatial plans are widely used as a basic tool for regulating urban expansion. However, land development beyond zones planned for urban development is prevalent worldwide, posing a serious challenge to the implementation of spatial plans and their effectiveness in regulating urban expansion. This paper presents a review of research progress relating to the measurement, interpretation, and governance of non-conforming urban expansion. Spatial conformance between actual land use and plans is the basic criterion for evaluating the effectiveness of plans in containing urban expansion. Accordingly, scholars have developed multiple indicators and methods for directly and indirectly measuring non-conforming urban expansion. Previous studies have elucidated external and internal factors influencing non-conforming urban expansion, revealing the external conditions of non-conforming urban land expansion and the factors driving decisions on site selection for non-conforming land development. To address the existing issue of non-conforming urban land and to prevent and control future non-conforming urban development, scholars have proposed multiple governance strategies. Drawing on existing research progress, we offer suggestions for future academic research in this field.

**Keywords:** non-conforming urban land; urban growth; spatial plan; plan implementation; spatial conformance

## 1. Introduction

Unregulated and excessive urban expansion has many negative effects, notably increased farmland erosion, ecological damage, and environmental pollution; excessive energy consumption and carbon emissions; rising costs of public facilities; and the exacerbation of social inequality [1–7]. Therefore, the governance of urban expansion has become an important issue for sustainable development [8,9], especially in the many developing countries that are experiencing rapid urban expansion [10–12]. Spatial plans are widely regarded as a basic tool for governing urban expansion [13,14]. They are used to restrict or block urban development, limiting it to specified ranges through the definition of growth boundaries, red lines demarcating protected areas, and land use zoning so as to achieve the purpose of controlling the scale of urban expansion, regulating the spatial layout, and protecting ecological and agricultural core functional areas [15–18]. Assessing spatial conformance between actual land use and plans has become a primary method for evaluating the effectiveness of plans in containing urban expansion [19–24]. Previous studies that applied this method found that urban land development outside of zones planned for urban development (ZUDs) was prevalent in many countries and regions within Europe [18,25–28], South America [29,30], North America [31–33], Asia [22,34–38], Africa [39,40], and Oceania [20,41,42]. In this paper, we refer to urban land located outside ZUDs as non-conforming urban land (NCUL). Case studies have shown that more than 35% of urban land development in some cities in mainland China has occurred outside ZUDs defined in urban or land use master plans [24,37,43,44]. In light of their studies of the

governance structure associated with spatial plans and spatial conformance between land use and plans, some scholars have argued that spatial plans have not played a positive role in the control of urban expansion in many regions; rather, they have become an important driving force for urban expansion and suburban urbanization [29,45,46]. Evidently, then, NCUL expansion has become an important issue in planning implementation and in the governance of urban expansion.

NCUL expansion has attracted the attention of researchers working in the field of spatial plan implementation and evaluation and the governance of urban expansion. The first step in this research entails the identification and measurement of NCUL. The preliminary identification of NCUL status that is based on an overlay analysis of actual land use and plans requires a simple assessment of whether the urban land falls within ZUDs; the available information is sparse [24,47,48]. Therefore, scholars have gradually developed more diversified direct indicators as well as indirect methods for measuring NCUL that can more comprehensively reflect the spatial relationships between actual urban expansion and plans.

As a second step, scholars aim to explain the mechanism of NCUL development. Many studies have found that large-scale NCUL expansion occurs despite the legally binding force of plans and the presence of not fully developed land within ZUDs [35,43,49]. The reason for this phenomenon is puzzling. An understanding of the mechanism of NCUL expansion would not only help to solve this puzzle but would also illuminate the factors driving urban expansion and the role of plans in governing urban expansion, thus providing insights for controlling NCUL development.

Another critical issue is how to control NCUL expansion. The control of urban expansion, optimization of the land use layout, and protection of natural resources and the ecological environment are important planning goals. Large-scale land development activities that are inconsistent with planning goals are destructive and disorderly, significantly hampering their realization [31,36,50]. However, several studies have shown that plans may become inapplicable because of the bounded rationality of plan makers and implementers, uncertainty about the future, and other human factors [24,47]. Moreover, some studies have found that it is neither possible nor advisable for the development outcomes to be precisely aligned with plans [51–53]. Land development that is inconsistent with plans may be a reasonable and expedient choice made by decision-makers that does not necessarily violate planning goals, potentially even playing a positive role in their realization [24,48]. Especially in developing countries with dysfunctional planning systems, non-conforming land development may have important positive economic and social impacts [28]. Therefore, NCUL development cannot be addressed using a one-size-fits-all approach; differentiated and targeted measures are required according to the actual situation.

This paper presents a review of the literature, focusing on research progress in the area of measurement methods, interpretations of mechanisms, and governance strategies for NCUL expansion. Accordingly, we propose suggestions for future research that can provide guiding inputs for the theoretical research and practical governance of NCUL expansion.

We used the following methods to search for and select studies within the literature. We used Google Scholar and the search engine developed by Lanzhou University to search for the related literature. Very few studies were found using the term—"non-conforming urban growth/sprawl/expansion/land development" in the literature search. Therefore, we used a combination of two terms to search for the literature. One is picked from the following terms—"plan implementation", "plan evaluation", "land use plan/planning/regulation", "urban plan/planning", "comprehensive plan/planning", "spatial plan/planning", "urban growth boundary", and "zoning". The other is picked from the terms, including "urban expansion", "urban land", "urban development", "urban growth", "urban sprawl", "land/housing/residential development", and "built-up area". The studies that directly focused on the measurement, interpretation, or governance of NCUL expansion were selected from the search result. We did not select studies on non-conformance between plans and outcomes unless they were specifically related to

NCUL development. However, the number of studies that we selected was still limited. Therefore, we also selected studies from the references listed in the selected studies. In addition, we drew on our understanding of China's status concerning rapid urbanization and the many initiatives aimed at governing urban expansion using spatial plans in China, as well as our knowledge of Chinese studies on NCUL expansion. Accordingly, we selected 12 papers published in Chinese. Moreover, a significant proportion of these Chinese studies have proposed new indexes and indicators for measuring NCUL expansion. Therefore, we believe that these Chinese studies can enlighten the research and practices in other countries and regions.

## 2. Methods of Measuring the Expansion of NCUL

### *2.1. Measurement Based on Spatial Conformance*

Using hand-drawn grids, Alterman [54] first performed overlay analyses to evaluate the consistency between land use and plans. With advancing technology, GIS-based spatial overlay analysis of land use and plans has been widely used for measuring the effects of planning in the governance of urban expansion [17,35,36,43]. As shown in Table 1, scholars have developed a set of evaluation indexes for assessing spatial conformance. These diverse indexes provide measurements of the overall conformance between urban expansion and plans, the direction and degree of deviation between urban expansion and plans, the distribution and evolution characteristics of NCUL development, direct factors driving NCUL expansion, the degree of planning violation, as well as the plans' effectiveness in governing urban sprawl.

**Table 1.** Indexes for measuring non-conforming urban expansion.

| Reference | Index | Index Introduction |
|---|---|---|
| [49,55,56] | Conformance of gravity center | The conformance between the trajectory of the gravity centers of urban land from the planning base year to the current situation and the trajectory of the gravity centers of urban land in the planning base year and urban land delimited by the ZUD |
| [49,55,56] | Spatial differentiation | The degree of consistency between urban land expansion and planning in different directions |
| [49] | Conformance rate | 1—(area of NCUL/area of the ZUD) |
| [55,56] | Spatial discretization | Spatial location relationship of urban land standard deviation ellipses in the base year, current year, and target year |
| [56] | Implementation rate | Area of new compliant urban land [1]/area of undeveloped land within the ZUD in the planning base year |
| [25] | Compactness differentiation | The difference in building quantity and density and their change trends inside and outside the ZUD |
| [29] | Containing rate | Area of new NCUL/area of new compliant urban land |
| [37,57] | Sufficiency rate | Area of new urban land/undeveloped land area within the ZUD in the planning base year |
| [37,57] | Adjacent development rate | The length of the urban growth boundary with new land development outside the ZUD/the length of the urban growth boundary without new land development outside the ZUD |
| [39] | Sufficiency of ZUDs | Area of urban land/area of the ZUD |
| [50] | Scale control rate | 1—(area of new urban land/area of planned increment of urban land) |
| [50] | Spillover rate | Area of new NCUL/area of planned increment of urban land |
| [50] | Average annual spillover rate | Area of new NCUL/the number of years of plan implementation at the time of evaluation |
| [50] | Leaping development | The average shortest distance from the centers of land patches of NCUL to the boundary of the ZUD |
| [50] | Axis development | The area of new NCUL adjacent to the traffic trunk road/the area of new NCUL |
| [48] | Compliance rate | Area of compliant urban land/area of urban land |
| [48] | Sufficiency of ZUDs | Area of undeveloped land within the ZUD/(area of total urban land + area of undeveloped land within the ZUD) |
| [17,58] | Compliance rate | Area of new compliant urban land/area of new urban land |
| [17] | Saturation rate | Area of compliant urban land/area of the ZUD |
| [17] | Sufficiency of ZUDs | Area of undeveloped land within the ZUD/area of new NCUL |
| [17] | Deviation degree | The degree of restriction on land development in the zones where the NCUL is located and the degree of protection for the type of land use before it was converted into urban land within the plans |

[1] New urban land, including new compliant urban land and new NCUL, refers to the land urbanized during the period of plan implementation.

### *2.2. Indirect Indicators of Non-Conforming Urban Expansion*

#### 2.2.1. Issuance of Land Development Permits

Permit management is a core element within the planning implementation used in many countries and regions [20]. Some studies have assessed the status of NCUL development by comparing the number of permits issued within and outside of ZUDs [18,20,34,41,59]. Because permits are approved and issued by local governments, a survey of the number of permits issued outside ZUDs can directly reflect their attitudes and responses to spatial plans. However, this measurement index is flawed in three ways. First, a project may require several permits. Second, the scale of land development in projects corresponding to different permits may vary considerably. Third, the method does not shed light on informal and unauthorized land development. The first two deficiencies imply that simply considering the number of permits does not accurately reflect the scale of land development outside ZUDs. Previous studies have found that the scale of informal development outside ZUDs is extensive and particularly prominent in developing countries [44,60,61]. Therefore, the third deficiency mentioned above may lead to a significant underestimation of the scale of land development outside ZUDs.

#### 2.2.2. Distribution of the Population and Its Movements

There are interactions between population size, distribution, mobility, and the layout of urban land [62,63]. Some studies assess the consistency between actual urban expansion and plans by comparing the spatial conformance of population size, distribution, mobility, and the ZUD. For example, Gennaio [25] reflected on plans' role in controlling urban expansion and promoting compact urban growth by the changes in population size and density in built-up areas and the spatial conformance between built-up area expansion and land use plans. Long [64] assessed the degree of NCUL expansion and the effectiveness of plans in containing urban growth using data from location check-ins, transit smart cards, and residential travel surveys, which record the distribution of people's movements and activities inside and outside ZUDs. The advantage of this indicator of NCUL expansion is that it extends from physical space to cover demographic factors, which, to some extent, reflect the degree of interaction and disconnection between planning schemes, social needs, and land use. However, it has a number of deficiencies. First, data on small-sized populations are relatively difficult to obtain. Second, population density and the degree of mobility vary for different land use types, which makes it difficult to judge the scale of NCUL expansion using this indicator. Third, spatial plans at small scales often lack goals of population control or agglomeration. Moreover, some of the population is distributed outside ZUDs, and daily movements of people occur between urban and rural areas and between cities. Therefore, there is a lack of criteria for evaluating the effects of plans in governing urban expansion and the expansion of NCUL based on this indicator. Consequently, it is difficult to determine to what extent differences in the population distribution inside and outside ZUDs and population movements across urban growth boundaries reflect the degree of NCUL expansion.

#### 2.2.3. The Value of Real Estate and the Tax Revenue That It Generates

The value of real estate and the tax revenue that it generates are closely related to the scale of land development. Some scholars assess NCUL expansion according to whether the total value and tax revenue from real estate and their increments are confined to ZUDs. Examples include Chapin [31] and Esnard [65], who used property-parcel polygons and property-appraisal tax rolls to analyze the development of housing in some areas located within ocean front hazard zones, where development was restricted in the plans. They reported significant increases in real estate values, the taxable base, and tax revenue in these areas, which, they argued, revealed the limits of local urban growth management policies. This indicator has the advantage of reflecting market forces driving urban development and its response to plans. However, it entails two deficiencies. First, it cannot directly

reflect the scale of NCUL development, and second, it is susceptible to changes in real estate prices.

#### 2.2.4. Econometric Models

Some studies use quantitative methods to analyze the effects of spatial plans in controlling urban expansion. For example, the difference-in-difference model, the logistic model, and the probit model were respectively used by Dempsey [32] and He [66], Tian [43] and Shen [17,67], and Cho [68,69] to test whether the possibility of developing land plots outside ZUDs was significantly lower compared with plot development within ZUDs. The test performed by Jun [70] using a housing supply model revealed that the dummy variable—whether land plots were inside the ZUD—did not significantly influence the location of new housing development projects in Portland, thus demonstrating the limited effect of the plans. The advantage of this measurement method is that it is generally effective in evaluating the inhibitory effect of plans on NCUL development, thereby reflecting the effectiveness of plans in controlling urban expansion and their binding effect on the selection of sites for land development projects.

### *2.3. Classification of NCUL*

#### 2.3.1. Types of NCUL Defined by Changes in Land Use Types

Loh [71] differentiated three categories of NCUL. The first is land that is planned but not yet developed as urban land, such as natural areas within ZUDs. The second is NCUL that has been developed before the plans, such as some types of urban industrial land that are to be developed commercially but have not been converted to commercial use. The third category is NCUL that has been urbanized during the planning period, for example, land that is planned as farmland but was developed into residential areas. The first two types of NCUL conceivably arise primarily because of delays in plans' implementation. However, if the land use type cannot be changed in accordance with the plans, the rationality of the plans should be considered. The third type reflects real land use behavior that conflicts with the plans.

Shen [48] divided land use conformance into four grades according to the consistency between land use types in the planning base year and current year and the plans. The first grade, in which the land use type at present and in the base year is consistent with the plan, is regarded as weakly effective. The second, in which the land use type was consistent with the plan in the base year but is currently inconsistent, is regarded as strongly ineffective. The third, in which the land use type was inconsistent with the plan in the base year but is currently consistent, is regarded as strongly effective. The fourth, in which the land use type in the base year and during the current period are both inconsistent with the plan, is regarded as weakly ineffective.

This classification system facilitates the identification of NCUL formation and enables the differentiation of the degree of non-conformance between plans and land development.

#### 2.3.2. Types of NCUL Defined According to Their Spatial Distribution

Menzori [29], who studied the distribution characteristics of urban expansion, especially the development of NCUL, divided newly increased urban land into three types: newly generated, edge-expansion, and infill development.

Shen [17] identified four grades of land development compliance according to the spatial relationship between the urban land parcels and the ZUDs, respectively reflecting complete conformity, partial conformity, adjacent inconformity, and dispersive inconformity (Figure 1).

Classification according to spatial distribution can reveal the direct cause of NCUL development. Partial consistency or adjacent inconsistency may be caused by the saturation of land development in a partial range within a ZUD. More importantly, it can reveal the extent to which NCUL expansion violates the plan and undermines the planning objectives of achieving compact growth and controlling leapfrog expansion.

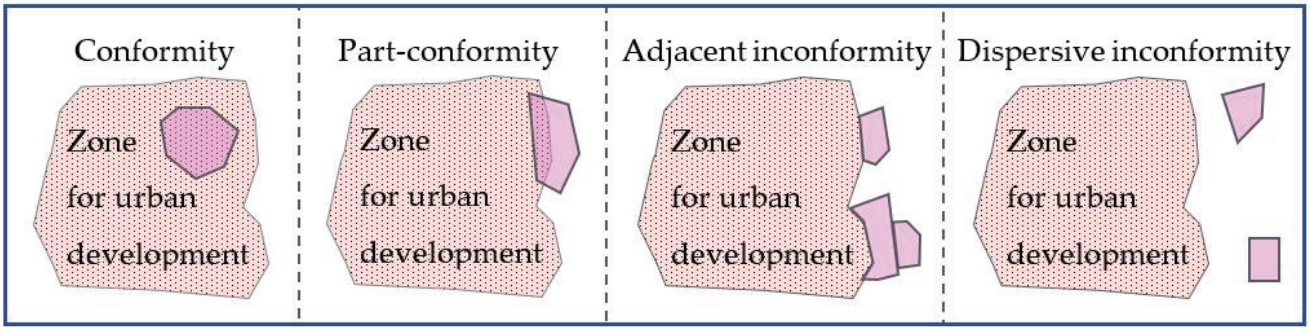


**Figure 1.** Degree of spatial conformance of urban land development. Figure 1 is drawn based on Shen [17].

#### 2.3.3. Types of NCUL Defined According to a Comprehensive Score

Considering the criteria derived from the terminologies and types of land use classification within planning schemes, Limb [42] assigned comprehensive scores based on an examination of overlapping layers (e.g., zones and plans) and component layers within land use regulations. Accordingly, three types of land parcels are defined. The first type is conforming areas in which land use is aligned with a score that reflects the planned use. The second type is under-developed areas in which the scale of land use is below the scale intended in the regulations. The third type is exceeding areas in which land use is of a type or scale that conflicts with or exceeds the level prescribed in the regulations.

#### 2.3.4. Types of NCUL Defined According to the Legality of Their Development

In some countries and regions, ratified spatial plans are legally mandated, defining the legal framework of land use [28]. Accordingly, all NCUL development is illegal. However, in other countries and regions, spatial plans do not have statutory force, and, more importantly, land development outside ZUDs is not totally forbidden [69,72]. Accordingly, not all NCUL areas are illegal. For example, farmland located outside of ZUDs can be converted in Israel if approval is obtained from the Committee for the Protection of Agricultural Land [73]. Moreover, in many US counties, low-density housing development outside urban growth boundaries is permitted [32,74,75]. A significant proportion of NCUL development is approved or even conducted by governments [36]. Therefore, many studies have used the locations where permits are issued to measure non-conforming urban expansion, as mentioned in Section 2.2.1. The NCUL that has been authorized and permitted by governments is perceived as formal land development, and others that are not authorized are perceived as informal land development [44].

Differentiating the formality of UCUL development reveals local governments' responses to spatial plans and their roles in NCUL development.

Table 2 summarizes the classification of NCUL by the above-mentioned studies.

**Table 2.** Classification of conformance between urban land use and plans.

| Perspective | Reference | Types of Non-Conformance |
|---|---|---|
| Land use change | [71] | (1) Undeveloped land inside ZUDs; (2) NCUL developed before the planning period; (3) NCUL developed during the planning period |
| | [48] | (1) The land use type at present and in the base year are both consistent with plans; (2) the land use type was consistent with plans in the base year but is currently inconsistent; (3) the land use type was inconsistent with plans in the base year but is currently consistent; (4) the land use type in the base year and during the current period are both inconsistent with plans |
| Spatial distribution | [29] | (1) Newly generated; (2) edge-expansion; (3) infill development |
| | [17] | (1) Complete conformity; (2) partial conformity; (3) adjacent inconformity; (4) dispersive inconformity |
| Comprehensive score | [42] | (1) Conforming areas; (2) under-developed areas; (3) exceeding areas |
| Legality | [28,44,75] | Formal development and informal development |

## 3. Interpretations of NCUL Expansion

### *3.1. External Factors*

As shown in Figure 2, some studies have analyzed the reasons for NCUL expansion from the perspective of the external conditions of planning implementation and NCUL development.

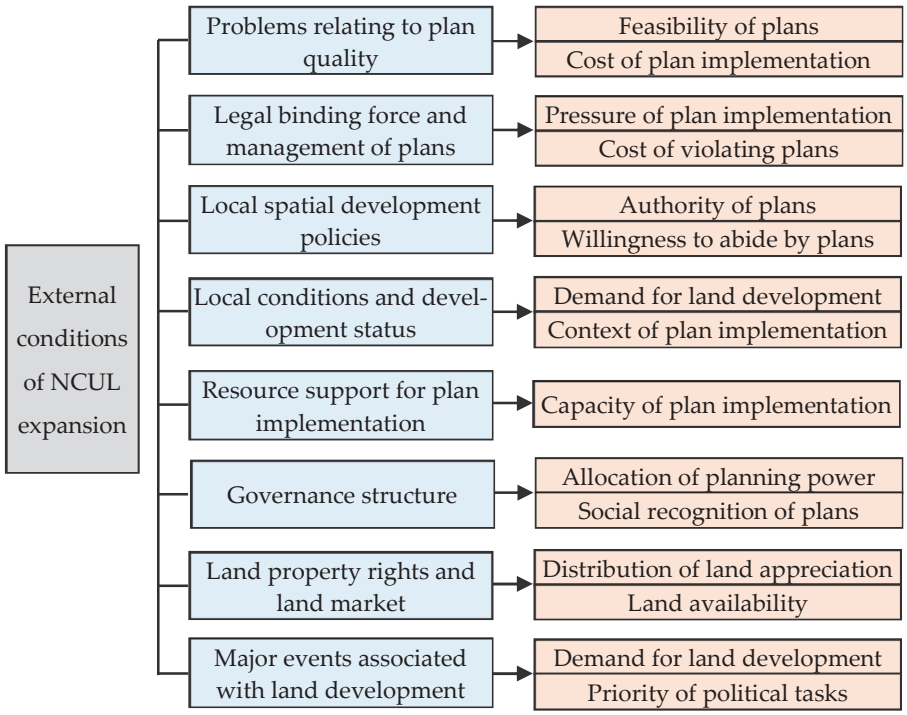


**Figure 2.** External factors influencing NCUL development.

#### 3.1.1. Problems of Planning Quality

The problems relating to plan quality result in the non-adaptiveness of plans to the actual needs of urban development and management. Consequently, economic costs increase and social welfare is reduced with the plan's implementation, leading to a failure to actualize the urban land development according to the plans. Previous studies have found that quality-focused problems such as the fragmentation, insufficient size, and unreasonable layout of the ZUD [17,24,48,57], conflicts between different types of plans [43,58], the ambiguous location of urban growth boundaries and unclear regulations [34,37,59], the bypassing and violation of the prevailing development mode in the plan [71], and unclear boundaries between ecological land and reserved urban development land [76] are common causes of UCUL expansion. The above evitable problems of quality are artificially caused during the formulation of plans because the information is intractable and incomplete, e.g., uncertainty about the future and the formulation of spatial plans is a bounded-rational process, resulting in a limited effect on regulating the location of unpredictable land development projects [77,78]. The problems of plans associated with bounded rationality are difficult to avoid and eliminate [67]. For example, for some development projects, a safe distance needs to be maintained between the projects and areas where human activities are concentrated. Consequently, the land provided for such projects is often located outside ZUDs [24]. Han [57] found that Beijing achieved the planned population increment, which was expected to be achieved over the entire planning period of nearly two decades, in just three years. Such rapid population growth was difficult to predict, resulting in a large number of areas of NCUL beyond the urban growth boundary defined according to the planned population.

#### 3.1.2. The Binding Force of Plans and the Intensity of Supervision and Punitive Measures Relating to NCUL Development

The legally binding force of plans and the method and intensity of supervision and management for implementing the plans determine the amount of pressure relating to plan implementation and the cost of violating plans, which, in turn, affect NCUL development. NCUL expansion can be limited by giving plans a clear and legally binding force, formulating specific implementation rules and management measures and fine-tuning complementary regulations and punitive measures [27,79]. Clarifying the responsibility and financing mechanisms for planning implementation, strictly supervising the revision and implementation of plans, and introducing drastic punitive measures for violating plans can lead to a significant reduction in the issuance of permits that are inconsistent with the plans [80]. A case study in the Netherlands showed that restrictive zoning was effective in containing urban growth, largely because of its rigidity and clarity [81]. Another case study in Saudi Arabia showed that the strong administrative and legal foundation of urban growth boundaries compensated for their technical weakness and significantly prevented non-conforming land use [82]. Conversely, the lack of dynamic monitoring, effective supervision, and necessary punitive measures during plan implementation provides external incentives for NCUL development [36,44,57]. In addition, land development outside ZUDs that is not explicitly prohibited leads to fragmented or large-scale NCUL expansion [22,34]. Wang [37] argued that the legal effect of statutory urban growth boundaries is higher than that of urban growth boundaries as a component of spatial planning. Thus, the former boundary type has a more significant inhibitory effect on NCUL development. Shen [17] found that most NCULs are distributed in zones with less stringent restrictions on land development. Moreover, most of the land converted into NCUL is not targeted for protection within the plans.

#### 3.1.3. Local Spatial Development Policies

Conflicts between local spatial development policies and plans affect the authority of the plans and interfere with their implementation, leading local governments to prioritize local policy implementation rather than plan implementation to realize local interests. Consequently, spatial plans can only play a limited role in containing urban growth, resulting in uncoordinated and incompatible spatial developments [40]. Case studies in China have shown that policies of industrial suburbanization encourage a large number of industrial land development activities that are inconsistent with the plans for suburbs [49,83]. Large-scale NCUL development results when the scope of development zones and industrial parks set by local governments exceeds the scope of ZUDs [36]. Development zones established by higher-level governments (e.g., provincial and national development zones) are regarded by local governments as "shields" to evade accountability relating to NCUL development [44]. The continuous adjustment of local spatial development policies aggravates their inconsistency with the plans and leads to intensified NCUL expansion [84]. Hence, spatial plans become increasingly ineffective in containing urban expansion close to the end of plan implementation [66]. The empirical studies by Shen [67] show that local spatial development policies can regulate the binding force of land use zoning on urban development. Specifically, if a zone in which urban development is restricted overlaps with a local economic development zone, the restrictive effect of the plans on urban development will be significantly reduced. Conversely, if the land use regulation policy in areas where urban development is restricted is combined with other policies (e.g., cultivated land and ecological protection policies and disaster prevention and reduction policies in disaster-sensitive areas), land development activities in the corresponding areas will be significantly reduced [85]. Moreover, if land use polices and restrictions make it difficult to develop land reserved for urban development inside the ZUD, the ZUD will fail to accommodate urban growth despite being large enough to do so [86].

3.1.4. Regional Development Status

Regional background factors, such as culture, society, and economy, affect the implementation of plans. Economic vitality, industrial structure, population dynamics, and land use conditions significantly affect the speed, scale, structure, and layout of land development. Regions with large economic aggregates and populations that are rapidly growing will face more problems and uncertainties in land use, making it more difficult to control urban expansion using plans [18,48]. The findings of an empirical study by Cho [33] indicated that inflated land prices within ZUDs stimulated the development of land of lower value outside the ZUD during a real estate boom. In addition, zoned agriculture parcels are more likely to be converted to housing developments during a recession period because local governments want to increase property tax revenues by re-zoning undevelopable land as developable land. Qian [76] has suggested that because central enterprises and wholly foreign-owned enterprises or joint ventures contribute more than 90.0% of the industrial output value of Nanjing, China, it is more difficult for local governments to implement plans, and they often passively accept sites selected for land development projects that are inconsistent with plans. Moreover, rapid population growth and the preference for suburban housing have stimulated the construction of new districts beyond ZUDs [64] and even induced informal housing development [46]. In regions characterized by slow-paced development, the demand for land is limited, and expansion of NCUL is relatively rare [32]. However, the case study by Gennaio [25] found that NCUL significantly expands at a low density under conditions of population decline.

3.1.5. Resource Support for Plan Implementation

The capacity to shape and influence the planning process, financial resources, power resources, and attitudes and skills within local governments are important factors affecting the implementation of plans and their ability to limit NCUL development [18]. The numbers and abilities of planning department personnel and their attitudes toward plans significantly affect their consideration and issuance of development permits for NCUL [20]. Local governments' lack of personnel and resources to implement plans, monitor land development, and carry out law enforcement are important factors accounting for NCUL expansion [87]. A case study in China has found that because the density of rural residential areas in the suburbs of cities is high, along with the cost of land expropriation, and financial resources are limited, local governments choose to expropriate a large amount of land outside ZUDs to promote the construction of large-scale industrial parks with low land expropriation costs [44]. A case study in the USA has shown that because of the lack of financial resources, planning measures such as the transfer and resettlement of populations and the reduction of construction land cannot be carried out in ecological and natural disaster-sensitive areas where land development is restricted by plans [31]. Consequently, large-scale residential districts remain and even expand in these areas.

3.1.6. The Governance Structure for the Planning Process

A governance regime is an important factor influencing the preparation and implementation of spatial plans [88]. The failure to give local governments autonomy to integrate considerations of local interest within top-down plans leads to a lack of incentives to implement the plans [85]. As a result, many mandatory restrictions on land development in high-level plans have not been effectively implemented at local levels [31]. The lack of participation of key actors, such as developers and property owners, in plan preparation and implementation reduces the social recognition and acceptance of plans and ultimately reduces the influence of the plans on land development [22]. However, Berke [41] argued that a rigid interpretation of planning policies, the strict implementation of regulations, and a lack of inter-subject consultations for approving and issuing development permits can reduce NCUL development. The excessive participation of property owners and developers in plan preparation and implementation may lead to the influence of personal economic agendas in the implementation of urban development boundaries [29]. More-

over, fragmented management, differences in development strategies at different levels of government, conflicts between departments, and the independent operations of various management committees will negatively affect the regulating effect of plans on urban expansion [49,76].

#### 3.1.7. Land Property Rights and the Market System

To a certain extent, land property rights and market systems determine the role and interactions of relevant subjects in land development, the availability and cost of the land needed for project development, and the distribution of land value-added income, thus affecting the feasibility, organizational method, and incentive mechanism of NCUL development. In China, the decentralization of administrative, finance, and land management authorities has resulted in local governments becoming the key decision-makers in urban land development [76]. As the implementers and managers of the plans and the land expropriators and suppliers, investment seekers, and beneficiaries of land development, local governments can meet their own demands and those of market investors' for NCUL development through strategic planning, whereby plans are modified to make land development compliant [43,76]. Some studies have found that the unavailability of land in the formal market and the lack of land development rights have led to the informal development of NCUL by disadvantaged developers and landowners [44,46].

#### 3.1.8. Major Events Related to Urban Construction

The occurrence of major urban events has a significant impact on the structure and scale of urban land use, with major events often accorded high political priority; to some extent, this creates an opportunity for local governments to breach plans and carry out large-scale urban construction. For example, in Portugal, the World Exhibition of 1998 motivated large-scale exceptional urban development in Lisbon [89]. In China, many projects entailing major events, such as the Nanjing National Games, the Beijing Olympic Games, the Shanghai World Expo, and the Guangzhou Asian Games, were simultaneously developed and submitted or developed first and submitted for approval later to enable the construction to be completed without delay, resulting in a large number of land development types and scales and layouts inconsistent with the plans [76,79]. In Laos, to build the Lao International Convention Centre for hosting the Ninth Asia–Europe Meeting through urban renewal, the Vientiane authorities chose to develop new residential communities within the planned agricultural zones in peri-urban areas, where land is cheap, to resettle the original community residents [36].

### *3.2. Internal Factors*

External factors provide external conditions for NCUL development, but they cannot fully explain why NCUL development occurs. Some scholars have explored the decision-making behaviors of key actors related to land development (local governments, developers, and land rights owners) to reveal the reasons for NCUL expansion, especially the driving factors, as shown in Figure 3.

#### 3.2.1. Local Governments

Local governments play an essential role in NCUL development and can determine whether investors are able to carry out land development outside the ZUD [73,90]. As a rational agent driven by interests, local governments tend to relax plan regulations and accept NCUL development [37,85]. They prefer large projects and actively work to satisfy large investors' selection of sites for development by relaxing restrictions on urban growth boundaries [27,39]. Especially after changes in local leadership and the consequent changes in development strategy, NCUL development may increase significantly [76]. To promote economic growth and increase financial revenue, local governments in China actively promote the development of new towns and zones, during which the costs of the supply of

large-scale public facilities and the expropriation of land, in turn, increase their dependence on land as a core tool for realizing local interests [46].

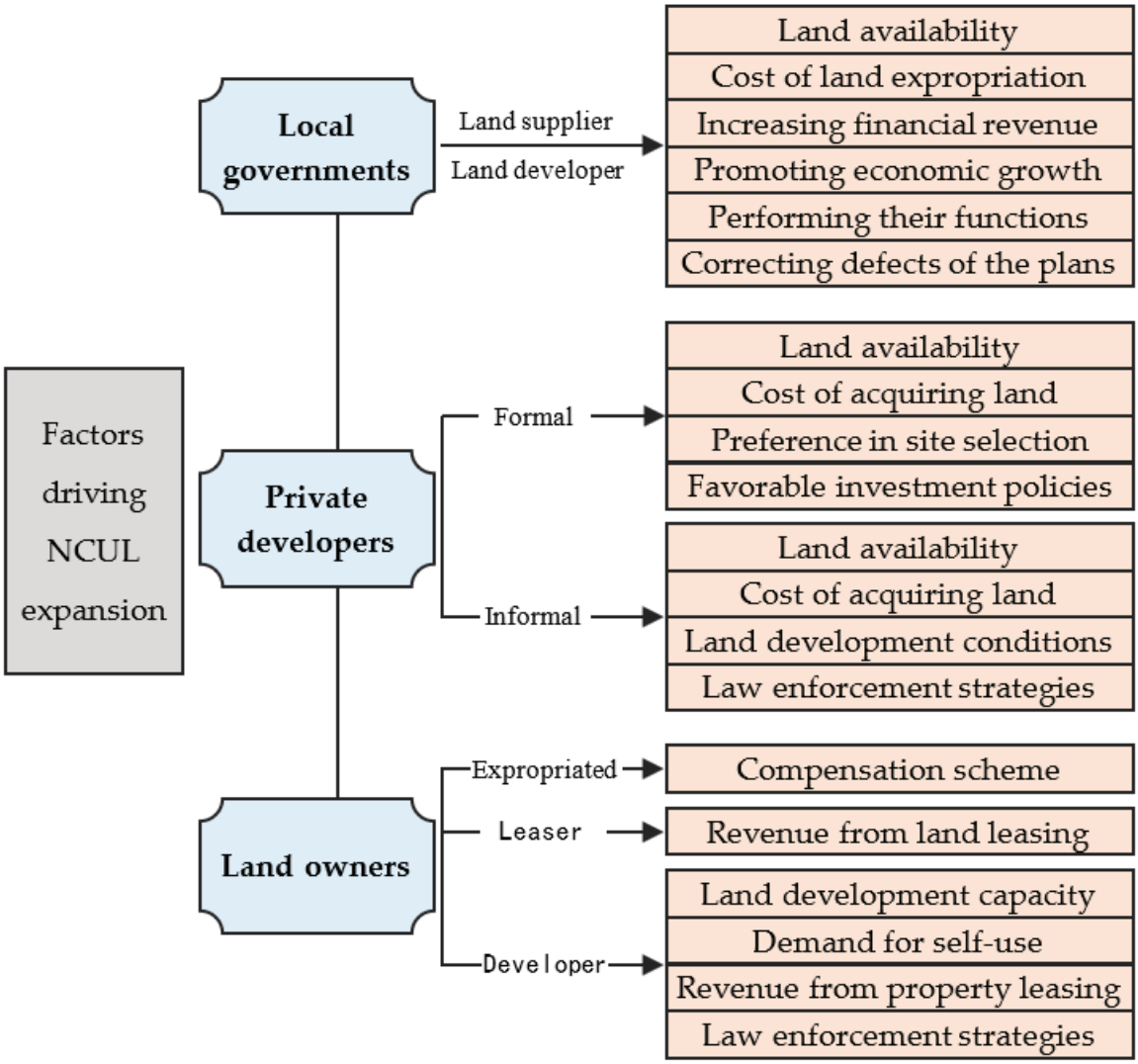


**Figure 3.** Internal factors driving NCUL development.

As the provider of land and public services, local governments will consider the availability and cost of land and the costs, social benefits, and economic returns (improving the development conditions and market value of the adjacent land) of public services and infrastructure supply. Thus, they tend to acquire land and build public facilities in suburbs that are more likely to be located outside ZUDs [44,83]. For example, in Laos, because of the limited amount and high value of land in the central urban area, the local government of Vientiane occupied the outer suburban farmland and woodland outside ZUDs to settle the people displaced by urban renewal and to attract investment [36].

As the designers and implementers of plans, agents of higher-level government, and maintainers of public order, local governments strategically accept or carry out NCUL development to balance local interests and the political risk of violating plans. Driven by financial incentives, they tend to take advantage of the weaknesses of planning systems to create opportunities for NCUL development [81]. To balance local interests, their governmental responsibilities, and the oversight of higher-level governments, local governments selectively enact law enforcement measures against the informal development of NCUL [44,91]. For example, Chinese case studies have found that in spite of the fact that local governments deploy land use plans to promote rather than constrain urban expansion

by setting aside excessive land for development, they still frequently conduct and accept NCUL development [92]. They do so by supplying plots for development that are mostly located in land use zones where strict restrictions on land development are lacking. They also occupy land types that are not strictly protected by plans so as to avoid the risk of being held accountable by higher-level governments for land use behaviors that are in violation of the plans [67]. In addition, when plans fail to promote the realization of planning goals such as cultivated land and ecological protection, instead of hampering reasonable urban construction, local governments may break through the restrictions of plans to carry out NCUL development [48].

Governing philosophies also affect the decision-making of local governments regarding NCUL development [29]. Economic development, ecological and environmental protection, and urban sprawl governance have different value weights within different political parties. Therefore, governments formed by different political parties have different attitudes toward NCUL development [25].

#### 3.2.2. Private Developers

The spatial conformance between urban land for profit-oriented projects development and plans is at a significantly lower level than that between urban land for public projects development and plans, reflecting the role of market forces in NCUL expansion [43]. Several empirical studies have shown that the variables used to reflect developers' preferences relating to site selection are statistically significant factors influencing the probability of land development outside the ZUD [68,69]. This is not the case for the dummy variable—whether or not the land parcel is located inside the ZUD. Developers engaged in land development have profit motives [93]. As long as land property rights and development permits can be obtained, developers mainly consider the degree of satisfaction regarding conditions for developing the land parcel in relation to their project site preferences; they do not care whether the selected land parcel is located within ZUDs. In China, developers who find it very difficult to acquire state-owned land legally through formal channels will consider the land availability, price, location, and local government's disposal strategy for informal land development when deciding whether to rent the collective land for informal development [44].

Chapin [31] and Brody [59] found that low land prices, improved transportation, proximity to coastal scenery, an increasing population, and housing demand drive developers to build residential areas in disaster-sensitive areas and wetland reserves, where land development is strictly restricted by plans. Zhang [83] has suggested that higher land availability, perfect infrastructure conditions, the agglomeration effect, and the government's incentivization policies attract manufacturing investors to carry out project development in the outer suburbs beyond the ZUD. Cho [69] found that urban growth boundaries stimulate an increase in land prices inside ZUDs, which encourages developers to locate development projects along the rural–urban margins outside of these boundaries. Bigelow [72] found that the prices of exurban land outside the boundaries are rising because the amenities of these land attract residents and, hence, housing developers. Conversely, developers usually lack the willingness to invest in areas with marginal locations, poor infrastructure conditions, and weak development foundations within ZUDs [43,44]. In Saudi Arabia, vacant land outside ZUDs fails to attract developers because they need to provide the entire infrastructure themselves [82]. In addition, developers with different attitudes toward risks respond differently to plans; those who prefer to take risks are more likely to adopt land development strategies that violate plans [37,94].

#### 3.2.3. Owners of Land Property Rights

Some studies have found that rapid rises in housing demand and price, driven by economic and population growth and the relaxation of government supervision, have stimulated owners of land property rights to carry out real estate development in violation of laws and plans to obtain considerable economic profits [36,43,87]. Driven by economic

interests, owners of land property rights and grassroots governments lead or cooperate with developers to illegally develop large-scale, commercial, residential areas in fringe areas of big Chinese cities [46,95]. A case study of Laos has also found that urban migrants and residents of original communities experiencing urban renewal choose to buy land in rural areas on the edge of the city to build houses for themselves because they cannot afford the high housing prices in urban areas [36].

Shen [44] found that collective landowners in China play three kinds of roles in NCUL development. The first relates to the object of land expropriation, with their willingness depending mainly on the compensation scheme for land expropriation. The second relates to developers. Whether they carry out development depends on development costs and capabilities, requirements for self-use, expected economic benefits, and the government's enforcement strategies against informal development. The final role is that of land leasers, wherein the willingness to lease land to developers depends largely on rent levels.

## 4. Governance of NCUL Expansion

### *4.1. Disposal of Existing NCUL*

As shown in Figure 4, previous studies have identified the following main strategies for the disposal of existing NCUL [71,91,96,97]. The first entails adjusting plans to enable the compliance of the NCUL with them. The second entails transforming the NCUL (remaining urban land use after the transformation) and then adjusting plans to enable the compliance of the NCUL with the plans after ensuring that land use meets specific conditions. The third entails the redevelopment of NCUL located within ZUDs to ensure that it conforms to the plans. The fourth is to maintain the status quo of NCUL according to certain conditions (e.g., not expanding the scale, controlling negative externalities, and not exceeding the prescribed period) without enforcing compliance with the plans. The fifth is to convert urban construction land into other land types according to the plans.

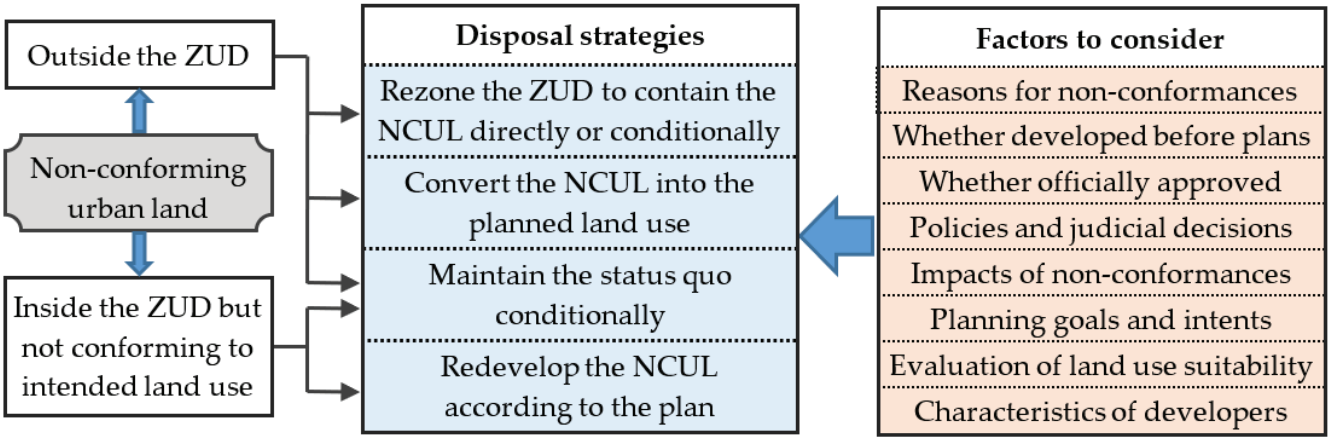


**Figure 4.** Strategies for the disposal of existing NCUL and their influencing factors.

When choosing a disposal strategy, the following factors should be taken into consideration. The first relates to the reasons for NCUL development and the associated decision-making process [71,97]. The second relates to whether the NCUL is developed during the plan implementation period [48]. The third relates to whether the development of the NCUL is officially approved and authorized [44]. The fourth concerns relevant laws, regulations, policies, and judicial decisions [71,97]. The fifth factor focuses on the comprehensive benefits of NCUL development and its impact on meeting the planning objectives of compact urban development, sprawl control, solving urban problems, maintaining cultivated land, and protecting the ecological environment [24,79]. The sixth factor relates to the assessment of land use as being appropriate [96]. The seventh and final factor relates to the characteristics of land developers [91].

The case study by Shen [44], for example, found that several hectares of farmland outside the ZUD had been converted for industrial development. These parcels of farmland were surrounded by built-up areas, and most of them had been abandoned before conversion because the farmers had already become urban migrant workers. The circumjacent urban traffic and industries had a negative impact on the quality of the agricultural products. Moreover, these parcels of farmland were not targeted for protection by the plan. Their conversion does not harm the planning objectives of farmland protection; instead, it is conducive to promoting contiguous and compact urban expansion. Therefore, the authors suggested adjusting the plan to enable compliance with the non-conforming farmland conversion.

Urban land that existed prior to the issue of plans may have been converted into NCUL because it was not included in ZUDs or because the type of planned construction land was not consistent with the current situation. According to Loh [71] and Shen [48], permission to retain such land should be accepted according to the premise of not harming public interests and sustainable development. If changing land use according to the plans by relying on market forces proves difficult, the rationality of the plans should be reconsidered.

Some researchers have contended that disposal strategies can be selected on the basis of the assessment of land use suitability; those NCULs that are suitable for urban development and do not have significant negative impacts on farmland and ecological land protection can be included in the scope of the ZUD directly or after transformation [96]. For NCULs located in ecological or natural disaster-sensitive areas that are not suitable for development, the land use type should be changed according to the plans. If it is difficult to change the land use type because of public financial constraints, the status quo should be conditionally preserved [31].

Shen [44], Qian [76], and Luo [97] found that, in China, formally developed NCUL is mostly done to conform to plans via plan adjustment, whereas most of the informally developed land is conditionally maintained or demolished according to the governments' requirements.

### *4.2. Reducing Future NCUL Development*

#### 4.2.1. Improving the Plans

The ZUD should be large enough to meet the reasonable needs of urban expansion [25]. The connectedness of the ZUD, according to the premise of protecting the ecological environment, should be enhanced, and spatial plans and local spatial development strategies should be coordinated [17]. Priority should be given to areas with good developmental conditions to be included in the ZUD, and a differentiated supply of infrastructure and public service facilities should be planned within and outside the ZUD [50,67]. The focus should be on controlling land development in urban fringe areas, establishing clear urban growth boundaries, encouraging high-density land development, and controlling leapfrog development [80]. "Top-down" control requirements and "bottom-up" construction needs should be fully considered in the planning scheme through the technological innovation and procedural optimization of planning to enhance the inclusiveness and adaptability of the plans [37].

#### 4.2.2. Improving the Governance Structure for Planning Formulation and Implementation

The functions of planning formulation and implementation, which are scattered across different departments, should be integrated; a unified management approach should be adopted, and supervision and a restriction mechanism for planning management should be established [58,84]. A network of government agents at different levels, land property owners, market developers, and other stakeholders should be created, and their contacts, communication, and collaboration should be strengthened in processes of planning formulation and implementation to form a participatory governance structure and coordinate the goals of all parties as well as to resolve conflicts arising among them. This participatory governance structure can help to improve the scientificity and execution of plans while

strengthening members' cognition, understanding, recognition, and consciousness of the plans and realizing the social supervision of planning implementation, which would lead to a reduction in NCUL development [59,76,85]. However, some studies have emphasized that the participation of the private sector should be limited, or else economic interests relating to land development could sabotage the implementation of plans, resulting in unsuccessful efforts to control urban expansion [18]. Flexible adoption of a participatory or non-participatory governance structure that responds to the specific situations relating to NCUL development is required [41,94].

#### 4.2.3. Optimizing the Rigidity or Elasticity of Plans

Local governments are strongly motivated to choose local interests over plan implementation, which calls for rigidity in spatial plans [85,92]. It is necessary to enact spatial planning laws and to formulate specific planning implementation rules, management methods, and complementary normative provisions to ensure that plans can constrain the selection of sites for land development [79]. Planning revisions driven by the inconsistency between land use and plans should be strictly controlled, and plans should be carefully adjusted and the frequency reduced [84]. Dynamic monitoring of plan implementation and urban expansion should be strengthened to deal with NCUL development in a timely and effective manner, and appropriate punitive measures should be taken against those who commit violations [50]. Moreover, the boundaries of urban development and red lines for protecting core ecological and agricultural functional areas should be defined to ensure that the land in protected areas is not occupied for urban development [17,35]. In terms of elasticity, differentiated and targeted management should be implemented. That is to say, the binding and controlling force related to planning for public purposes, the maintenance of open spaces, and the protection of ecological environments should be strengthened. In contrast, flexibility should be enhanced for market-oriented land use to reduce planning restrictions [43,44]. As suggested by Pu [98], a rigid boundary of urban growth outside the urban growth boundary should be defined. Accordingly, projects conforming to specific regulations can be implemented outside the urban growth boundary, but they should not be allowed to extend beyond the rigid boundary. Moreover, changes that are based on prediction and authority should be made in the planning system, and indicators such as land use efficiency and the effectiveness of ecology and farmland protection should be considered an important basis for plan implementation and land use management [58].

#### 4.2.4. Improving Supportive Measures for Plan Implementation

The scope of ZUDs should be clarified, and onsite signs should be placed at the boundaries [34]. Guidance should be provided on the selection of sites for urban development, in line with the plans through the implementation of differentiated infrastructure and tax and price policies [99]. For example, in Saudi Arabia, the infrastructure inside ZUDs is provided by the government, whereas that located outside ZUDs is to be provided by the developers [82]. In Oregon in the United States, the establishment or extension of municipal services outside urban growth boundaries is forbidden [89]. Policies relating to the attraction of investments, land expropriation and supply, and spatial development should be coordinated with the spatial plans and their implementation [100]. In addition, local governments should compensate for negative impacts caused by growth management policies and plans [101]. For urban growth boundaries spanning administrative regions, coordinated policies on land supply, the distribution of benefits, and compensation should be established to encourage regions that make more effort to protect farmland and ecological environments and to adhere to the plans [43]. Experience from the Netherlands shows that policy instruments, such as land acquisition and financial or fiscal incentives for landowners, help to reduce land development in zones set aside for open-space preservation [81].

4.2.5. Improving Dynamic Plan Management

To cope with uncertainties and various challenges, dynamic plan management should be strengthened, and norms for plan adjustment, supervision, and monitoring should be formulated [79]. The dynamic monitoring and evaluation of plan implementation should be improved, and overall monitoring and special monitoring (in key areas, including the urban fringes) should be conducted using GIS and big data to enable the timely detection of NCUL expansion and the adoption of appropriate measures [39,40,80]. Moreover, dynamic feedback and an adjustment mechanism for managing the implementation of plans should be established to solve problems in plans and those relating to their implementation promptly [48]. For example, Wang [92] argued that plans should be re-examined and properly modified according to present conditions and the needs of stakeholders, while Puertas [30] suggested that the modification of spatial plans should be done according to reliable predictions of urban expansion, as large-scale NCUL development could occur if the plans conflict with the current developmental trend.

4.2.6. Regulating NCUL Development

NCUL development is significantly influenced by the criteria applied by governments to determine allowable development outside ZUDs [88]. Specific control targets inside and outside the ZUDs should be defined, and detailed regulations should be formulated for managing and controlling NCUL development [25]. A decision-making procedure for NCUL development should be established according to the premise of supervision and restriction [44]. Conversion of farmland and ecological land that does not conform to spatial plans should be examined and approved by specially established agencies or committees [73]. Requirements for the different types of land use and projects, site selection, the scale of land occupation, development intensity, and compensation measures relating to NCUL development should be formulated [80]. In the decision-making process relating to land supply, a disposal scheme for newly added NCUL should be clarified [48]. For example, in Ventura County, California, countywide voter approval is required to carry out non-conforming development [75]. Moreover, in Queensland, Australia, a performance-based planning system has been developed to determine whether non-conforming development can be approved [42]. Decisions are based on the merits of the non-conforming development and assessed according to aspects related to broader strategic intentions.

## 5. Summary and Suggestions for Future Research

This review of the existing literature has revealed that previous studies on NCUL expansion have made several important contributions, as summarized below. A variety of direct and indirect methods for measuring NCUL expansion have been developed, which, to a certain extent, reflect the causes and characteristics of spatial layout, the forms and locations of NCUL expansion, and the degree of conflict between NCUL development and the plans. This research has also identified external and internal factors influencing NCUL development, which is helpful for understanding the context of plan implementation and NCUL development and the drivers of site selection decisions of the concerned parties and their responses to the plans. Governance strategies relating to NCUL expansion were explored from two perspectives: the disposal of existing NCUL and limiting the increase in NCUL. Specifically, multiple strategies have been proposed for dealing with NCUL, and the factors that should be taken into consideration when selecting the strategies that have been discussed. Policy suggestions relating to planning formulation and management, governance structures, and institutional environments have been proposed to limit NCUL development. In light of the above achievements, here, we provide a number of suggestions for future research.

First, although spatial conformance has become one of the most commonly used methods for evaluating the effectiveness of plan implementation, it has two inherent flaws. It is too simplistic to consider the consistency between results and plans as the sole criterion for assessing the effectiveness of a plan. Nevertheless, plans may have an impact on the

decision-making relating to NCUL development [17,22,24]. The other flaw relates to the exclusive focus on results in the conformance evaluation approach [19]. Little is known about how plans affect behavior and how behavior produces results. To what extent is urban spatial expansion influenced and controlled by planning? Is it just coincidental when its outcomes are consistent with the plans? These questions remain to be addressed. Therefore, it is necessary to combine conformance evaluation with other methods for evaluating spatial plans and other public policies so as to achieve a breakthrough in the theory and methodology for evaluating plan implementation, thus helping to answer the above questions.

Second, previous studies that have attempted to explain NCUL development have not succeeded in fully combining and integrating external and internal factors. The development of NCUL stems from decisions relating to the selection of project sites. The plans also need to have practical impacts by influencing the decision-making relating to the selection of sites for land development. Internal factors explain the drivers of site selection for NCUL development, while external factors also influence land developers' decisions on site selection. Therefore, to establish a comprehensive analytical framework of the factors and relevant subjects influencing decisions on site selection, we recommend integrating external and internal factors. Furthermore, plans should be viewed as just one of the explanatory factors, and their influence on decision-making should be considered from the perspective of the behavioral logic of the actors' decision-making. This comprehensive framework would help to advance the understanding of the mechanisms of urban expansion and the role that plans play in urban expansion.

Previous studies have proposed many governance strategies and their selection criteria. However, they have not fully clarified the relationship between them. It is, therefore, necessary to conduct further studies to reveal how these criteria can be applied to guide the selection of governance strategies. It is also necessary to carry out studies on the reasons for and effects of NCUL expansion as well as to compile a summary of the practical experiences of NCUL development governance. Research on differentiated and adaptive governance strategies for NCUL expansion should continue to be promoted, and the impacts of governance strategies should be evaluated.

To conclude, the existing literature reveals that the phenomenon of NCUL expansion is widespread globally, posing serious problems in many areas. However, research in this field remains limited, and more case and cross-case comparative studies and empirical studies of the sampled land parcels or cities are needed to test the universality of existing findings and to generate new findings.

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# The Impact of Land Use on Time-Varying Passenger Flow Based on Site Classification

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**Abstract:** During the different periods of a day, the imbalanced distribution of inbound ridership, that is related to land use, results in extreme flow, which makes metro management challenging. The causes of imbalanced passenger flow from the perspective of land use in metro station areas are studied in this paper. More specifically, based on site classification, the impact of land use, including the floor area ratio and gross floor area on passenger flow, was explored by using a multiple linear regression model. The results first indicate that the impact intensities of the floor area ratio on peak hourly flow were 0.41, 0.21, and 0.20 around business, residential, and mixed sites, respectively. Second, for the abovementioned sites, the types with the greatest impact intensities of gross floor area on peak hourly flow were commercial and business facilities (B), residential (R), as well as administration and public services (A), which were 0.73, 0.32, and 0.87, respectively. Finally, for the land-development-control schemes for business, residential, and mixed sites, the maximum values of the floor area ratio were roughly 7.2, 5.3, and 8.2, respectively. The results presented in this study provide guidance for land development in metro station areas and contribute to avoiding the emergence of extreme passenger flow.

**Keywords:** land use; site classification; metro station areas; time-varying passenger flow; Xi'an

## 1. Introduction

With the rapid construction of metros, due to its characteristics of high efficiency and rapid speed, it has become the main means of public transport in domestic and foreign cities [1–3]. At the same time, metros also cause a series of urban safety management problems as a result of an increase in passenger flow on weekdays [4]. As the first city in Northwest China to open a metro, the explosive growth in construction in Xi'an in recent years has impacted upon the concentrated development of land in station areas. In turn, this has stimulated extreme flow, which has resulted in safety management issues, such as platform congestion and flow blockage [5,6]. Furthermore, for 80% of stations in Xi'an, the inbound passenger flow during off-peak periods is only around one-third of that during peak periods, and the passenger flow during peak periods exceeds the designed carrying capacity of the metro. Transportation demand is shaped by urban land use, and irrational land development stimulates extreme passenger flow [7,8]; therefore, identifying the impact of the floor area ratio and gross floor area on time-varying passenger flow is essential to controlling the high volume of metro users [9]. This study reviewed the literature with these research questions in mind. A growing body of work has explored the "source-flow correlation" following the proposed integration of transportation and land that [10,11]. This included the following two aspects: theoretical and methodical analysis. The first research aspect identified high-density land use as a key factor stimulating urban rail flow [12]. Kuby et al. proposed that land use is the dominant factor in metro ridership [13]. Related studies showed that the built environment in various station areas significantly impacts the

travel behavior of residents, and the characteristics of passenger flow distribution at a metro station (i.e., the time-varying passenger flow) may differ between different periods [14]. Voulgaris et al. applied a variable set with 20 indicators concerning built environmental characteristics in order to investigate the relationship between the built environment and residents' travel activity [15]. Previous studies examined the mechanism of how the built environment impacts this flow [16–19]. It was suggested that the development of rail transit station land can yield passenger flow data [20]. The core factors pertaining to land in the station area that affect the time-varying passenger flow include form, intensity, and mixedness [21–24]. For instance, Cynthia et al. and Ding et al. adopted empirical location data and showed that intensity is one of the most important factors affecting passenger flow. More specifically, intensity exerts a positive effect on passenger flow [25,26]. Hence, the control of land use intensity in the station area has been proposed as a key measure to address this issue [27–29]. In a case study of the Shenzhen metro, both temporal and spatial features of passenger travel behaviors were examined using land use information to determine local land use development patterns [30].

The second aspect of this study established a regression model to explain the correlation between land and flow of travel. This model could identify a particular linear causal correlation between multiple independent factors and the dependent variable of flow [31]. Su et al. adopted this regression model to explore the correlation between passenger flow and various land use indicators, including density, diversity, and other elements, within an impact radius of 500 m around each Shanghai station [32,33]. With a similar methodology, by drawing on cases from Shenzhen and Xi'an, Gu and Duan et al. applied chart and linear regressions as essential approaches [34,35]. Moniruzzaman and Páez analyzed the relationship between railway service demand and land use in Hamilton, Canada, using a regression model that considered spatial auto correlation [36]. In addition, site classification is also a critical factor influencing station-level transit ridership [37,38].

From the abovementioned literature, it can be observed that the relationship between flow and land use has been explored in depth; however, the research regarding the imbalanced distribution of time-varying passenger flow caused by irrational land use in the station area has not been explored to the same extent. More specifically, previous studies examined the total daily passenger flow, which tends to obscure the imbalanced distribution characteristics of passenger flow at different times of the day. This paper examined the impact that the mechanism of land use around stations has on time-varying passenger flow. The aim of this study is to clarify the root causes of extreme flow, and to ensure the maximum values of land use in order to provide control schemes for local land development practices.

In comparison to previous studies, this paper emphasized the classification of site types, discussed the distribution characteristics of time-varying passenger flow, and proposed land development control schemes that are tailored to each type of metro station. On the one hand, from the perspective of the time-varying distribution of passenger flow within a day, this study focused on the problems arising from extreme flow at stations. It then explored the logical relationships behind the inbound passenger flow that is generated by land use around different types of stations; this can enrich the theoretical and methodological systems of land development in metro station areas. On the other hand, in many areas, the metro is still in the construction stage. Whether in newer districts or older districts, the areas around the station are faced with major tasks such as land development and renewal; therefore, in terms of solving practical problems, this study proposed control schemes for different types of stations to more accurately and effectively avoid extreme passenger flow and to ensure public safety.

## 2. Data and Methods

### *2.1. Data*

As the metro line with the highest regional passenger volume, Xi'an metro line 2 runs through the Chang'an, Yanta, Beilin, Lianhu, and Weiyang districts, with an average daily

passenger volume of 1.25 million [39]. In addition, the development of the surrounding land around 21 stations tends to be advanced (Figure 1).

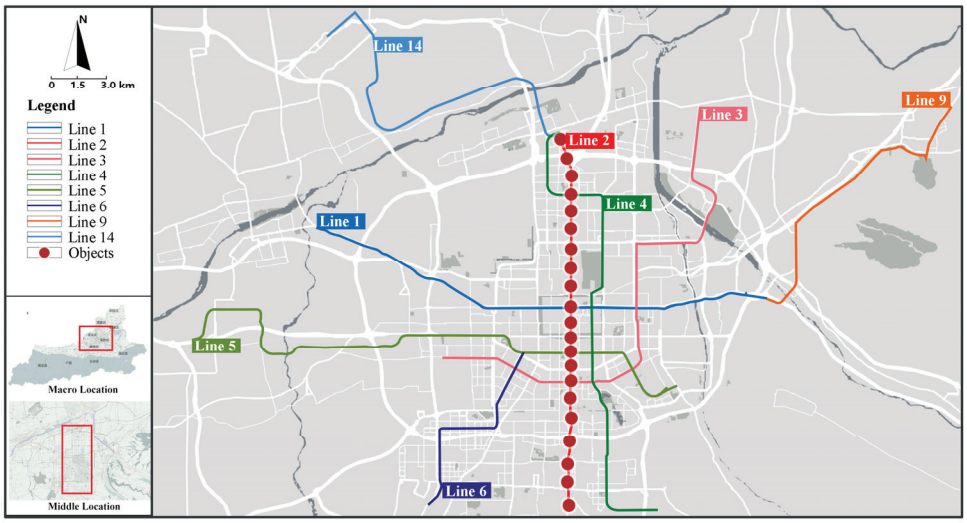


**Figure 1.** Station location schematic.

After selecting the abovementioned stations as the research object, in order to delineate the metro station areas, two main aspects were relied upon: pedestrian scale and site spacing. In particular, this study first considered the spatial distance that can be reached by pedestrians leaving the metro station on foot within 10 min, and then, the station radius was set within the range of 500–800 m due to the variation in walking speed. Second, for different countries, regions, and cities, the spacing of metro stations should be considered in accordance with local conditions. Generally, the radius of the station areas is set to half that of the station spacing in order to prevent the scope from overlapping [40,41]. In this study, based on a spacing distance of approximately 1000 m between metro stations in Xi'an, the buffer zone radius was determined to be 500 m. Inside the buffer zone (Figure 2), the data included land use and passenger flow (Table 1). First, the land use data aided the design by utilizing the Autodesk computer from the station area; the data were processed using high-definition satellite images (https://maps.google.com/ (accessed on 23 August 2021)), the GIS database, and field research conducted in 2021 which concerned the total floor area ratio (FAR) and gross floor area of different types of land (GFAs) (one unit: 10,000 $m^2$). The floor area ratio is the relationship between the total amount of usable floor area that a building has, or has been permitted to have, and the total area of the lot upon which the building stands. The gross floor area represents the sum of the gross floor area of all floors of all buildings on a site; it is measured by the exterior faces of the exterior walls or from the centerlines of walls separating two buildings. Second, the hourly passenger flow data were collected from the station's automatic fare collection (AFC) system from 23 to 27 August 2021.

**Table 1.** Data categories and sources.

| Data Categories | Index | Significance | Sources | Unit |
|---|---|---|---|---|
| Land use | Floor area ratio (FAR) | Land develop-ment intensity | maps.google.com<br>GIS database<br>field research | / |
| | Gross floor area (GFA) | Land development function | maps.google.com<br>GIS database<br>field research | $m^2$ |
| Passenger flow | Hourly flow | Passenger flow per hour | AFC system | person/hour |

**Figure 2.** Processed land use data showing the scope of the research.

Each small graphic inside Figure 2 depicts the scope of the research; there are 21 discrete graphs that map the surroundings of the stations of line 2, and 11 land use types are colored differently, which refer to the cutlines.

According to the code for classifying urban land use, and the planning standards for developing land in China [42], the types of land in the station areas are divided into 11 categories, and the area of each type of land is measured. As the areas that contain streets and transportation services (S), logistical services and warehouses (W), railways (H21), special services (H4), structures under development (E9), municipal utilities (U), and industrial services (M) account for less than 5% each, the GFAs were calculated with the other four land types in mind. These four land types are: residential (R), administration and public services (A), commercial and business facilities, (B) and green spaces and squares (G) (Figure 3a). The GFAs of the four types are symbolized as R-GFA, A-GFA, B-GFA, and G-GFA. The ratios of the GFAs (R-GFA, A-GFA, B-GFA, and G-GFA) amount to the buffer area, which is the FAR, and they are plotted in Figure 3b, thus providing an essential indicator for determining the amount of construction land used [43].

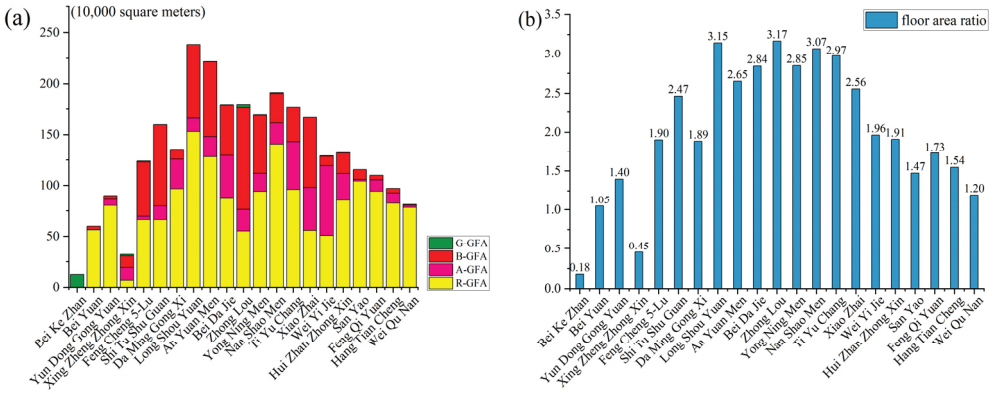


**Figure 3.** *Cont.*

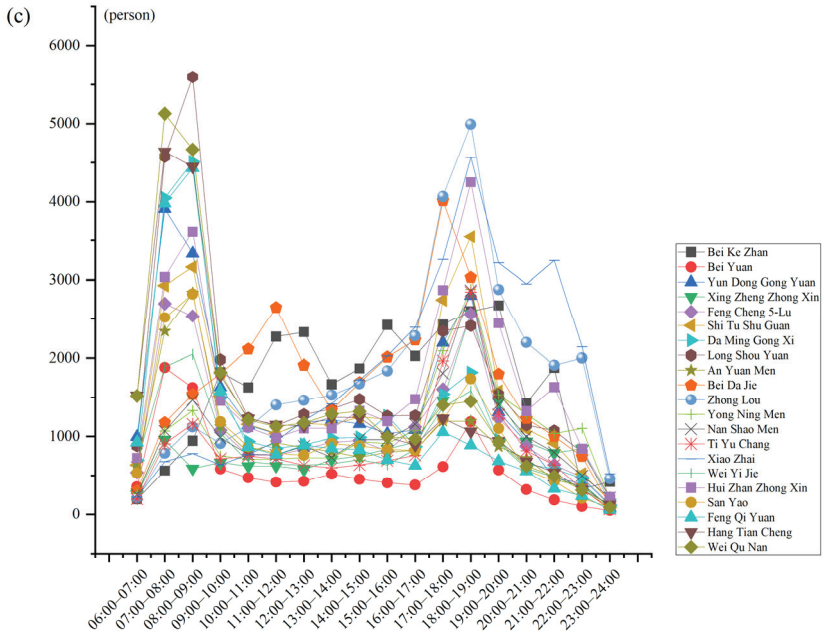


**Figure 3.** (**a**) Gross floor area of different types of land (GFAs); (**b**) total floor area ratio (FAR); (**c**) hourly passenger flow.

For the passenger flow, because the volume fluctuation of the total flow in different hours is slight, the time-varying distribution characteristics (adopting the total flow in and out of the station) may diminish. Compared with the outbound flow occurring on weekdays, the inbound flow has a higher degree of agglomeration, thus imposing greater pressure on the station's operation and management [32]; hence, the hourly inbound flow was adopted as the research index, and the data were collected from 06:00 to 24:00 in the week of 23 to 27 August 2021, as shown in Figure 3c.

### *2.2. Methods*

In this study, a "data collection characteristics analysis model and construction index control" research path was proposed (Figure 4), and specific research content was applied.

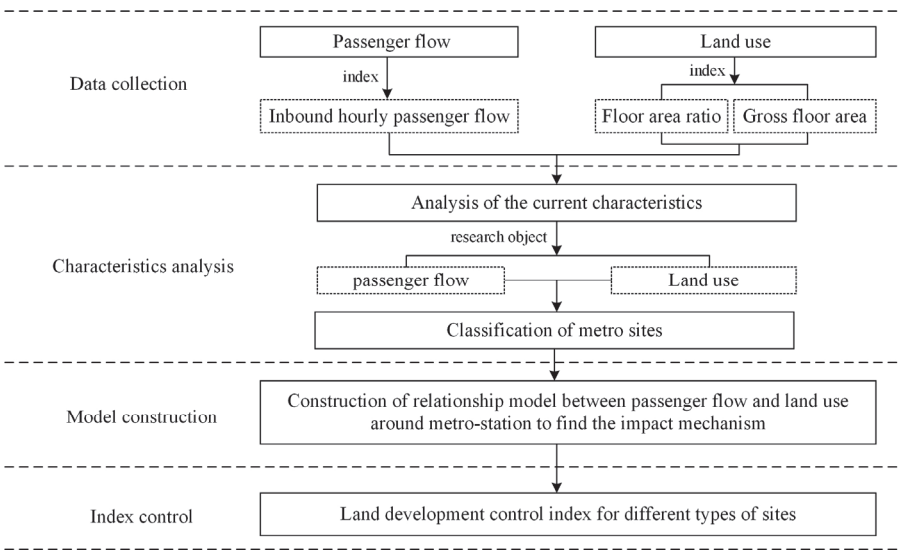


**Figure 4.** Research path.

- Classification of metro sites. According to the characteristics of land use around the station at present, and the time-varying law of the hourly coefficient on weekdays, the metro sites were classified into several types. Based on the site classification, a specific period division to vary the time periods was proposed.
- Impact mechanism of land use on hourly flow at various stations. Based on the independent variable types determined after applying the Pearson parameter dimensionality reduction, a linear regression model connecting the hourly flow with different land use indicators was constructed for different periods.
- Land use control for different types of sites. According to the fitting equation through the multiple linear regression model, the maximum values of the floor area ratio and gross floor area were proposed.

The methods were further refined for the above content. The probes on categorizing sites were conducted by using local land use mixtures [44] and the hourly coefficient for each station [45]. Then, the correlation of land use and the time-varying flow was analyzed with the Pearson correlation index. The multiple linear regression model was used to determine the separate impact of the factors. Finally, the reliability of the results was corroborated by the use of the mean absolute percentage error (MAPE).

1. Land use mixture

Land use mixture quantifies the abundance and complexity of land use types in the station area. Normally, it is abbreviated $H$ with the general form:

$$H = -\sum_{k=1}^{n} P_k ln(P_k) \tag{1}$$

where $P_k$ is the proportion of the total area of the site of the type in $k$, and $n$ is the type of land use.

2. Hourly coefficient

The hourly coefficient normalizes the unit passenger volume, which can be used to characterize the volume variations in the time-varying distribution. Its general form is:

$$Y = \frac{a}{b} \times 100\% \tag{2}$$

where $a$ is the passenger volume per hour, and $b$ is the total passenger volume over the entire day.

3. Pearson correlation coefficient

The Pearson correlation coefficient can help to screen for indicators that are less correlated with dependent variables, while avoiding the covariance between independent variables. The value is bounded by $-1$ and 1 and it embodies the correlation between land use indicators and hourly flow. Its general form is:

$$r = \frac{\sum_{i=1}^{n}(X_i - X)(Y_i - Y)}{\sqrt{\sum_{i=1}^{n}(X_i - X)^2}\sqrt{\sum_{i=1}^{n}(Y_i - Y)^2}} \tag{3}$$

where $r$ is the Pearson correlation coefficient, $X$ represents the GFAs of four area types (i.e., residential, administration and public services, commercial and business facilities, as well as green spaces and squares), and $Y$ represents the hourly flow that corresponds with different periods.

4. Multiple linear regression model

The multiple linear regression model is more accurate than using one variable to estimate the dependent variable; this can reflect the actual situation in a realistic and effective way. Moreover, multiple linear regression is suitable for simulations using multiple

scenarios and the model is relatively simple and easy to manipulate. In this study, a multiple regression analysis by IBM SPSS Statistics Version 22 software was employed to quantify the impact that different land use indicators have on the hourly flow in the station area. Equation (4) is the general equation for the regression model(s), comprising one dependent variable, $Y$, and $k$ independent variables, $X_1$, $X_2$, ..., $X_k$.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \beta_0 \quad (4)$$

where the dependent variable $Y$ represents the average hourly flow in a certain period, the independent variable $X$ symbolizes the FAR and GFAs, $\beta_0$ is a constant, and $\beta_1$, $\beta_2$, ..., $\beta_k$ are unstandardized regression coefficients.

5. Mean absolute percentage error
6. To test the reliability of the fitting equation, the mean absolute percentage error (MAPE) was calculated using Equation (5). This formula was used in this study to measure the difference between the actual and fitted flow. If the value is less than 30%, the fitting equation is valid.

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \times 100\% \quad (5)$$

where $Y_i$ represents the actual value, $\hat{Y}_i$ represents the fitted value, and $n$ represents the sample size.

## 3. Results and Discussion

### *3.1. Site Classification*

There were four categories for all sites that were distinguishable with the hourly coefficient: residential, business, mixed, and traffic type (Table 2). The proportional variation on the hourly inbound volume, displayed in the broken-line graphs of Figure 5, embodied the time-varying flow distribution for each station category. Remarkably, the result of the site classifications through land use mixture was convergence with an hourly flow percentage (Figure 6). This indicates that certain correlations existed between land use and hourly flow in the station area.

**Table 2.** Site classification.

| Type | Station(s) | Number |
|---|---|---|
| Residential [1] | Bei Yuan, Yun Dong Gong Yuan, Da Ming, Gong Xi, Long Shou Yuan, An Yuan Men, Wei Yi Jie, San Yao, Feng Qi Yuan, Hang Tian Cheng, and Wei Qu Nan | 10 |
| Business [2] | Xing Zheng Zhong Xin, Bei Da Jie, Zhong Lou, Yong Ning Men, Nan Shao Men, Ti Yu Chang, and Xiao Zhai | 7 |
| Mixed [3] | Feng Cheng 5-Lu, Shi Tu Shu Guan, and Hui Zhan Zhong Xin | 3 |
| Traffic [4] | Bei Ke Zhan | 1 |

[1] For stations at 07:00–09:00, the coefficient is 10–25%; [2] for stations at 17:00–19:00, the coefficient is 10–25%; [3] for stations at 07:00–09:00 and 17:00–19:00, the coefficient is 5–15%; [4] and for stations at 06:00–24:00, the coefficient is 1–10% [46].

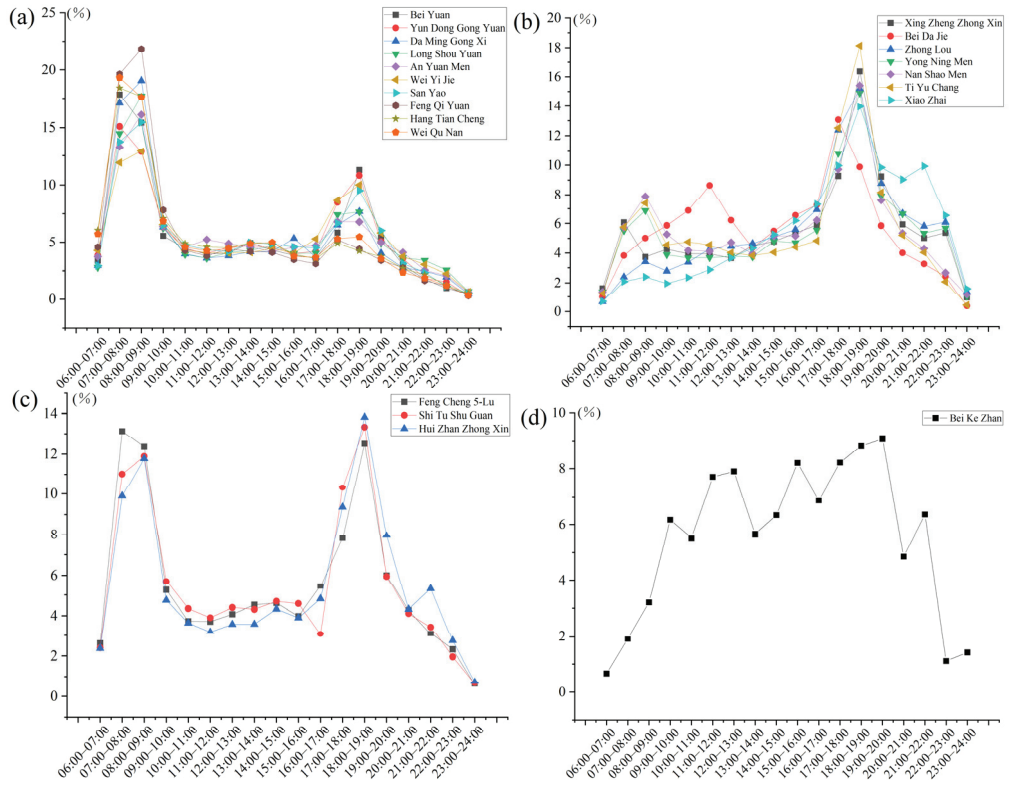


**Figure 5.** (**a**) Residential; (**b**) business; (**c**) mixed; and (**d**) traffic sites.

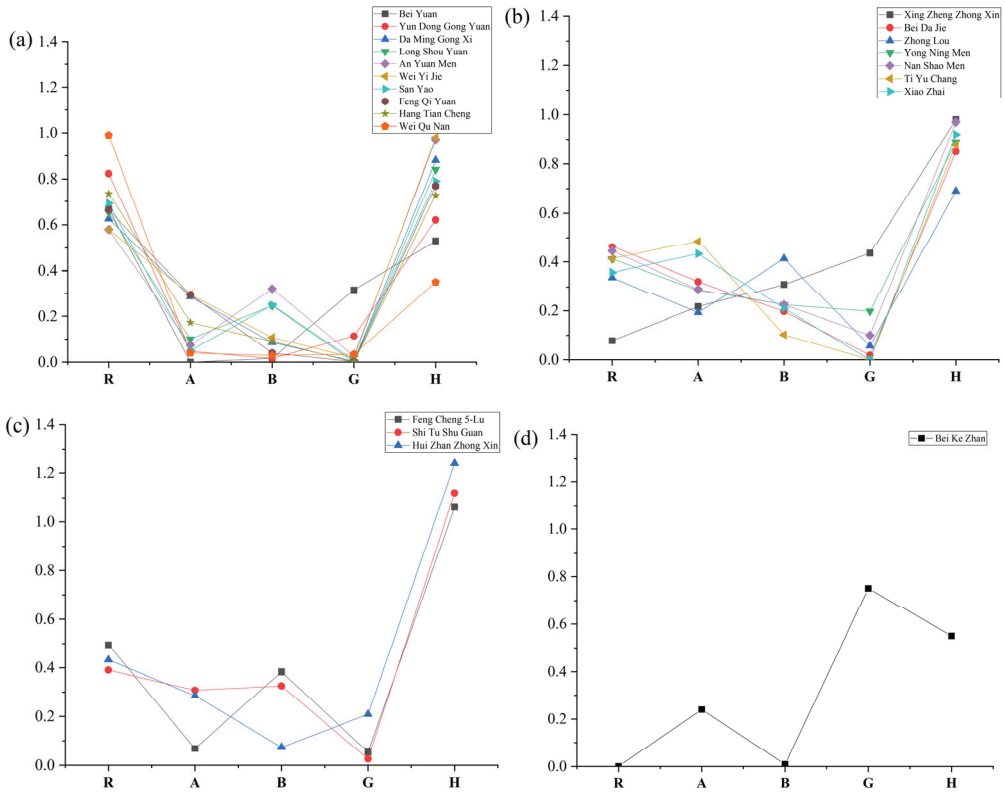


**Figure 6.** (**a**) Residential; (**b**) business; (**c**) mixed; and (**d**) traffic sites.

As shown in Figure 5a–d, with the varying times for flow distribution at all stations, different peak and off-peak periods existed at different sites, in accordance with the hourly

coefficient. At the residential sites, 07:00–09:00 was set as the peak period because significant tidal phenomena can be observed in those stations, and the off-peak periods referred to the two periods, 06:00–07:00 and 09:00–24:00. At the business sites, 17:00–19:00 was set as the peak period, with two off-peak periods at 06:00–17:00 and 19:00–24:00. At the mixed sites, the peak periods were 07:00–09:00 and 17:00–19:00, which displayed a double peak feature as the volume character and the off-peak periods were 06:00–07:00, 09:00–17:00, and 19:00–24:00. Conversely, as shown in Figure 5d, the passenger volume had no particular distribution in terms of time for the traffic site, with primarily flexible travelers using the service (non-commuting).

According to the land characteristics at present, R-type land use occupied a major proportion of the residential sites; it accommodated a high number of residents, and the mixture was less than 1.0 (Figure 6a). Most inbound passengers during 07:00–09:00 on weekdays originated from R-type land and commuted to work. Around the business sites, the main land use categories were generally identified as B-types with a large, employed population; the mixture was less than 1.0 (Figure 6b). Most inbound passengers during 17:00–19:00 on workdays originated from B-type land and commuted to their households. For mixed sites, the mixture of land use types was relatively higher, exceeding 1.0 (Figure 6c). Lastly, the land surrounding the traffic site, where *H* was less than 1.0, contained a lower residential population and fewer business premises (Figure 6d), thus resulting in a lower overall volume and a balanced distribution.

Additionally, the passenger volume variation was largely determined by the railway operation schedule in the only railway–metro hinge on line 2, called Bei Ke Zhan; therefore, the pressure on station management as a result of extreme flow was relatively low, which shows that a traffic-type station is not an interesting subject for research.

### *3.2. Impact of Floor Area Ratio on Hourly Flow*

Multiple linear regression was used to explore the impact of FAR ($X$) on the hourly flow ($Y$), where three independent variables, $X_1$, $X_2$, and $X_3$ represent the FAR of the residential, business, and mixed sites, respectively, and the dependent variables, $Y_1$ and $Y_2$, represent the hourly flow during peak and off-peak periods, respectively (Table 3). The standardization coefficient ($k$) represents the impact intensity of FAR on the hourly flow. The impact intensities of FAR on the hourly flow change in residential, business, and mixed sites were 0.21, 0.41, and 0.20 during peak periods, respectively, and 0.42, 0.33, and 0.23 during off-peak periods, respectively. In Table 3, *a* represents the unstandardized coefficient and *k* represents the standardized coefficient.

**Table 3.** Corresponding coefficients.

| | **Residential** | | | **Business** | | | **Mixed** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **a** | **Constant** | **k** | **a** | **Constant** | **k** | **a** | **Constant** | **k** |
| $Y_1$ | 403.46 | 2841.24 | 0.21 | 422.36 | 1961.39 | 0.41 | 331.99 | 2284.76 | 0.20 |
| $Y_2$ | 167.40 | 602.56 | 0.42 | 136.18 | 755.26 | 0.33 | 15.14 | 976.63 | 0.23 |

The results indicate a positive impact between FAR and hourly flow, which is consistent with the results of previous studies [47–49]. Total development intensity addresses the increase in the local population which imposes an increase in the hourly flow. In short, a reduction in FAR contributes to reasonable restrictions on local developments, which indirectly and effectively controls the flow rate for station management.

### *3.3. Impact of Gross Floor Area on Hourly Flow*

The Pearson correlation was adopted to analyze the correlation between GFAs and passenger hourly flow in order to filter the types of GFAs; then, linear regression was used to explore the impact of this correlation and filtration on the hourly flow.

3.3.1. Pearson Correlation

The Pearson correlation was used for correlating the GFAs of four area types (i.e., residential, administration and public services, commercial and business facilities, as well as green spaces and squares) and the peak (PHF: person/hour) or off-peak hourly flow (OPHF: person/hour). Figures 7–9 show the matrix results, in which the panels marked with *a* represent peak periods and those marked with *b* represent off-peak periods.

7. Residential Sites

During the peak periods, PHF was positively correlated with R-GFA and B-GFA (the coefficients were 0.45 and 0.07, respectively), and negatively correlated with G-GFA and A-GFA (the coefficients were −0.43 and −0.30, respectively). During the off-peak periods, the OPHF was positively correlated with R-GFA and B-GFA (the coefficients were 0.53 and 0.30, respectively), and negatively correlated with G-GFA and A-GFA (the coefficients were −0.12 and −0.11, respectively); therefore, the positive correlation between R-GFA and the hourly flow was the strongest, as the R-GFA had a greater proportion in the station area, which may result in higher passenger flow rates.

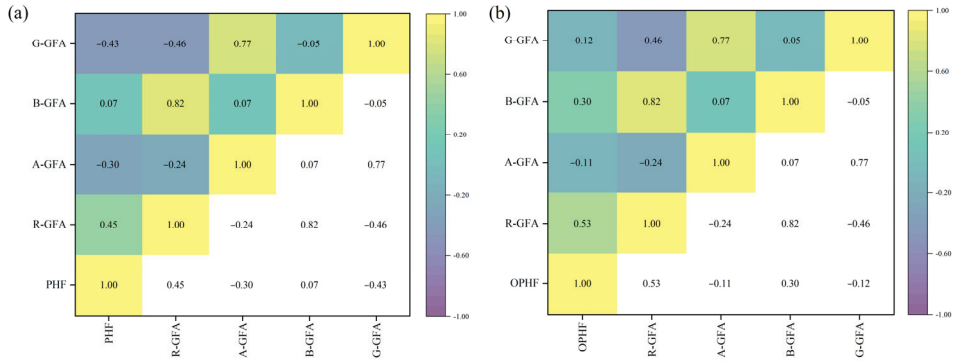


**Figure 7.** Correlations at residential sites, (**a**) peak periods; (**b**) off-peak periods.

8. Business Sites

For the business sites during the peak periods, a positive correlation was observed between PHF and B-GFA, A-GFA, and G-GFA, as indicated by the positive coefficients (0.91, 0.29, and 0.29, respectively). Nevertheless, the PHF was negatively correlated with R-GFA, as indicated by a coefficient of −0.17. During the off-peak periods, the OPHF was positively correlated with the floor areas of B, A, and G (the coefficients were 0.77, 0.33, and 0.12, respectively). Conversely, a negative correlation was observed for R-GFA (the coefficient was −0.15). A positive correlation was observed between the B-type GFA with an hourly flow, which addressed a large proportion of the employed population.

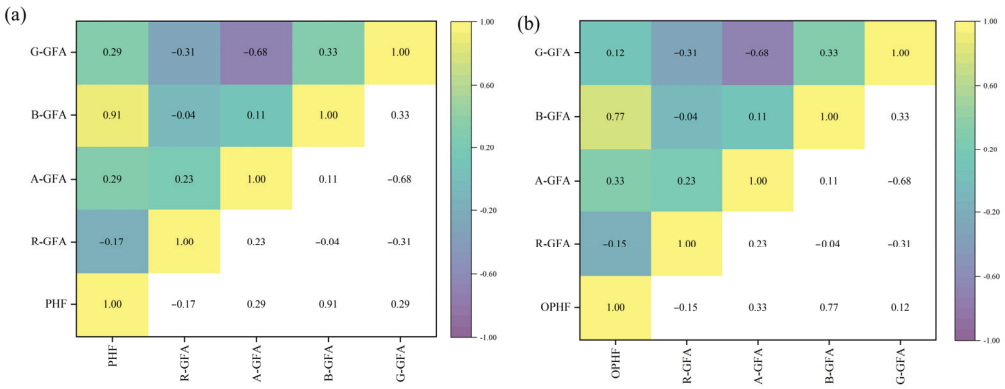


**Figure 8.** Correlations at business sites, (**a**) peak periods; (**b**) off-peak periods.

9. Mixed sites

The floor area types of A and R and the hourly flow at mixed sites were all positively correlated during the peak (coefficients of 0.96 and 0.75, respectively) and off-peak (coefficients of 0.99 and 0.85, respectively) periods. Conversely, the hourly flow was negatively correlated with G-GFA and B-GFA during the peak (coefficients of −0.84 and −0.37, respectively) and off-peak (coefficients of −0.73 and −0.52, respectively) periods. Consequently, A-GFA was identified as the most relevant factor that affected the local inbound flow.

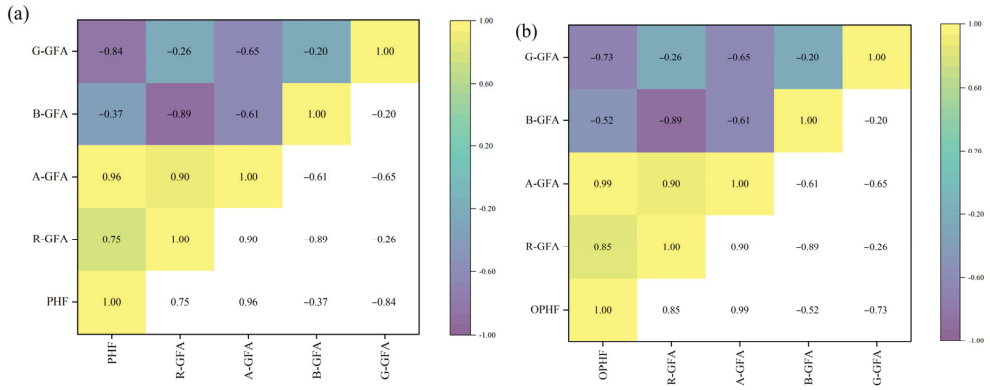


**Figure 9.** Correlations at mixed sites, (**a**) peak periods; (**b**) off-peak periods.

3.3.2. Impact Intensity

According to Yao and Dong [50], a threshold value greater than 0.2 and lower than 0.8 was proven as a valid coefficient to screen out the types of GFAs (Table 4). R-GFA, A-GFA, and G-GFA were obtained and used to compute the respective impact intensity on the PHF in residential sites. R-GFA and B-GFA were sorted for intensity computations with OPHF. For the business sites, A-GFA, B-GFA, and G-GFA were applied for computing the impact intensity on PHF, and A-GFA and B-GFA were adopted for OPHF. At the mixed sites, the land use factors A-GFA, B-GFA, and G-GFA were linked to different periods. Linear regression was employed in order to identify the impact of GFAs on flow using IBM SPSS Statistics Version 22 software. The correlation coefficients shown in the following tables, $R$ and $R^2$, of the regression model both exceed 0.4; thus, the fitting equation is reliable.

**Table 4.** Types of gross floor area after screening.

| Types of Sites | Residential | Business | Mixed |
|---|---|---|---|
| Peak hourly flow | R, A, G | A, B, G | A, B, G |
| Off-Peak hourly flow | R, B | A, B | A, B, G |

10. Peak periods

Tables 5 and 6 shows the multi-regression results of PHF and R-GFA, A-GFA, and G-GFA at the residential sites. The following model-fitting equation was constructed:

$$Y = 12.82R - 0.99A - 2512.61G + 2613.14 \quad (6)$$

**Table 5.** Summary of models for residential sites.

| R | $R^2$ | Adjusted $R^2$ | Standard Error | Sig. |
|---|---|---|---|---|
| 0.54 | 0.51 | 0.48 | 1286.51 | 0.03 |

**Table 6.** Corresponding coefficients.

| | Non-Standard Coefficient | | Standard Coefficient | T | Sig. |
|---|---|---|---|---|---|
| **Model** | **B** | **Standard Error** | **Beta** | | |
| | 2613.14 | 593.96 | | 4.40 | 0.02 |
| R-GFA | 12.82 | 1.25 | 0.32 | 10.29 | 0.00 |
| A-GFA | −0.99 | 0.17 | −0.02 | −5.82 | 0.01 |
| G-GFA | −2512.61 | 592.98 | −0.27 | −4.32 | 0.02 |

From the standardized coefficient, it can be observed that the impact intensity of R-GFA on PHF was highest at 0.32.

Tables 7 and 8 shows the multi-regression results for the PHF and A-GFA, B-GFA, and G-GFA at the business sites. The following model-fitting equation was constructed:

$$Y = 31.13A + 23.88B + 360.54G + 609.90 \quad (7)$$

**Table 7.** Summary of models for business sites.

| R | $R^2$ | Adjusted $R^2$ | Standard Error | Sig. |
|---|---|---|---|---|
| 0.95 | 0.91 | 0.81 | 413.65 | 0.04 |

**Table 8.** Corresponding coefficients.

| | Non-standard Coefficient | | Standard Coefficient | T | Sig. |
|---|---|---|---|---|---|
| **Model** | **B** | **Standard Error** | **Beta** | | |
| | 609.90 | 143.51 | | 4.25 | 0.03 |
| A-GFA | 31.13 | 6.90 | 0.47 | 4.51 | 0.02 |
| B-GFA | 23.88 | 7.26 | 0.73 | 3.29 | 0.04 |
| G-GFA | 360.54 | 62.70 | 0.37 | 5.75 | 0.01 |

From the standardized coefficient, it can be observed that the impact intensity of the B-GFA on PHF was highest at 0.73.

For the mixed sites, Tables 9 and 10 shows the multi-regression results for PHF and A-GFA, B-GFA, and G-GFA. The following model-fitting equation was constructed:

$$Y = 20.15A - 10.39B - 1244.61G + 4077.70 \quad (8)$$

**Table 9.** Summary of models for mixed sites.

| R | $R^2$ | Adjusted $R^2$ | Standard Error | Sig. |
|---|---|---|---|---|
| 0.73 | 0.62 | 0.56 | 413.65 | 0.02 |

**Table 10.** Corresponding coefficients.

| | Non-standard Coefficient | | Standard Coefficient | T | Sig. |
|---|---|---|---|---|---|
| **Model** | **B** | **Standard Error** | **Beta** | | |
| | 4077.70 | 959.50 | | 4.24 | 0.03 |
| A-GFA | 20.15 | 1.78 | 0.87 | 11.34 | 0.00 |
| B-GFA | −10.39 | 3.05 | −0.41 | −3.41 | 0.04 |
| G-GFA | −1244.61 | 216.93 | −0.33 | −5.74 | 0.01 |

From the standardized coefficient, it can be observed that the impact intensity of A-GFA on PHF was highest at 0.87.

11. The results presented above indicate that the inbound flow originates from regions with different land use types. During the peak periods, R-type land around residential sites provided the majority of the flow due to the high number of people traveling to work, and the peak times for mixed sites was the result of people commuting on weekdays. B-type land around the business sites provided the majority of the flow as individuals were returning to their accommodation [51,52]. Notably, the lower $R$ and $R^2$ of the PHF and GFAs that are fit for residential sites may have been due to the fact that during weekday peak hours, other factors have a greater impact on the flow because of the requirements for compressed commuting times; for instance, residents may consider whether to transfer, bus stop density, and so on. These factors create a strong interference with the dependent variable, thus resulting in a slightly lower fitting effect of R-GFA, A-GFA, and G-GFA on passenger flow.
12. Off-peak periods

Tables 11 and 12 shows the results of the multi-regression analysis between the OPHF of the residential sites and the R-GFA and B-GFA. The following model-fitting equation was constructed:

$$Y = 7.43R - 3.99B + 289.60 \quad (9)$$

**Table 11.** Summary of models for residential sites.

| R | $R^2$ | Adjusted $R^2$ | Standard Error | Sig. |
|---|---|---|---|---|
| 0.59 | 0.45 | 0.43 | 232.17 | 0.03 |

**Table 12.** Corresponding coefficients.

| | Non-Standard Coefficient | | Standard Coefficient | T | Sig. |
|---|---|---|---|---|---|
| Model | B | Standard Error | Beta | | |
| | 289.60 | 45.67 | | 6.34 | 0.02 |
| R-GFA | 7.43 | 0.82 | 0.90 | 9.06 | 0.01 |
| B-GFA | −3.99 | 0.78 | −0.45 | −5.12 | 0.03 |

From the standardized coefficient, the impact intensity of R-GFA on OPHF was highest at 0.90.

Tables 13 and 14 shows the results of the multi-regression analysis between the OPHF, A-GFA, and B-GFA at the business sites. The following model-fitting equation was constructed:

$$Y = 6.63A + 9.83B + 417.66 \quad (10)$$

**Table 13.** Summary of models for business sites.

| R | $R^2$ | Adjusted $R^2$ | Standard Error | Sig. |
|---|---|---|---|---|
| 0.80 | 0.65 | 0.47 | 283.13 | 0.02 |

**Table 14.** Corresponding coefficients.

| | Non-Standard Coefficient | | Standard Coefficient | T | Sig. |
|---|---|---|---|---|---|
| Model | B | Standard Error | Beta | | |
| | 417.66 | 42.10 | | 9.92 | 0.01 |
| A-GFA | 6.63 | 0.31 | 0.24 | 21.39 | 0.00 |
| B-GFA | 9.83 | 2.05 | 0.74 | 4.79 | 0.04 |

From the standardized coefficient, the impact intensity of B-GFA on OPHF was highest at 0.74.

For the mixed sites, Tables 15 and 16 shows the results of the multi-regression analysis between OPHF and A-GFA, B-GFA, and G-GFA. The following model-fitting equation was constructed:

$$Y = 19.25A - 4.81B - 426.41G + 1453.02 \quad (11)$$

**Table 15.** Summary of models for mixed sites.

| R | $R^2$ | Adjusted $R^2$ | Standard Error | Sig. |
|---|---|---|---|---|
| 0.95 | 0.89 | 0.88 | 416.22 | 0.03 |

**Table 16.** Corresponding coefficients.

| | Non-Standard Coefficient | | Standard Coefficient | T | Sig. |
|---|---|---|---|---|---|
| Model | B | Standard Error | Beta | | |
| | 1453.02 | 429.50 | | 3.38 | 0.04 |
| A-GFA | 19.25 | 3.23 | 0.84 | 5.96 | 0.01 |
| B-GFA | −4.81 | 1.09 | −0.53 | −4.42 | 0.03 |
| G-GFA | −426.41 | 96.93 | −0.29 | −4.40 | 0.03 |

From the standardized coefficient, the impact intensity of A-GFA on OPHF was highest at 0.84.

The results presented above show that during the off-peak periods, for the sites with different types, the inbound flow of people primarily originates from residential, commercial, and business facilities, as well as administration and public services land. This is generally consistent with the findings of previous studies [53,54]. These types of land are the primary sources of station space which generate a steady flow of people into the station. Moreover, cumulative passenger flow during off-peak periods is lower than during the peak periods at all stations, which is due to the reduced travel demand.

The actual and fitted passenger flow for the peak and off-peak periods of each station is obtained using Equations (6)–(11), as shown in Figure 10a–f, respectively. The trend of the value was basically similar, and the average MAPE values of the three types of sites during peak and off-peak periods were all less than 30%, within an acceptable range (Table 17); therefore, all fitting equations were reliable for ascertaining the correlations between the GFAs and hourly flow. Additionally, they can be employed for forecasting the trend when the flow changes; however, other factors, beyond those pertaining to land, can also impact the hourly flow, and thus, the fitting equations need to be perfected in subsequent research.

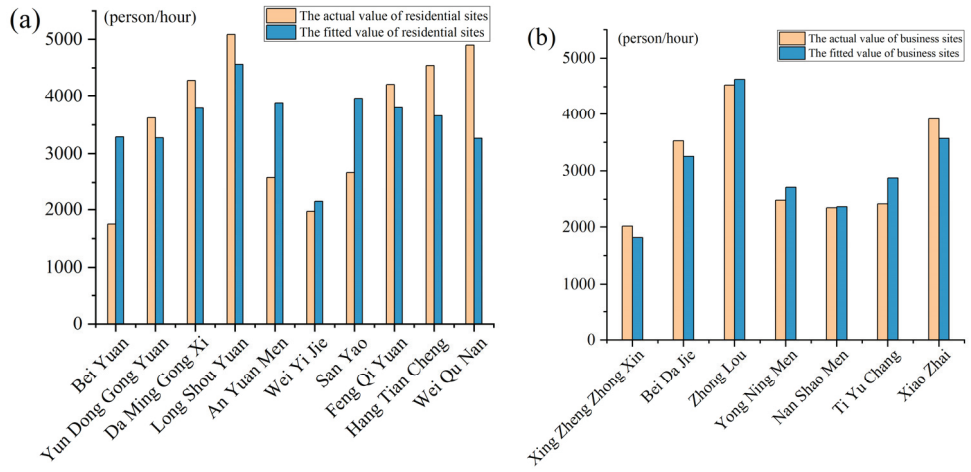


**Figure 10.** *Cont.*

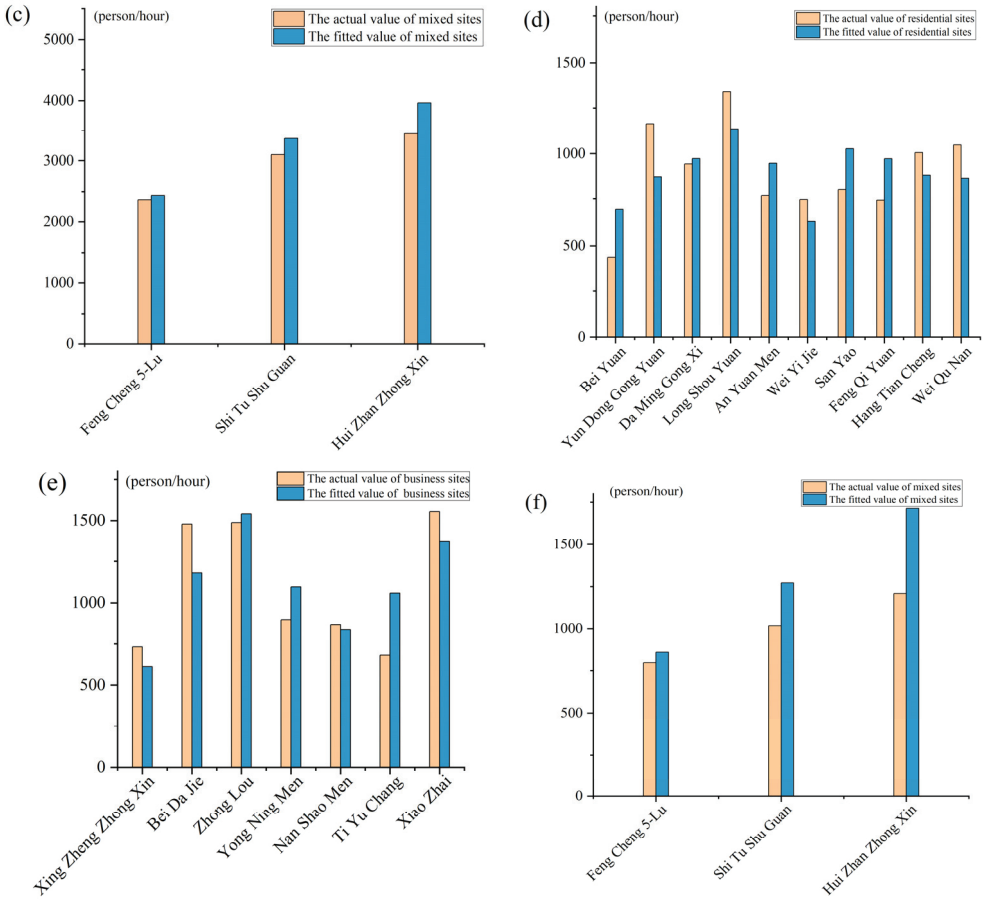


**Figure 10.** (**a**–**c**) the actual and fitted passenger flow values during peak periods; (**d**–**f**) the actual and fitted passenger flow values during off-peak periods.

**Table 17.** Mean absolute percentage error (MAPE).

| Periods | Residential | | Business | | Mixed | |
|---|---|---|---|---|---|---|
| | Peak | Off-Peak | Peak | Off-Peak | Peak | Off-Peak |
| MAPE (%) | 28 | 22 | 8 | 19 | 8 | 25 |

### *3.4. Land Development Control*

The rational development of the area surrounding the station ensures that the appropriate population type provides a reasonable passenger flow for public transportation. According to the empirical analysis of Xi'an metro line 2, the flow was positively correlated with the FAR and GFAs in the station area. The three types of land (R, B, and A) had the greatest impact intensities on the PHF of the metro. As a result, these types of land use are more important than others to curb the appearance of extreme flow during peak periods. According to previous research, the constraint values can be determined by combining the long-term peak hourly flow [55,56]. From the above research results presented in Sections 3.2 and 3.3, it can be observed that the control suggestions mainly target the orbit of the FAR and GFAs for these three types of different sites (Table 18).

**Table 18.** Maximum development values for control.

| Site Type | FAR | GFA (One Unit: 10,000 $m^2$) |
|---|---|---|
| Residential sites | 5.3 | 204.68(R-GFA) |
| Business sites | 7.2 | 132.29(B-GFA) |
| Mixed sites | 8.2 | 101.19(A-GFA) |

- Residential sites

The proportion of residential land in the station area is close to 50% with a simple land structure, and less than 10% of land is dedicated to office, commercial, and municipal utilities. As indicated by the fitting formula, the maximum development values of the FAR and R-GFA of the station area should be approximately 5.3 and 204.68, respectively (one unit: 10,000 $m^2$).

- Business sites

The proportion of land is mainly used for offices and residences, the total proportion of which exceeds 50%, and there are few commercial or municipal utilities, or green spaces. B-GFA presented the greatest number of impact intensities on the flow during peak periods. As indicated by the fitting formula, the maximum development values of the FAR and B-GFA of the station area should be approximately 7.2 and 132.29, respectively (one unit: 10,000 $m^2$).

- Mixed sites

In terms of land use, spatial distribution, and passenger flow characteristics, the mixed sites area lies between residential and business areas, as it has a high land use mix and the most balanced flow distribution. Overall, mixed sites present outstanding conditions in all aspects. As indicated by the fitting formula, the maximum values for the development of the FAR and A-GFA of the station area should be approximately 8.2 and 101.19, respectively (one unit: 10,000 $m^2$).

In this study, the impact of land use on the hourly flow was identified by adopting a multiple linear regression model, including two aspects concerning the FAR and GFAs. As shown in Figure 11, these two aspects representing land use intensity and function impact the increase in hourly flow in residential, business, and mixed sites. Moreover, the intensity control of land use development can be guided by assuming the maximum flow as the threshold.

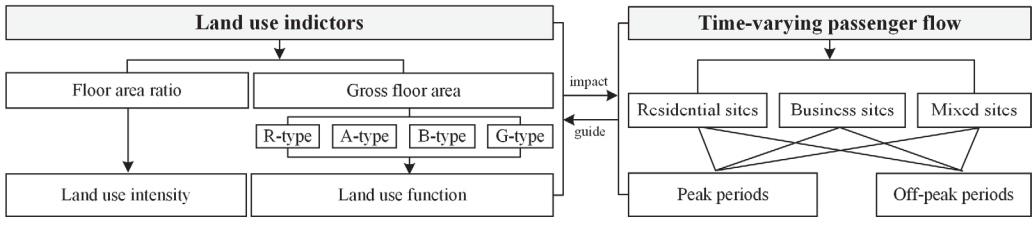


**Figure 11.** Results framework.

## 4. Conclusions

In recent years, we have witnessed the rapid construction of metros. Identifying the impact of land use around stations on passenger flow is of great significance for obtaining a scientific understanding of the time-varying distribution of flow, and it provides a theoretical basis for avoiding extreme flow. According to the results framework presented above (Figure 11), the following conclusions can be summarized.

Based on the distribution characteristics of the hourly flow during the day, all stations were classified as residential, business, mixed, and traffic, and each type of site had a different division between peak and off-peak periods. The impact mechanism of land use on hourly flow obtained by multiple linear regression at different stations may differ.

In terms of the methodological application, the study also followed the linear regression method adopted by Chang et al. and Su et al. [31,32]; however, it is worth noting that the Pearson correlation coefficient was used to filter out the independent variable indicators beforehand, which can improve the fitting degree of the gross floor area to passenger flow.

For the theoretical study, the surrounding land use was the main factor influencing the passenger flow and there was an objective "source–flow correlation" between the two factors. The floor area ratio and different types of gross floor area were core indicators that represented land use development intensity and function, which is similar to the results obtained by Yoshiharu et al. and Ding et al. [21,26]. In particular, the types of gross floor area that had the greatest impact on the hourly flow during peak periods were residential areas (R), commercial and business facilities (B), and administration and public services (A). At the same time, this paper was based on site classification, and therefore, development control values also differed. At the residential, business, and mixed sites, these indicators could be subject to the strongest control factors, with values of 204.68, 132.29, and 101.19 (one unit: 10,000 $m^2$), and the maximum values of the total FAR should be approximately 5.3, 7.2, and 8.2, respectively. In the future development of new districts and the renewal of old cities, the results can be used to guide site classification and land development strategies.

- The emergence of extreme passenger flow at metro stations was influenced by a number of complex factors, including the built environment of the station area; therefore, there were some limitations to this study. In particular, spatial factors other than land use were not considered, and the sample size was small, as only line 2 was considered for the study. Finally, the presented study failed to consider the spatial variability of station distribution; therefore, subsequent studies should be improved in the following three ways:
- More consideration should be given to the factors concerning the built environment that impact passenger flow at the station, including the distribution of public stations, the amount of parking, and the quality of the pedestrian environment, so that extreme passenger flow can be more accurately and effectively managed to ensure public safety.
- The diversity of the study sites can further improve the accuracy of the results; therefore, the number and type of sample sites needs to be expanded in future studies. For example, all 116 sites within the main city of Xi'an could be selected for the study.
- The GWR and GTWR models consider the spatial variability of different sites, and therefore, they have the advantage of being more accurate. Further research can introduce spatial parameters through these models to propose more reasonable diversified development strategies for different types of sites.

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# Hierarchical Correlates of the Shrinkage of Cities and Towns in Northeast China

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**Abstract:** The growth and shrinkage of cities and towns are normal phenomena in the evolution of regional town systems. The growth and shrinkage of different levels of cities and towns are mutually influential. This study uses ArcGIS and the Hierarchical Linear Model to analyze the hierarchical differences and correlations in the characteristics and mechanisms of shrinking cities and towns in Northeast China from 2000 to 2020. The results indicate that the shrinkage of cities and towns is characterized by hierarchical differences. High-level cities show widespread and slight shrinkage, while low-level towns show the most severe and continued shrinkage. The population shrinkage of cities and towns within the same municipality is not fully synchronized. In terms of spatial patterns, the multi-level relationship between cities and towns is divided into growth-driven, central siphon, peripheral growth, local growth, and global shrinkage. The shrinkage of high-level cities is mainly influenced by economic and industrial development and built-up environment. The shrinkage of low-level towns is constrained by population concentration, economic development, enterprise scale, local arable land resources, and environmental quality. Wages, jobs, and infrastructures in high-level cities have a strong siphoning effect on low-level towns, while technology and industrial development drive the population and economic development of low-level towns.

**Keywords:** urban shrinkage; difference and correlation; Hierarchical Linear Model; Northeast China

## 1. Introduction

Urban shrinkage, first proposed by Häußermann and Siebel [1], has become a global socio-economic issue [2]. The related results cover the concept, patterns, causes, governance, and socio-economic effects of urban shrinkage [3–8]. The number of shrinking cities in the world has shown accelerated growth since the mid and late 20th century. The phenomenon of urban shrinkage began to spread from developed to developing countries and from small towns to large- and medium-sized cities [9]. Most of the existing studies have taken the same level of towns as the object of study, focusing on large cities and metropolitan areas [10]. However, insufficient attention is given to small- and medium-sized towns [11,12] and longitudinal observations of the differences and correlations of multi-level towns [13,14]. There are significant hierarchical and scaling patterns in the spatial distribution, spatial–temporal evolution, and interaction mechanisms of socio-economic factors [15]. The spatial distribution and spatial–temporal evolution of urban shrinkage show scale variability and dependence [16]. There may be variability in the characteristics and mechanisms of the formation of shrinking towns with different levels, and the picture of regional town shrinkage limited to one level is not comprehensive. Accordingly, conclusions based on one level of cities may not be valid for another level [17].

Urban shrinkage is a multidimensional and complex process [18]. Urban shrinkage is not only affected by local factors such as population aging, natural disasters, environmental degradation, and unemployment but contextual factors such as post-socialist transition,

deindustrialization, suburbanization, and globalization [19,20]. Shrinking cities and towns are rooted as part of a regional town system. Different levels of cities and towns are interconnected and interact [13], and there is a close socio-economic division of labor and relationships. Resources and factors in the region are transferred to regional core cities, leading to a gradual shrinkage of disadvantaged towns [21]. The population and economic development of peripheral small- and medium-sized towns in the region (lower-level towns) are influenced by the central or big cities of the region (higher-level cities) [22].

China's cities and towns are experiencing rapid urbanization and urban shrinkage at present [23]. At present, there are 266 shrinking cities and towns in China [24], mostly resource-based cities and small towns [25], concentrated in the northeast and southwest of China, with obvious marginal location characteristics [10]. The "Key Tasks of New Urbanization Construction in 2019" published by the National Development and Reform Commission specifically proposes that China's shrinking cities should be "slimmed down and strengthened", changing the inertial thinking of incremental planning, strictly controlling the increment, revitalizing the stock, and promoting centralized distribution of population and infrastructure in small- and medium-sized towns [26,27].

Northeast China is an old industrial base and a rust belt region characterized with a serious and typical urban shrinkage [24,28]. There are various types of cities in Northeast China, including old industrial cities, resource-based cities, border-crossing cities, and tourist cities [29]. The study of urban shrinkage in Northeast China has implications for other regions. This study analyzes the patterns, characteristics, and urban shrinkage mechanisms from a multi-level perspective, taking prefecture-level cities (higher-level cities), county-level towns, and ordinary towns (lower-level towns) in Northeast China as subjects. First, this study identifies town shrinkage and analyzes the differences and spatial correlation characteristics of town shrinkage from a multi-level perspective; then, based on the Hierarchical Linear Modeling (HLM) model, this study reveals the interrelationship between different levels of city and town shrinkage and investigates the formation mechanism of multi-level town shrinkage. Finally, the conclusions and discussion of the study are presented. Based on the perspective of multi-level differences and associations, this study analyzes the hierarchical differentiation of town shrinkage, classifies the types of regional co-evolution of towns, and explores the interaction between towns at different levels. Furthermore, the study provides ideas for the governance of old industrial cities and regions, such as the relationship between towns and the important role of high-level cities in multi-level co-evolution.

## 2. Literature Review

### *2.1. Unbalanced and Dynamic Change of Cities and Towns*

The development of cities and towns in the region is a dynamic and unbalanced process, with a wide range of complex and interrelated relationships [30]. Towns of different levels and functions are interconnected and maintain a delicate balance. The dynamic balance of the development of any town collapses when facilities, resources, and policies change in the region. Due to the mobility and volatility of labor, capital, and investment [2], some cities experience shrinkage due to a lack of investment and quality assets, the decline of many industrial enterprises, and a decrease in population attractiveness [31,32]. The object of urban shrinkage studies mainly focuses on a few cases, such as Leipzig in Germany [33], St. Louis and Youngstown in the United States [34,35], Yiwu in China [7], or single-level studies of shrinking cities, such as the study of prefecture-level cities and county-level cities in China [10,11]. However, this study focuses on the differentiation and spatial co-evolution of cities and towns at different levels (prefecture-level cities, county-level towns, and ordinary towns).

### *2.2. Factors Influencing the Shrinkage of Cities and Towns*

City and town shrinkage is characterized by complexity, diversity, and integration [20]. Macroscopic impacts at the regional scale and local impacts at the town scale work to-

gether to shrink towns [18]. In addition to regional factors such as deindustrialization, suburbanization, and globalization [36], city and town shrinkage is also affected by local factors such as aging rates, resource depletion, and difficulties registered in industrial transformation [37]. The decline in the young population and the increase in the elderly population have led to a sharp drop in consumer demand and the breakdown of physical space and infrastructure in cities and towns [38]. Infrastructure such as education and health care are a guarantee for the lives of urban residents and the production of enterprises, which influences the attractiveness of the population [39]. The decline in fiscal revenues negatively affects the investment and construction of urban public services, which leads to lagging services and further loss of population [16]. A change in the original political status or a transportation location of a city can also cause a town to shrink [40]. As the material basis of town development, the depletion of natural resources in cities and towns can lead to shrinkage [25]. There are also complex effects of COVID-19 on urban shrinkage. On the one hand, compared to large cities, small towns with low population density and high public green areas per capita have a relatively low risk of transmission and spread of COVID-19, which weakens the incentive and motivation for population movement and migration from small towns to large cities [41]. At the same time, the Chinese government has adopted strict epidemic prevention and control policies, such as quarantine, silence, and closing cities, which have also reduced the intensity of population movement and migration between cities to a certain extent. COVID-19 has affected the socio-economics of consumer-oriented cities with tourism, retail, and entertainment as dominant industries [42], increasing urban unemployment, lowering income levels, and increasing the likelihood that urban dwellers will move to surrounding areas [43,44].

Urban shrinkage has a multi-level spatial correlation. There are frequent flows and close connections of population, economic, and other factors between core cities and peripheral small towns [45]. Theories, such as growth pole theory, cyclic cumulative causation theory, unbalanced growth theory, and core–periphery theory, emphasize the active role of large cities and top–down multilevel town linkages centered on large cities [46,47]. The growth of central cities in the region is not only the result of migration from rural areas but can also be the result of population movement from other towns in the region [10]. The population and economic development of low-level towns are influenced by the "agglomeration and diffusion effects" of high-level towns [45,48,49]. Central cities in the agglomeration development stage have a strong "siphon effect" on subordinate towns, attracting the population and socio-economic factors of surrounding towns to large cities. This process undermines the economic development of small towns [45]. Central cities in the diffusion development stage have the function diffusion or borrowing size effect on their subordinate towns. By borrowing the performance or functions of large cities, small towns share the advantages of agglomeration of large cities and increase the level of town services and attractiveness of the population [49]. Existing studies have neglected the interaction of multi-level influences in shrinking cities and towns. This study explores the interactions between different levels of cities and towns and enriches the literature on urban shrinkage from a multi-level perspective.

### *2.3. Mutil-Level Cities and Towns in China*

The urban system consisting of prefecture-level cities, county-level towns, and ordinary towns has become the basic unit of regional development in China (Figure 1) [50]. The connectivity of cities and towns at multiple levels is mainly reflected between prefecture-level cities and low-level towns under their jurisdiction. Unlike developed Western countries, China has transformed from a planned economy into a market economy. The administrative hierarchy of cities and towns largely corresponds to the administrative power of the city, the economy, and scale of the facilities. High-level cities play a central role in the region, while low-level towns play peripheral roles [48]. Under the role of administrative divisions and top–down hierarchies, China's county-level towns and ordinary towns are guided and constrained by prefecture-level cities and do not have full autonomy in urban

development, facility distribution, and industrial development. The growth and shrinkage of county-level towns and ordinary towns are not only related to their social and economic development but may also be affected by prefecture-level cities.

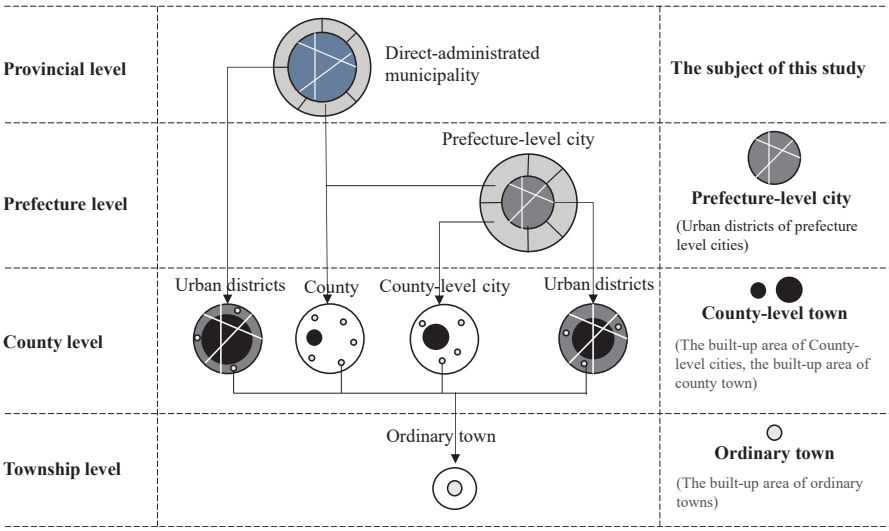


**Figure 1.** A multi-level perspective of Chinese cities and towns (revised from Li and Mykhnenko [50]).

*2.4. A Multi-Level Framework for Understanding the Shrinkage of Cities and Towns*

Based on a multi-level perspective, this study investigates the influencing factors and multi-level correlation patterns of urban shrinkage, which can more comprehensively reflect the multi-level spatial pattern and formation mechanism of urban shrinkage in Northeast China (Figure 2).

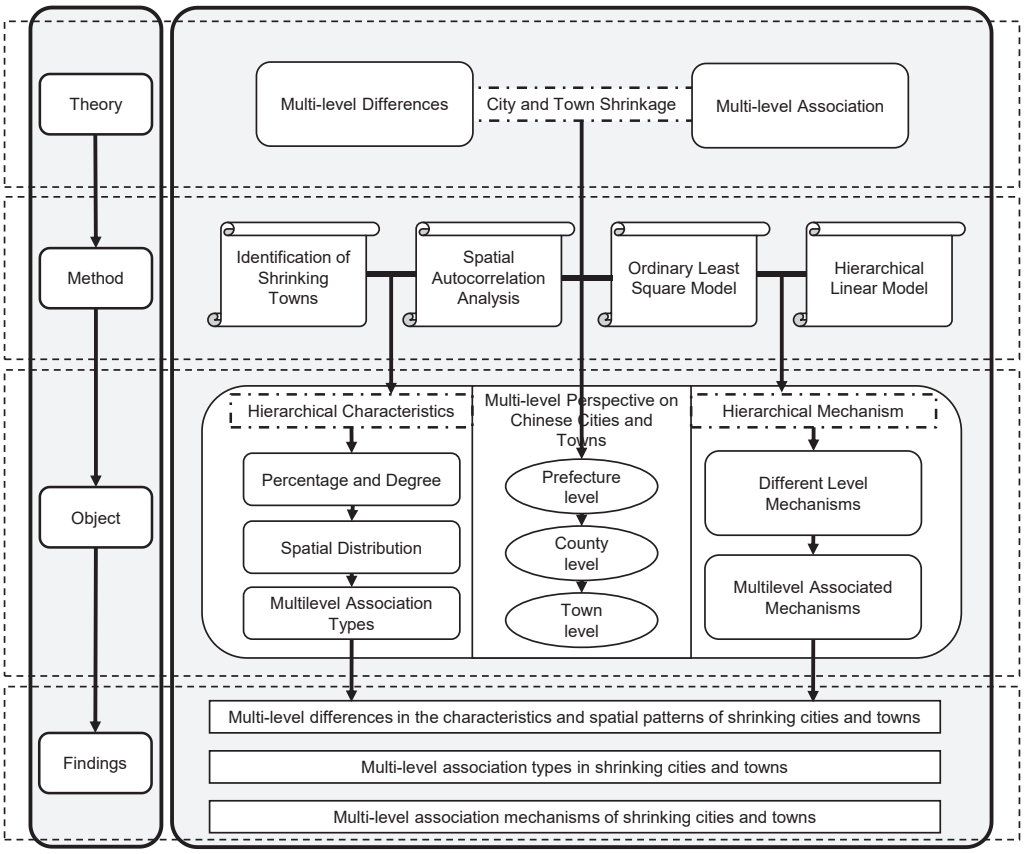


**Figure 2.** A multi-level framework for understanding the shrinkage of cities and towns.

## 3. Study Area, Data Sources, and Research Methods

### *3.1. Study Area*

Northeast China, an important old industrial base and a major grain-producing region, is facing the serious challenges of population loss and slowing economic growth. Since the reform and opening up, problems such as stagnant industrial evolution, regional polarization and dual economic structure have gradually become prominent. Since the 21st century, the economic status of Northeast China continues to decline, with some cities and towns even experiencing economic decline. Northeast China is also experiencing increasing population loss of more than 10 million between 2010 and 2020. Except for Shenyang, Changchun, and Dalian, the total population (urban and rural areas) of the 31 prefecture-level cities all declined in different degrees. Therefore, the study chose the period 2000–2020 to observe the multi-level shrinkage of cities and towns in Northeast China. As of 2020, Northeast China includes 34 prefecture-level cities, Daxing'anling Prefecture and the Yanbian Korean Autonomous Prefecture, 147 county-level towns, and 1718 ordinary towns (Figure 3). In this study, three county-level towns with missing data and 538 ordinary towns with zoning adjustments and missing data were excluded.

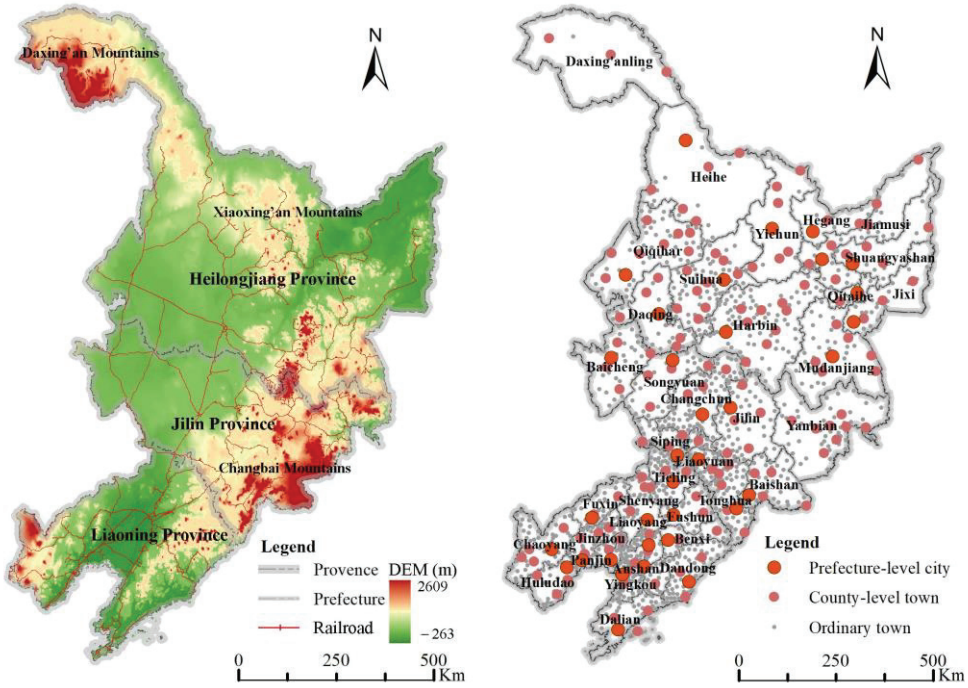


**Figure 3.** Cities and towns in Northeast China.

### *3.2. Indicators and Data Sources*

Referring to the relevant studies of scholars [10,13,16], this study selects the factors affecting the urban shrinkage in Northeast China from five aspects, including population, economy, industry, infrastructure, and environment (Table 1). Population data are mainly derived from information from the fifth, sixth, and seventh Chinese censuses. In addition, the data in the regression analysis include some socio-economic statistics and environmental data. The relevant variables are provided below.

**Table 1.** Factors influencing the shrinkage of cities and towns.

| Categories | Variables | Explanations |
|---|---|---|
| Population | Aging level (POP1) | Percentage of the population aged 65 and over |
| | Percentage of floating population (POP2) | Percentage of non-local resident population |
| | Population centrality (POP3) | Urban population as a percentage of the total population |
| Economic | Economic development level (ECO1) | Rate of GDP (or nighttime light value) change |
| | Fixed asset investment (ECO2) | Fixed asset investment completion |
| | Average wage (ECO3) | Average wage of urban workers in employment |
| Industry | Enterprise size (IND1) | Number of industrial enterprises above the scale |
| | Secondary industry share (IND2) | Secondary industry value-added ratio |
| | Tertiary industry share (IND3) | Tertiary industry value-added ratio |
| | Technology level (IND4) | Number of high-tech enterprises |
| Infrastructure | Medical level (INF1) | Number of medical and health institutions per 10,000 people |
| | Traffic level (INF2) | Length of road per capita |
| Environment | Air pollution index (ENV1) | PM2.5 average value |
| | Arable land (ENV2) | Arable land per capita |

#### 3.2.1. Dependent Variable

The average annual rate of population change is expressed using the average annual rate of change of resident population in municipal districts of prefecture-level cities, the average annual rate of change of population (sum of registered and temporary population) in the built-up area of county-level cities, the average annual rate of change of resident population in the built-up area of county-level towns (Chengguan towns), and the average annual rate of change of resident population in urban areas of ordinary towns[1].

#### 3.2.2. Independent Variable

Population data were obtained from census data and statistical yearbooks of ordinary towns. The aging rate uses the proportion of the population aged 65 or older; the proportion of floating population uses the proportion of non-local resident population in municipal districts, counties, and towns in the total resident population; and population concentration uses the ratio of the urban population to the total population of the area. The level of economic development uses the change rate of GDP of municipal districts and counties and the nighttime light value of ordinary towns. Investment in fixed assets uses the amount of investment in fixed assets completed in municipal districts and counties, and average urban wages use the average salary of urban workers in municipal districts and counties. Data on economic performance are obtained from statistical information of provinces and cities and global NPP-VIIRS-like nighttime light data [51]. Enterprise scale uses the number of industrial enterprises in municipal districts and counties, and the number of industrial enterprises with registered capital above 500,000 in ordinary towns; the ratio of secondary and tertiary industries uses the ratio of added value of secondary and tertiary industries in municipal districts and counties; the number of high-tech enterprises uses the number of high-tech enterprises in municipal districts, counties, and towns; and data on industrial development are obtained from statistical information of cities and counties and the commercial query platform Tianyancha (https://www.tianyancha.com, accessed on 14 December 2021). The medical level uses the number of beds per 10,000 people in municipal districts and counties and the number of medical and health facilities per 10,000 people in

ordinary towns; the level of road traffic uses road length per capita in municipal districts, counties, and towns. Medical level and road level data are from statistical yearbooks of provinces and cities for 2011 and POI data for 2014. Air pollution index data were obtained from global PM2.5 raster datasets published by the Atmospheric Composition Analysis Group of Washington University in St. Louis (https://sites.wustl.edu/acag/datasets/surface-pm2-5/, accessed on 16 June 2022) [52]. Finally, arable land data were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn, accessed on 14 December 2021).

### *3.3. Research Methods*

#### 3.3.1. Identification of Shrinking Cities and Towns

Most scholars use population decline as the primary criterion for identifying shrinking towns [8,23,53]. Some scholars also identify shrinking towns from multiple dimensions such as demographic, economic, and social [54] or with the help of nighttime light data [12,28]. In this study, the average annual change in urban population was used as an indicator for identifying urban shrinkage.

$$R_{POP} = \left( \left( \frac{M_{n2}}{M_{n1}} \right)^{\left( \frac{1}{(n2-n1)} \right)} - 1 \right) \times 100 \quad (1)$$

Here, $R_{POP}$ is the rate of shrinkage of the town, $M_{n1}$ and $M_{n2}$ are the population numbers in the initial and final years, and $n2 - n1$ is the population change during the study period. When $R_{POP} < 0$, the town is experiencing shrinkage, and the higher the absolute value of $R_{POP}$, the higher the shrinkage of the town. When $R_{POP} < -2\%$, the town experiences a significant shrinkage.

#### 3.3.2. Methods of Spatial Autocorrelation Analysis

Global autocorrelation is usually illustrated using Moran's $I$ [55], which measures the general trend of the spatial correlation of the shrinkage rate of shrinking towns. It is calculated as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})} \quad (2)$$

Local autocorrelation is usually illustrated using the local Moran's $I$ [56], which measures the local spatial relationship between the shrinkage rate of shrinking towns and the shrinkage rate of surrounding shrinking towns. It is calculated as follows:

$$I = \frac{n(x_i - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \sum_{j=1}^{n} w_{ij}(x_j - \overline{x}) \quad (3)$$

where $n$ is the total number of shrinking towns. $x_i$ and $x_j$ are the shrinkage rates of towns $i$ and $j$, respectively; $\overline{x}$ is the mean value of the shrinkage rate; and $w_{ij}$ is the spatial weight matrix indicating the proximity of towns $i$ and $j$; $i = 1, 2, 3, \ldots, n$; $j = 1, 2, 3, \ldots, n$; $i \neq j$.

#### 3.3.3. Methods of Influencing Factors Analysis

This study analyzes the factors influencing the shrinkage of cities and towns in Northeast China. First, this paper uses an ordinary least square (OLS) model [57] to identify the key factors of urban shrinkage in prefecture-level cities, county-level towns, and ordinary towns. The OLS model is as follows:

$$Y = kX + b \quad (4)$$

where $Y$ is the average annual rate of change of the urban population as a dependent variable, and $X$ is an independent variable, i.e., indicator that affects the change of the urban population.

However, OLS models can usually only regress data for towns at the same level, making it difficult to observe the impact of higher-level towns on lower-level towns. Based on the HLM model, this study further analyzes the impact of high-level towns on the shrinkage of lower-level towns under their jurisdiction in order to explore the extent and path of the influence of high-level towns on lower-level towns [58]. Specific forms of HLM models can be divided into zero models, random effects models, and full models. The HLM model of the "prefecture-level city-county town" is taken as an example.

Zero model: The null model is the premise and basis for the construction of the HLM model. This model is used to explain the between-group and within-group effects and to determine whether the town shrinkage of each county town is affected by the prefecture-level city and the county town. In the null model, only the dependent variable is added to the first-level (county-level town) model and to the second-level (prefecture-level city) model in order to construct the model directly (as shown in Equations (5)–(7)):

$$\text{Level 1: } Y_{ij} = \beta_{0j} + \varepsilon_{ij} \tag{5}$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + \mu_{0j} \tag{6}$$

$$\text{Mix model: } Y_{ij} = \gamma_{00} + \mu_{0j} + \varepsilon_{ij} \tag{7}$$

Random effects model: A random effects model is used to add explanatory variables to the first level of the null model in order to investigate the effects of prefecture levels and county levels on county-level town shrinkage (as shown in Equations (8)–(11)):

$$\text{Level 1: } Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij} \tag{8}$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + \mu_{0j} \tag{9}$$

$$\beta_{1j} = \gamma_{10} + \mu_{1j} \tag{10}$$

$$\text{Mix model: } Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \mu_{0j} + \mu_{1j}X_{ij} + \varepsilon_{ij} \tag{11}$$

Full model: The full model is based on a random effects model with the addition of prefecture-level and city-level variables to the second tier of the model. This approach not only allows testing the multiple effects of influencing factors on county-level town shrinkage at the prefecture-level and county-level but also enables analysis of the effects of prefecture-level and county-level influencing factors on county-level town shrinkage (as shown in Equations (12)–(15)):

$$\text{Level 1: } Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij} \tag{12}$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \mu_{0j} \tag{13}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}W_j + \mu_{1j} \tag{14}$$

$$\text{Mix model: } Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}X_{ij} + \gamma_{11}W_jX_{ij} + \mu_{0j} + \mu_{1j}X_{ij} + \varepsilon_{ij} \tag{15}$$

where $i$ and $j$ denote units at the county town and prefecture-level city; the explanatory variable $Y_{ij}$ denotes the shrinkage rate of county town $i$ within the $j$th prefecture-level city; $X_{ij}$ denotes the county town effects on the shrinkage rate of county town $i$ in prefecture-level city $j$; $\beta_{0j}$ and $\beta_{1j}$ denote the intercept and slope, respectively; $\varepsilon_{ij}$ is the residual variance at the first level; $W_j$ denotes the prefecture-level city influences; $\gamma_{00}$ and $\gamma_{10}$ show the intercepts of the equation; $\gamma_{01}$ and $\gamma_{11}$ show the regression coefficients of the cross-level effects of the prefecture-level city influences on the county town; and $\mu_{0j}$ and $\mu_{1j}$ represent intercept and slope residuals.

## 4. Hierarchical Differences and Correlations of City and Town Shrinkage

### *4.1. Hierarchical Differences*

Urban shrinkage in Northeast China mainly occurs in the period 2010–2020 and shows multi-level variability (Table 2). From 2000 to 2010, Northeast China shows a normal urbanization trend with population moving from small towns to large and medium cities. Most prefecture-level cities and county-level towns maintain growth and only some ordinary towns experience urban shrinkage. From 2010 to 2020, the spatial polarization of the urban population in Northeast China is becoming more pronounced. More than half of the prefecture-level cities, county-level towns, and ordinary towns will be among the shrinking towns, showing an "overall" shrinkage trend.

**Table 2.** Number of shrinking cities and towns in Northeast China.

| Level | 2000–2010 | | | 2010–2020 | | |
|---|---|---|---|---|---|---|
| | **Shrinkage** | **Slight Shrinkage** | **Significant Shrinkage** | **Shrinkage** | **Slight Shrinkage** | **Significant Shrinkage** |
| Prefecture level | 5<br>14.7% | 5<br>14.7% | 0<br>- | 20<br>58.8% | 14<br>41.2% | 6<br>17.6% |
| County level | 11<br>7.6% | 10<br>6.9% | 1<br>0.7% | 78<br>54.2% | 56<br>38.9% | 22<br>15.3% |
| Town level | 518<br>44.2% | 232<br>19.8% | 286<br>24.4% | 594<br>52.2% | 290<br>24.7% | 304<br>25.9% |

The shrinkage of cities and towns in Northeast China varies significantly depending on their level. Prefecture-level cities showed the most widespread shrinkage, with 17.6% showing a significant shrinkage and 41.2% showing a slight shrinkage in the period 2010–2020. The proportion of both slight and significant shrinkage at the county level is slightly lower than at the prefecture level. However, the proportion of shrinking towns at the county level is growing rapidly, from 7.6% in the period 2000–2010 to 54.2% in the period 2010–2020. The ordinary towns showed the most severe and continued shrinkage, with almost half experiencing shrinkage and about 25% experiencing significant shrinkage in both periods.

The spatial distribution of urban shrinkage in Northeast China shows significant differentiation at multiple levels (Figure 4). Shrinking prefecture-level cities are mostly land border cities, showing a spatial pattern of "marginal shrinkage". Shrinking towns at the county level show evolutionary characteristics from "sporadic" clustering to "balanced" distribution. Most county-level towns in prefecture-level administrative divisions show the coexistence of "growth and shrinkage". The shrinkage of ordinary towns generally shows an expanding trend from north to south. Shrinking towns at all levels in Northeast China are concentrated in the Changbai Mountains in the east and the Xiaoxing'an Mountains in the north, showing the significant characteristic of "mountain shrinkage".

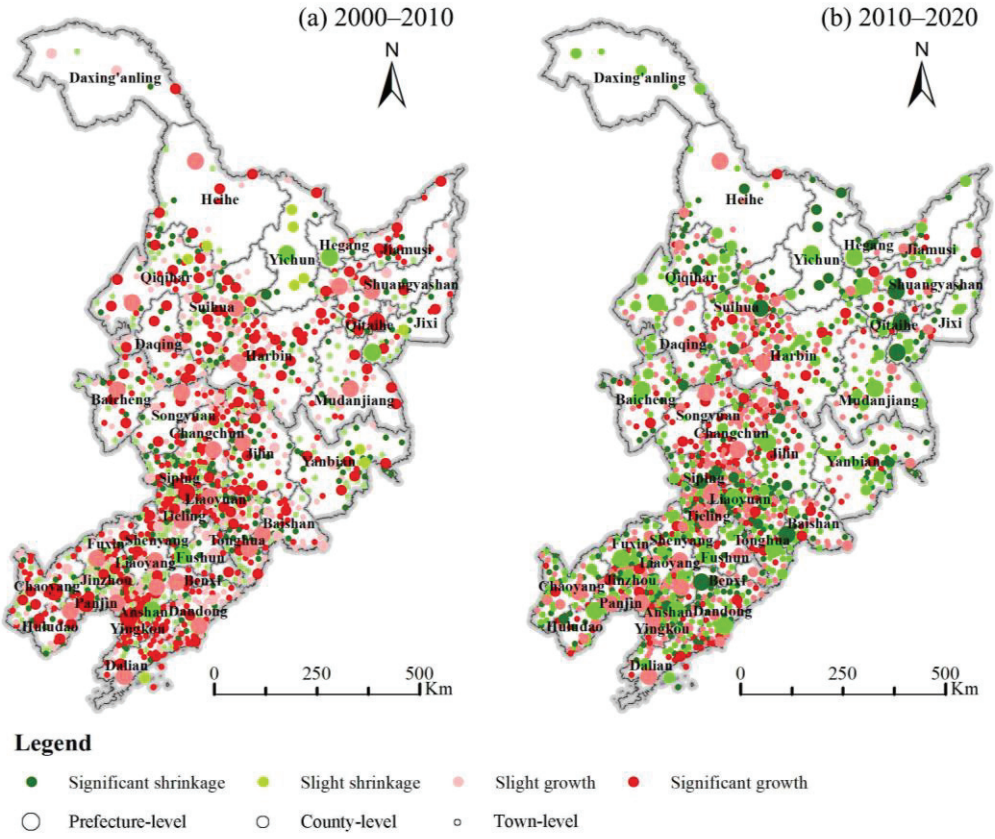


**Figure 4.** Spatial pattern of multi-level town shrinkage in Northeast China. Subfigure (**a**) shows the spatial pattern of multi-level town shrinkage in Northeast China during the period 2000–2010; Subfigure (**b**) shows the spatial pattern of multi-level town shrinkage in Northeast China during the period 2010–2020.

The global spatial autocorrelation of city and town shrinkage in Northeast China is not significant, and its spatial agglomeration characteristics are only reflected in local space. There are four types of local spatial autocorrelation. They include High-High type, where both the town and surrounding towns with no shrinkage or low shrinkage are located; High-Low type, where the town with no shrinkage or low shrinkage and surrounding towns with high shrinkage are located; Low-Low type, where both the town and surrounding towns with high shrinkage are located; and Low-High type, where the town with high shrinkage and surrounding towns with no shrinkage or low shrinkage are located.

There are hierarchical differences in the spatial clustering characteristics of urban shrinkage in Northeast China (Figure 5). Spatial agglomeration of cities at the prefecture level is increasingly pronounced in the "high south and low north". The High-High and Low-High types are concentrated in the coastal areas of Liaoning Province, while the Low-Low types are concentrated in northeastern Heilongjiang Province. The spatial clustering characteristics of county-level towns shift from "localized clustering" to "random distribution", with the Low-Low type in the northern and western regions of Heilongjiang Province and the Low-High type in the coastal region of Liaoning Province decreasing significantly. The most significant feature of local autocorrelation is noticed in ordinary towns. The High-High and Low-High types gradually shift from the coastal areas of Liaoning Province to the Ha-Chang urban agglomeration, and the Low-Low types are concentrated in the western and eastern parts of Heilongjiang Province and the eastern part of Jilin Province.

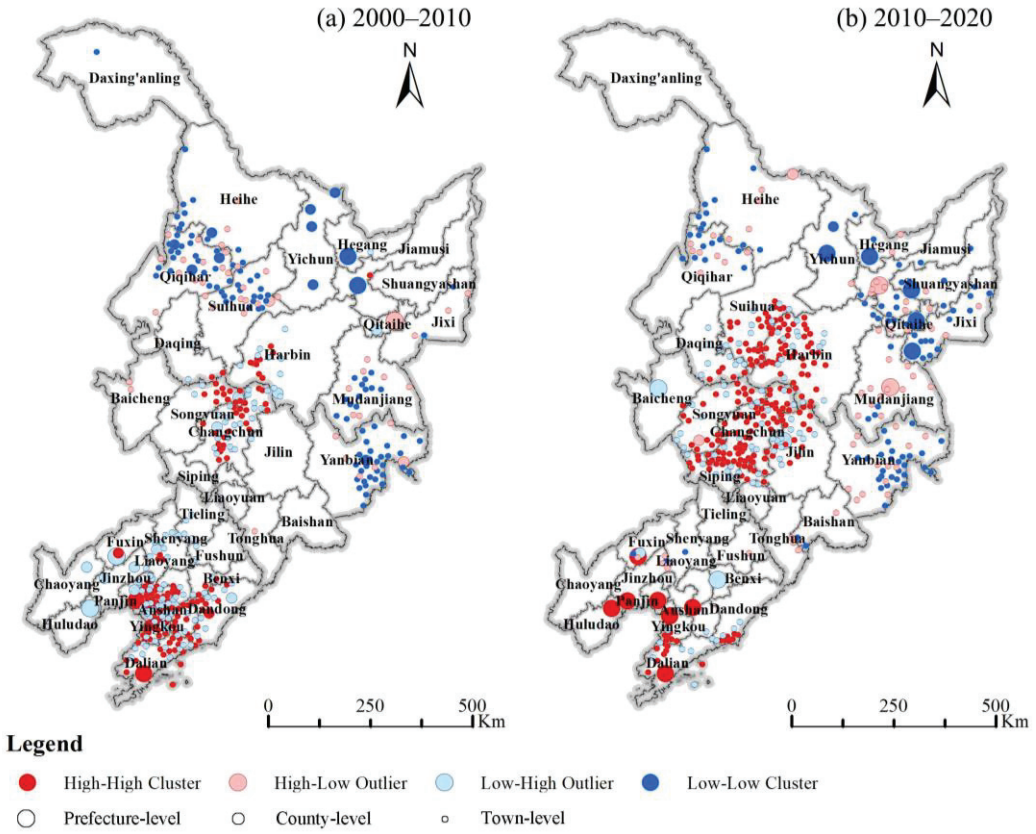


**Figure 5.** Local spatial autocorrelation of multi-level town shrinkage in Northeast China. Subfigure (**a**) shows the local spatial autocorrelation of multi-level town shrinkage in Northeast China during the period 2000–2010; Subfigure (**b**) shows the local spatial autocorrelation of multi-level town shrinkage in Northeast China during the period 2010–2020.

General results indicate that: (1) the High-High and Low-High types of the prefecture-level cities, the Low-High types of county-level towns, and the High-High types of ordinary towns overlap in the coastal area of Liaoning Province, which indicates that the development of all levels of towns in the region is generally high; (2) the Low-Low types of prefecture-level cities, county-level towns, and ordinary towns overlap around Yichun City, which indicates that the development level of all towns in the region is much lower than the development level of the surrounding areas; and (3) the High-Low and Low-Low types of prefecture-level cities and ordinary towns overlap in northeastern Heilongjiang Province, and the spatial types of county-level towns are not significant. The main shrinkage in the region is noticed in prefecture-level cities and ordinary towns, and the shrinkage of county-level towns is not significant.

### *4.2. Hierarchical Correlations*

Shrinking towns are a product of the development of a regional town system and do not exist in isolation. In China, prefecture-level cities, county-level towns, and ordinary towns form several relatively common and closely related regional town systems, which are important units of regional development. These regional town systems are an organic whole with prefecture-level cities as the core and a range of towns of different sizes and functions. By changing the constituent elements within the regional system, the dynamic balance of the development of towns in the region also changes. Some towns quickly develop into new growth poles, and those that do not take advantage of the opportunity gradually shrink.

Based on the growth and shrinkage patterns of regional towns, this study classifies the regional town system into five types: growth-driven, central siphon, peripheral

growth, local growth, and global shrinkage (Figure 6). Growth-driven type suggests that prefecture-level cities, county-level towns, and ordinary towns are generally in a state of growth. Central-siphon type indicates that prefecture-level cities maintain growth, while most county-level towns and ordinary towns shrink. Peripheral-growth type shows that prefecture-level cities and most ordinary towns are shrinking, but half or more of the county-level towns are still growing. Local-growth type indicates that prefecture-level cities, most county-level towns, and ordinary towns are shrinking. Global-shrinkage type suggests that prefecture-level cities, county-level towns, and most ordinary towns are also shrinking.

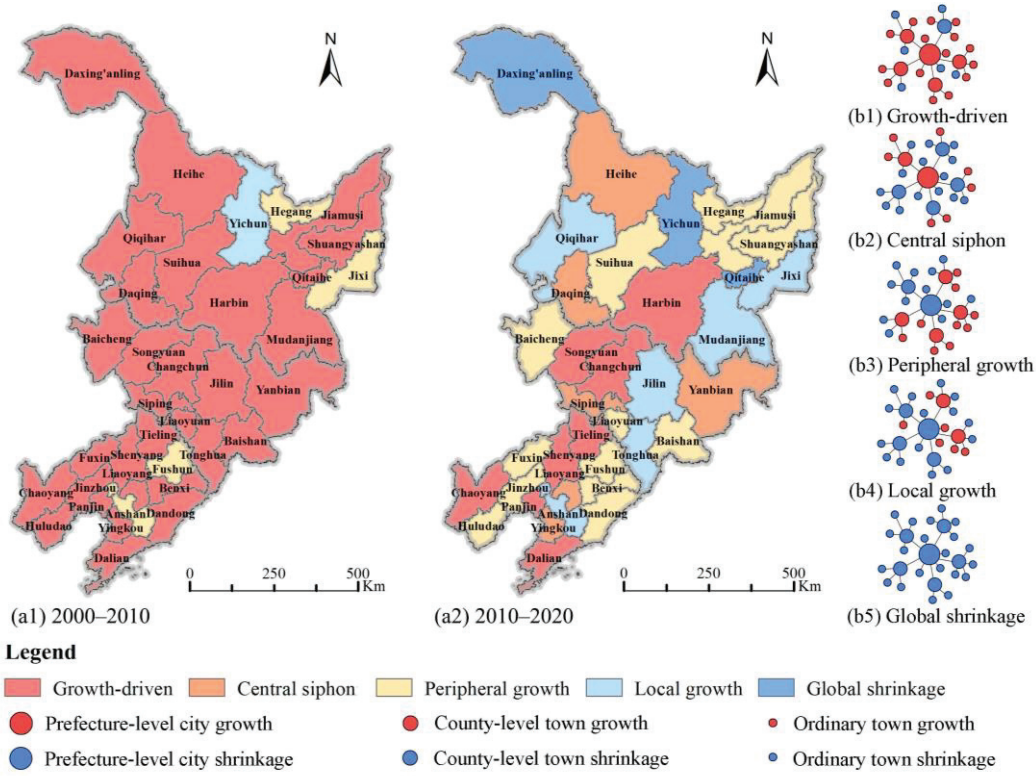


**Figure 6.** Types of multilevel associations of urban shrinkage in Northeast China. Subfigure (**a1**) and (**a2**) show the types of multilevel associations of urban shrinkage in Northeast China during the period 2000–2010 and the period 2010–2020, respectively; Subfigure (**b1**–**b5**) show the five types of multilevel associations of urban shrinkage, respectively.

The spatial differentiation of urban shrinkage in Northeast China regarding multiple levels and types of association became prominent after 2010. The spatial polarization of the population became more pronounced, shifting from the pattern of "small towns partially shrinking, while large and medium-sized towns maintain growth" to the pattern of "small and medium-sized towns widely shrinking, while some large cities polarize and grow".

The "growth belt" along the Harbin–Dalian Railway contrasts with the "shrinking belt" in the mountainous areas in the east and north from 2010 to 2020. The growth of cities and towns at all levels in Northeast China has been slow, and in some areas, all cities and towns at the "prefecture-county-town" level have shrunk. The drivers of growth are mainly concentrated around the "Harbin-Dalian Railway", which is the growth belt of Northeast China. The central cities in this region drove the rapid development of the surrounding small- and medium-sized towns through the decentralization and diffusion of functions and industries. The central siphoning type is represented by Daqing and Heihe City. Cities at the prefecture level have a weak economic and industrial driving ability to subordinate towns, and the diffusion effect is not significant, i.e., it is still in the siphoning development stage. The population and resource factors of subordinate small and medium

towns are concentrated in central cities. The peripheral growth type is mainly located in northeastern Heilongjiang Province and northeastern and western Liaoning Province. The central cities are mostly resource-based towns, which are not strongly connected to the industry of county-level towns and ordinary towns under their jurisdiction. When the central cities experience industrial and population decline due to resource depletion, the county-level towns and ordinary towns under their jurisdiction have a certain degree of resilience based on their resource endowments and industrial bases and do not shrink in tandem with the central cities. Local growth and global shrinkage types are mostly found in remote areas away from economic centers and transportation arteries. Central cities of this type suffer from economic and industrial decline, and small and medium towns are also in a state of shrinkage, making it the most severe area of urban shrinkage in Northeast China.

## 5. Associated Mechanisms of City and Town Shrinkage in Northeast China

### *5.1. Factors Affecting Shrinkage of Multi-Level Cities and Towns*

This paper uses the OLS model to identify the factors influencing different levels of shrinkage of cities and towns in Northeast China (Table 3). The obtained results show that the shrinking of cities at the prefecture level is mainly caused by the lower level of economic development (ECO1), insufficient investment in fixed assets (ECO2), lagging in the development of tertiary industry (IND3), and poor level of traffic facilities (INF2). The shrinkage of county-level towns is mainly caused by a smaller percentage of floating population (POP2), smaller size of county towns (POP3), slow economic development (ECO1), smaller number of enterprises (IND1), proportion of secondary industry (IND2), and a low level of high-tech industry (IND4). The shrinkage of ordinary towns is mainly caused by a smaller number of rural inhabitants (POP3), a larger proportion of secondary industries (IND2), a lower proportion of tertiary industries (IND3), insufficient level of high-tech industry (IND4), poor medical care (INF1), air pollution (ENV1), and lack of arable land (ENV2). However, what is interesting is that more enterprises (IND1) would not stop the population decline in small towns. The robustness tests of the OLS model are shown in Appendix A.

**Table 3.** Factors influencing city and town shrinkage in Northeast China.

| Categories | Variables | Prefecture Level | County Level | Town Level |
|---|---|---|---|---|
| Population | POP1 | | | |
| | POP2 | | 0.248 ** | |
| | POP3 | | 0.315 *** | −0.562 *** |
| Economic | ECO1 | 0.577 *** | 0.396 *** | |
| | ECO2 | 0.268 * | | |
| | ECO3 | | | |
| Industry | IND1 | | 0.678 *** | −0.097 *** |
| | IND2 | | 0.315 ** | −0.337 *** |
| | IND3 | 0.639 *** | | 0.101** |
| | IND4 | | 0.552 ** | 0.313 *** |
| Infrastructure | INF1 | | | 0.099 *** |
| | INF2 | 0.211 ** | | |
| Environment | ENV1 | | | −0.085 *** |
| | ENV2 | | | 0.129 *** |
| $R^2$ | | 0.514 | 0.311 | 0.338 |

*, **, and *** denote values that are significant at the 0.1, 0.05, and 0.01 levels, respectively.

There are significant correlations and differences in the factors affecting the shrinkage of cities and towns at different levels in Northeast China. Poor infrastructure is a common problem in the shrinkage of cities and towns at all levels and has a significant negative impact on the attractiveness of the population, average life expectancy, and natural growth

rate of towns. The shrinkage of low-level towns is more limited by factors such as industry, infrastructure, and environment, while the factors affecting the shrinkage of high-level cities are related to economy, technology level and infrastructure. Differences in demographics and average wages between shrinking cities and towns of the same level are small, which leads to insignificant regression results for the aging rate and average wages in towns.

### *5.2. A Multilevel Correlation Analysis of Factors Influencing Shrinking Cities and Towns*

#### 5.2.1. Cross-Level Impact of Prefecture-Level Cities on County-Level Towns

The obtained results show significant cross-level interactions between prefecture-level cities and county-level towns (Table 4). At the prefecture level, the indices of economic level, average wage, medical level, and transportation level pass the significance test. These prefecture-level indicators have significant cross-level effects that can be superimposed to the share of floating population, population concentration, economic level, and proportion of secondary industry of county-level towns.

**Table 4.** The cross-level impact of prefecture-level cities on county-level towns.

| County-Level Variables | Regression Coefficient | Prefecture-Level Variables | | | |
|---|---|---|---|---|---|
| | | **ECO1** | **ECO3** | **INF1** | **INF2** |
| POP2 | 0.248 ** | 4.386 | 0.045 | −4.017 * | −8.842 |
| POP3 | 0.315 *** | 4.882 | −4.775 ** | 3.296 * | −1.241 |
| ECO1 | 0.396 *** | 2.226 * | −0.504 | −2.115 | −0.302 |
| IND2 | 0.315 ** | −1.715 | −0.560 | −3.406 * | −5.213 * |

*, **, and *** denote values that are significant at the 0.1, 0.05, and 0.01 levels, respectively.

Improving the level of economic development of prefecture-level cities will slow down the shrinkage of county-level towns under their jurisdiction, while improving the salaries, medical care levels, and traffic levels of prefecture-level cities will aggravate the shrinkage of county-level towns under their jurisdiction. With the improvement in the level of economic development, the influence of prefecture-level cities on county-level towns under their jurisdiction has gradually shifted from the siphoning effect to the diffusion effect. Furthermore, county-level towns have increased their population and economic scale and enhanced population attractiveness in the process of industrial and functional expansion of prefecture-level cities. Increasing the average wages in prefecture-level cities increased the willingness of the labor force in subordinate areas to work and move to municipal districts, relatively weakened the attractiveness of the population in county-level towns, and led to a gradual decline in the population center and population scale of county-level towns under their jurisdiction. The huge gap in the level of infrastructure between prefecture-level cities and county-level towns has reduced the attractiveness of county-level towns to the population. Many county populations are driven by the level of service facilities in order to move to prefecture-level cities. The level of traffic in prefecture-level cities can strengthen the socio-economic links between prefecture-level cities and county-level towns, reduce the temporal and spatial costs of population migration, and aggravate the process of population transfer from county-level cities to prefecture-level cities.

#### 5.2.2. Cross-Level Impact of Prefecture-Level Cities on Ordinary Towns

The obtained results indicate significant cross-level interactions between prefecture-level cities and ordinary towns (Table 5). At the prefecture level, average wage, enterprise size, share of tertiary production, high-tech level, medical level, and traffic level pass the significance test. These prefecture-level indicators show significant cross-level effects that can be superimposed to population concentration, the share of secondary production, the share of tertiary production, and the high-tech level of ordinary towns.

**Table 5.** The cross-level impact of prefecture-level cities on ordinary towns.

| Town-Level Variables | Regression Coefficient | Prefecture-Level Variables | | | | | |
|---|---|---|---|---|---|---|---|
| | | ECO3 | IND1 | IND3 | IND4 | INF1 | INF2 |
| POP3 | −0.562 *** | 0.483 ** | 0.688 | 0.155 | −1.115 * | 0.344 * | 0.290 |
| IND2 | −0.337 *** | −0.035 | −4.638 ** | 0.888 * | 3.576 | 0.792 | 0.898 |
| IND3 | 0.101 ** | −0.690 | 1.006 | −0.196 | −0.702 | −1.975 ** | −1.410 ** |
| IND4 | 0.313 *** | 0.471 | 1.095 | −1.194 * | 0.214 | −1.196 | −0.963 |

*, **, and *** denote values that are significant at the 0.1, 0.05, and 0.01 levels, respectively.

Improving enterprise scale and high-tech level in prefecture-level cities will slow down the shrinkage of lower-level ordinary towns, while increasing salary, the share of third industry, medical level, and traffic level in prefecture-level cities will intensify the shrinkage of lower-level ordinary towns. Due to industrial upgrading and transformation, industrial enterprises in prefecture-level cities begin to shift to key ordinary towns under their jurisdiction. This process improves the scale and high-tech level of industrial enterprises in the surrounding ordinary towns and slows down their shrinkage. The increase in wage levels in prefecture-level cities enhanced the willingness of workers in lower jurisdictions to work and move to municipal areas, which leads to a gradual decline in the population centrality and population size of towns under their jurisdiction. The rapid expansion of tertiary industry in prefecture-level cities created many jobs with lower employment thresholds, attracting the population of subordinate ordinary towns to prefecture-level cities. The higher the level of medical services in prefecture-level cities, the stronger the attraction of the population of subordinate ordinary towns, which further promotes the migration of the population of subordinate ordinary towns to prefecture-level cities. Improving the level of road traffic in prefecture-level cities shortens the time distance from subordinate ordinary towns to prefecture-level cities, which promotes socio-economic connections between prefecture-level cities and subordinate ordinary towns. This process further intensifies the siphoning effect of prefecture-level cities on subordinate ordinary towns.

#### 5.2.3. Cross-Level Impact of County-Level Towns on Ordinary Towns

This study obtained significant cross-level interactions between county-level towns and ordinary towns (Table 6). At the county level, the indices of population concentration, economic level, average wage, high-tech level, medical level, and traffic level pass the test of significance. These prefecture-level indicators have significant cross-level effects that can be superimposed on population concentration, enterprise size, the share of secondary production, the share of tertiary production, high-tech level, medical level, and environmental pollution of ordinary towns.

**Table 6.** The cross-level impact of county-level towns on ordinary towns.

| Town-Level Variables | Regression Coefficient | County-Level Variables | | | | | |
|---|---|---|---|---|---|---|---|
| | | POP3 | ECO1 | ECO3 | IND4 | INF1 | INF2 |
| POP3 | −0.562 *** | −0.434 *** | 0.601 *** | 0.019 | −0.346 * | −0.039 | 0.046 |
| IND1 | −0.097 *** | −0.011 | −0.074 | 0.437 *** | −0.111 | −0.086 | 0.066 |
| IND2 | −0.337 *** | 0.059 | −0.771 | −0.027 | 0.656 | −0.591 | −0.209 |
| IND3 | 0.101 ** | −0.620 ** | 0.299 | 0.078 | −0.566 | 1.382 | −0.302 * |
| INF1 | 0.099 *** | −0.117 | 0.001 | −0.051 | 0.172 | 0.306 ** | −0.076 |
| EVO1 | −0.085 *** | 0.084 | 0.193 | 0.234 | −0.051 | 0.350 ** | 0.139 |

*, **, and *** denote values that are significant at the 0.1, 0.05, and 0.01 levels, respectively.

Technological improvement of enterprises in county-level towns will slow down the shrinkage of ordinary towns, while population concentration, economic level, average wages, medical level, and traffic level of county-level towns will intensify the shrinkage of

ordinary towns. The greater the population centrality of county-level towns, the greater the degree of development of the county town and its attractiveness for the population of subordinate towns. The higher the average wages in county-level towns, the stronger the attraction for the labor force of lower-level ordinary towns. This is not conducive to the development of industries in ordinary towns and accelerates the migration of the population of ordinary towns to county cities. Due to industrial upgrading and transformation, industrial enterprises in county-level towns begin to shift to key ordinary towns under their jurisdiction. This process largely increases the competitiveness of industrial enterprises in ordinary towns, expands the scale of industrial enterprises and employment in ordinary towns, and slows down the shrinkage of ordinary towns. Improving traffic level in county-level towns can weaken the positive effect of the scale of the three industries on the population of ordinary towns, which in turn aggravates the shrinkage of ordinary towns. Furthermore, the improvement of traffic level in county-level towns decreases the time distance from lower ordinary towns to county towns and accelerates the socio-economic flow between county towns and lower ordinary towns. This makes the residents of ordinary towns more inclined to go to county towns for medical treatment and consumption, which decreases the local consumption in ordinary towns. In turn, the positive effects of the scale of tertiary industry and medical treatment level in ordinary towns on the population of the ordinary towns are weakened.

### *5.3. Associated Mechanisms of Multi-Level Shrinking Cities and Towns*

The effects of agglomeration and diffusion are important mechanisms of multi-level shrinking towns in Northeast China. Wages, medical care, and road traffic in higher-level cities have a strong siphoning effect on lower-level towns, while the high-tech level and industrial development of higher-level cities have a significant diffusion effect on lower-level towns. However, there are more complex hierarchical differences in population shrinkage due to the interconnectedness of factors at multiple town levels. When a central city shows a shift from growth to shrinkage, population shrinkage between high- and low-level towns will show different effects of aggregation and diffusion.

When a central city grows, it attracts large numbers of people from the low-level towns due to higher wages, better health services, better infrastructure, and more jobs, which in turn expands the size of the central city. When the size of the central city reaches a certain level, the marginal effect of the agglomeration economy tends to decline, and the diffusion effect of the central city to subordinate towns becomes prominent. By absorbing the industry of the central city and borrowing the functions and facilities of the central city, the economy and industry of the low-level towns under its jurisdiction are developing rapidly. When the agglomeration effect of the central city is much greater than the diffusion effect, the population of the central city grows while small- and medium-sized towns continue to lose population. Furthermore, when the diffusion effect of the central city is dominant, the central city and the subordinate small- and medium-sized towns maintain the overall growth trend.

When the central city shrinks, the economic and industrial development of the central city stagnates, and the cross-level influence on the subordinate county-level towns and ordinary towns diminishes. While some county towns with a certain population and industry size have not declined along with the central city, they have shown a resilience and independent development.

Ordinary towns are influenced by central cities and county towns. There is a huge difference between ordinary towns and high-level towns regarding industry, infrastructure, and habitat. Thus, it is difficult for ordinary towns to reverse their shrinking trend by expanding their economies and industries. Most ordinary towns experienced population decline, except for those with abundant arable land resources, which barely maintained a certain population size.

## 6. Discussion

Northeast China's multi-level urban system can be seen as a co-evolutionary process, with cities and towns interacting within and between levels. The co-evolutionary process is complex and diverse due to differences in socio-economic status and interactions between cities and towns [59,60]. Industry and infrastructure play a key role in the co-evolution of urban systems. The socio-economic condition of the central city directly affects the growth and shrinkage of other towns in the urban system. However, even when the central city shrinks, the subordinate county-level towns and ordinary towns can still maintain a strong population and economic vitality. As the political, economic, and cultural center of the region, the stage of central city development plays an important role in influencing the spatial patterns of socio-economic development, growth, and shrinkage of towns at all levels under its jurisdiction. The sustainable development of towns' industries is the basis for harmonious development of multi-level towns in the region. In areas such as Harbin, Changchun, Shenyang, and Dalian, the transformation and upgrading of industry in the central cities have been largely completed. By taking over the original industries of the central cities or by incorporating them into the system of industrial production and borrowing the facilities and functions of the central cities, small- and medium-sized towns in the region grow rapidly. In regions such as Daqing, the central city has a strong industrial base and well-developed infrastructure, which attracts young people from low-level towns and rural areas on the periphery. Due to the over-dependence of the central city's industrial development on oil extraction and the limited role of industrial diffusion to the low-level towns under its jurisdiction, Daqing developed a spatial pattern of extensive shrinkage of towns under the growth of the central city. In Hegang, employment opportunities and wages in the central city plummeted as the depletion of original coal resources and the decline of related manufacturing industries lagged behind the development of alternative industries and services. The decline of industry and economy in the central cities has accelerated the process of population return to the towns under their jurisdiction. County-level towns in the region have become a new pole of population growth. In Yichun, the central city was the first to experience population loss due to the depletion of forest resources and the decline of the steel and forestry industries. County towns are generally smaller in size, with poorer levels of facilities and sparsely populated rural areas under their jurisdiction and with insufficient arable land resources. Towns at all levels face the challenges of falling behind in industrial development, population loss, and marginalization.

The concept of multi-level coordination and the research framework of shrinking town governance is also important. In the process of shrinking town governance, hierarchical differences and correlations of shrinking towns should be taken into account, and the role of multi-level coordination of "prefecture-county-town" should be emphasized in order to guide the shrinking towns policy in Northeast China. Shrinking cities should solve the unresolved problems and shortcomings in urban development, change the real-estate-based development and construction mode to an intensive construction mode in order to improve urban quality, optimize the distribution of capital and land, and promote the transformation of the urban development mode from the source [61]. Shrinking county-level towns should return the focus of development to the county, which is the preferred settlement and place of employment for rural workers to enter the city. They should also improve the infrastructure and public services of the county, promote the concentration of surrounding rural workers in the county, promote industrial clustering, and improve economic efficiency. Shrinking ordinary towns should first change the homogenous construction pattern and select key towns for priority development. It is also necessary to strengthen the infrastructural development of general towns in order to improve living and production conditions.

## 7. Conclusions

Urban growth and shrinkage are dynamic and interrelated processes, and there is a significant influence of high-level cities on low-level towns. This study found that: (1) Urban shrinkage has become a common phenomenon at all levels of cities and towns

in Northeast China, showing an increasing trend in the number of shrinking cities and towns and a deepening degree of shrinkage. (2) The shrinkage of cities and towns in Northeast China varies significantly by level, with prefecture-level cities having the largest shrinkage percentage, county-level towns having a small shrinkage percentage but the fastest shrinkage speed, and ordinary towns having an earlier shrinkage and a continuous shrinkage trend. (3) The decrease in the population of cities and towns within the same municipality is not completely synchronized. In terms of spatial patterns, the multi-level relationship between cities and towns is divided into growth-driven, central siphon, peripheral growth, local growth, and global shrinkage. (4) Significant differences exist in the factors influencing town shrinkage at each level. The shrinkage of prefecture-level cities and county-level towns is affected by similar factors, mainly economic development, industrial development, and built environment, while the shrinkage of county-level towns can be significantly reduced by increasing the ratio of floating population and population centrality. In areas with poor arable land resources and environment, ordinary towns are more likely to shrink. (5) There is a significant cross-level effect of high-level cities on the shrinkage of low-level towns in Northeast China. With the benefits of higher wages, better medical services, better infrastructure, and more jobs, high-level cities have a powerful effect of siphoning population from low-level towns; meanwhile, high-level cities accelerate the economic and industrial development of low-level towns through industrial transfer and technology diffusion.

A multi-level analysis of urban shrinkage is a useful perspective. Little attention has been paid to the multi-level character of urban shrinkage. This study attempts to theoretically investigate the multi-level variability and correlation of town shrinkage and practically analyzes the correlation and variability of different levels of town shrinkage in Northeast China. However, due to the limitations of the HLM model, the multi-level analysis of towns in this study has certain limitations. The study neglects the differences in the strength of connections between lower and high-level towns. Factors such as the spatial distance between low-level towns and high-level towns and the degree of industrial linkages can cause large differences in the linkages between high-level towns and low-level towns. Due to data availability limitations, this study cannot adopt a quantitative approach to explore the effects of COVID-19 on urban shrinkage. It can only theoretically and qualitatively analyze the effect of COVID-19 on migration and the mobility of people between cities. The pre-2000 population census's statistical standard and data precision are insufficient to support a longer time series study of urban growth and shrinkage.

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## Appendix A

**Table A1.** The robustness tests of the OLS model.

| Categories | Variables | Prefecture Level | County Level | Town Level |
|---|---|---|---|---|
| Population | POP1 | | | |
| | POP2 | | 0.274 *** | |
| | POP3 | | 0.219 ** | −0.099 ** |
| Economic | ECO1 | 0.347 * | 0.440 *** | |
| | ECO2 | 0.493 *** | | |
| | ECO3 | | | |
| Industry | IND1 | | 0.885 *** | −0.100 ** |
| | IND2 | | 0.341 ** | −0.037 |
| | IND3 | 0.342 * | | 0.054 |
| | IND4 | | 0.546 *** | 0.109 ** |
| Infrastructure | INF1 | | | 0.013 |
| | INF2 | 0.180 * | | |
| Environment | ENV1 | | | −0.236 *** |
| | ENV2 | | | 0.084 ** |
| $R^2$ | | 0.384 | 0.378 | 0.165 |

This study tests the robustness of the OLS model by replacing the dependent variable. In Appendix A, the rate of change of resident population in municipal districts of prefecture-level cities was replaced by the number of population changes (sum of registered and temporary population) in the built-up area of prefecture-level cities. Considering that the statistical yearbook does not count the number of permanent residents in built-up areas of county-level towns and ordinary towns, the rate of population change for county-level towns and ordinary towns is replaced by the number of population changes. *, **, and *** denote values that are significant at the 0.1, 0.05, and 0.01 levels, respectively.

## Notes

[1] Data on the population of the townships in this study were obtained from the China Township Statistics and the China Statistical Yearbook (Township). Considering that the China Statistical Yearbook (Township) no longer counts the population of the built-up area of the town after 2018, statistics from 2018 were used for the town population. Using the average annual rate of population change (Equation (1)) to identify urban shrinkage minimizes the effect of time period on the identification of shrinking towns and comparisons between multiple levels. Missing data in this study are filled in using adjacent years.

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# Triple Spatial Effects of the Administrative Hierarchy on Urban Built-Up Areas in Fujian Province, China: Heterogeneity, Radiation, and Segmentation

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**Abstract:** The expansion of urban built-up areas is one of the most prominent characteristics of land use change in China. A growing body of literature has emphasized the triple spatial effects of the administrative hierarchy on urban built-up areas expansion, including heterogeneity, radiation, and segmentation. However, the existing studies have mainly focused on the administrative hierarchy at the prefectural level and above and have primarily concentrated on one single effect; few have integrated the triple effects as a whole. Based on high-resolution land use data and taking Fujian province as a study case, this study proposes an integrated theoretical framework and modeling approach and investigates the triple spatial effects of administrative hierarchy on built-up areas at the prefectural level and below. Descriptive statistics show the following: (1) Built-up areas of municipal districts are significantly larger than those of county-level units, showing the heterogeneity characteristics of urban land distribution across different levels of administrative hierarchy; (2) The county-level units adjacent to municipal districts exploit more built-up areas than other county-level units, indicating the radiation effects of municipal districts; (3) The radiation effects tend to be reduced if a municipal district and its adjacent county-level units are not located in the same prefectural city, revealing the segmentation effects among the different prefectural cities. Using the spatial econometric model with regimes, we further find the following: (1) The strengths of driving forces of built-up areas are heterogeneous between municipal districts and county-level units, and there are significant spatial interactions among administrative units; (2) The spatial interactions between municipal districts and county-level units are stronger than those between two county-level units, but the strength is restricted by the prefectural boundary, reflecting the radiation effects of municipal districts and the segmentation effects of the prefectural boundary, respectively. By investigating the triple spatial effects of the administrative hierarchy on urban built-up areas, we conclude that comprehensively considering these triple effects as a whole will result in a fuller understanding of the rapid built-up areas expansion in China, especially at the prefectural level and below.

**Keywords:** administrative hierarchy; built-up areas; spatial effects; heterogeneity; radiation; segmentation; Fujian province; China

## 1. Introduction

Rapid urbanization worldwide is changing land cover significantly [1]. The world's urban population accounted for about 33% in 1950 and increased to 54% in 2014 [2]. At the global scale, the percentage of urban land to the total land increased from 0.23% in 1992

to 0.53% in 2013 [1]. The implementation of China's economic reform and open policy in 1978 stimulated dramatic urbanization and land expansion. In 1978, the urbanization rate of China was only 17.92%, exceeded 60% at the end of 2019, and is expected to increase to 70% by 2030 [3]. From 1985 to 2018, the mean growth rate of built-up areas in China was 4663 $km^2$ per year, which was much faster than that in other countries. In 2015, China became the country with the most built-up areas in the world [4]. This unprecedented urban growth in China has significant impacts on ecological security [5], environmental quality [6], and agricultural production [7], all of which finally influence human health and well-being [4].

To inform sustainable development and land use planning, a rich body of literature has already investigated the driving factors of urban land expansion in China. Scholars have found that urban land expansion has been driven by urbanization [8], marketization [9], industrialization [10], and transport networks [11]. Furthermore, political and institutional factors are also extensively mentioned in the literature, suggesting that urban expansion is not merely a result of market forces but also shaped by government behavior [8]. Under the current land use system in China, local governments are the sole legitimate providers of newly increased urban construction land [12]. Especially after the reform of tax-sharing and the land market in China, land conveyance fees have rapidly increased and become the most important resource for local revenue, which enable local governments to attract investments, develop infrastructures, and stimulate urban economic growth [9,13]. Thus, the ability and incentive of local government to expand urban land have inevitably triggered unprecedented land urbanization in China.

By emphasizing government behavior and the inflexible administrative system in China, recent studies have paid more attention to the triple spatial effects (i.e., heterogeneity, radiation, and segmentation) of the administrative hierarchy on urban land development, which can be attributed to the vertical and horizontal structure of the urban administrative system.

From the vertical perspective, the urban administrative units are structured into three primary levels of local government, namely the province level, the prefecture level, and the county level [14]. In the transition process of decentralization, important administrative powers have devolved from the central state, level by level [9]. Higher administrative levels correspond to stronger land administration power (e.g., the autonomy of land use planning) [9,15] and higher political capability to make locally privileged policies to attract the impetuses of urban growth (e.g., development zones and foreign investment) [9]. Thus, urban land expansion tends to coincide with the administrative level, presenting heterogeneity across different administrative levels. For example, Liu et al. found that cities with higher administrative levels tended to expand at a higher speed [3].

From the horizontal perspective, the urban administrative units at the same level engage in intense cooperation and competition, leading to radiation and segmentation effects on built-up areas [16,17]. On one side, to realize industrial upgrading and the scale economy, close cooperation has been formed among local governments [18,19]. Especially in the emergence process of urban agglomeration, communication enhancement and integration development have emerged through the high-dense connection between central and adjacent administrative units [20]. In this case, the spatial spillover between central and adjacent administrative units is stronger than between two peripheral units. For example, Cen et al. stated that administrative central cities demonstrated a radiation effect on the surrounding cities in terms of urban land development [17]. On the other side, local governments are controlled by the central government via gross domestic product (GDP) centric promotion competition [21]. To gain an advantage in the competition, local government often establishes market barriers and administrative interventions to maximize local economics based on administrative division [22]. As urban land is the most important resource for local government to acquire revenue and promote economics [15], it also demonstrates the segmentation characteristics across an administrative boundary. For

instance, Wang et al. revealed that provincial boundaries significantly restrict the spatial spillover effect between county-level units that are not located in the same province [16].

To summarize, due to the vertically tiered structure and horizontal cooperation and competition, the administrative hierarchy has shown multiple spatial effects on urban land development, including heterogeneity, radiation, and segmentation. A rich body of literature has paid attention to these effects, but the existing research has mainly focused on a single effect. The parallel and distinct research have provided limited understanding and resulted in partial and potentially misleading conclusions about land urbanization in China. Thus, a more comprehensive theoretical and modeling framework is urgently needed to fully reveal the land urbanization mechanisms under the Chinese administrative hierarchy.

Drawing upon high-resolution land use data extracted from remote sensing images, this study aims to fill this research gap and contribute a comprehensive and integrated framework to investigate the link between Chinese administrative hierarchy and urban built-up areas, taking Fujian province as a study case. Based on descriptive statistics, this study will demonstrate that the administrative hierarchy has triple spatial effects on built-up areas (i.e., heterogeneity, radiation, and segmentation), stemming from the vertical and horizontal interaction among the administrative units. By applying a spatially explicit model named the spatial lag model with regimes, this study will further deal simultaneously with the triple effects of the administrative hierarchy in a single spatial econometric model, showing that the administrative hierarchy not only plays a proactive role in built-up area development but also has a profound impact on other driving forces of built-up area expansion.

## 2. Recent Urban Development in China

Urban development in China is by no means disconnected from the legitimate power and hierarchical structures in the national administrative system [9]. Under the inflexible administrative hierarchy, Chinese cities are endowed with tiered administrative authorities and are affected by collaboration and competition with surrounding cities. Thus, the administrative hierarchy has triple evident effects on urban built-up areas' development: heterogeneity, radiation, and segmentation.

### *2.1. The Heterogeneity Effects of Administrative Levels on Built-Up Areas*

Urban administrative levels are closely connected with social mobility between regions, which further affects regional land use. First, administrative status is a crucial impact factor of population development. A study of East Germany showed that losing county capital status has a significant negative effect on annual changes in population after the administrative reforms have been implemented, and this effect continues to increase over time [23]. Second, scholars in the USA and the Netherlands found that interregional migration flows are disaggregated by age and show radically different patterns of net population redistribution in the sense of upward and downward movements within the urban hierarchy [24,25]. For example, elderly Americans tend to congregate in micropolitan and rural counties, while younger adults like to flock to large metropolitan areas [24]. Third, in the urbanization process in China, millions of poor and low-income rural migrant workers migrate to urban areas at high administrative levels, and the expansion of urban areas has potential impacts on the social mobility of their children. For example, a study of Beijing (i.e., the capital city of China) showed that the process of eliminating villages in the city (chengzhongcun) to urban areas hampers the social mobility of migrant youth in the context of the rigid class structure in late-socialist China [26]. Furthermore, the rural migrant workers in cities at high administrative levels can neither apply for the urban residence certificate (hukou) of these cities nor have the motivation to permanently stay in cities at the cost of abandoning their agricultural land and rural houses. Therefore, the rural migrant workers work and live in cities, but few sell out their rural houses, resulting in ubiquitous "hollow villages." More importantly, most migrant workers have remitted a

large proportion of the money earned in cities to build new houses in their hometowns, leading to the abnormal expansion of rural residential land [27].

As the administrative powers of urban land are endowed diversely, and the driving forces of built-up areas are distributed unevenly across Chinese cities at different administrative levels, urban built-up areas show notable spatial heterogeneity, reflecting the tiered administrative hierarchy. First, Chinese cities are institutionalized under rank-based land administrative authorities. For instance, only four province-level municipalities directly under the Central Government have limited legislative power of land administration [9], and cities at higher administrative levels tend to receive a higher construction land quota [28]. Second, the urban administrative system reinforces the uneven distribution of impetuses underlying urban growth. For example, as higher-level cities have advantages in resource allocation and institutional arrangement, they can attract more immigration and foreign investment and establish higher-level development zones, which are the main driving forces of built-up areas expansion [9,29]. Consequently, urban built-up areas highly coincide with the administrative hierarchy; cities with higher administrative levels tend to develop more built-up areas.

Besides exploring divergence, previous studies have employed several modeling approaches to reveal that the driving mechanisms of built-up areas also show significant differences across cities at different administrative levels. Ma et al. found that the key influencing factors of urban land varied substantially across the county, prefectural, and provincial levels through three independent ordinary least squares models at each level [14]. Li et al. demonstrated that socioeconomic and policy factors of urban expansion differed between the county and provincial levels with a single regression model using the multilevel modeling technique [30]. Li et al. further revealed that the strengths of economic and demographic drivers of urban growth were also sensitive to a city's administrative rank based on the spatial regimes modeling approach, which can produce comparable regression coefficients dedicated to each city level [9].

In short, the heterogeneity characteristics of urban land across different administrative levels have been extensively studied. However, previous studies have mainly focused on the prefectural level and above, and the divergence pattern of built-up areas at the prefectural level and below is still lacking. Under China's system of "city administering counties (shi guan xian)," county-level units are under the administrative control of the prefectural government, which has greater administrative power (e.g., urban planning and land use management) than county-level governments [13,21,31]. In the Chinese administrative system, the administrative territory of prefecture-level cities is divided into two categories: municipal districts and county-level units (i.e., counties and county-level cities). Municipal districts are directly controlled by the prefecture-level government. As a result, administrative conflicts between prefecture-level cities and county-level units are mainly manifested as conflicts between municipal districts and county-level units [13,21]. For example, many prefecture-level cities have annexed county-level units and transformed these units into municipal districts. In this process, the prefectural government expropriated the land resources of county-level units and significantly increased their land conveyance fees [13]. Surprisingly, although administrative differences between municipal districts and county-level units have been thoroughly discussed from an institutional perspective [13,21,31], studies investigating the heterogeneity characteristics of built-up areas between them are still limited.

### *2.2. The Radiation Effects of Administrative Centers on Built-Up Areas*

Besides the heterogeneity effect on built-up areas, previous studies have shown that central cities of the urban agglomeration can have a radiating effect on the surrounding city areas [16,17], which can be attributed to industrial upgrading and the scale economy.

First, to promote economic development, urban governments tend to adopt an industrial upgrading strategy and relocate the secondary industry from central cities to nearby cities to make room for tertiary industry [18]. In addition, increased land prices in central

cities also force low-value-added sectors to move to surrounding cities [32]. Consequently, the land eliminated from central cities spills into nearby cities where land rent is affordable, and there is convenient access to the adjacent central city [33].

Second, in industrialization, various production factors are driven by agglomeration and scale economies. They gradually concentrate on urban areas and drive the expansion of urban land [32]. However, if the urban land in central cities continues to expand and surpasses the turning point, the scale economies of urban land can fade out or even shift to scale diseconomies [19]. With new urbanization in China, urban agglomeration has emerged as a new city form consisting of a high-density connection between central cities and adjacent small cities. Through inter-city connection, urban agglomeration can effectively extend scale economies beyond administrative boundaries and continue to improve urban economic efficiency [19,20]. Consequently, the urban land driving effects of the scale economy can spread to adjacent cities that are closely connected to central cities.

To summarize, due to industrial upgrading and the scale economy, central cities have a radiating effect on adjacent lower-level cities, which expand much more rapidly than cities far from the administrative central cities.

In terms of methodology, spatial visualization is employed as a qualitative tool to demonstrate the radiation pattern of provincial central cities [17]. Furthermore, Zeng et al. proposed a quantitative framework of spatial econometric models using different spatial weight matrices to represent various scenarios. In their empirical study, 15 scenarios were established by considering five different administrative statuses (i.e., urban district, suburban district, county, county-level city, and district). They found that administrative status has evident effects on the spatial spillover of land-use intensity in the Wuhan urban agglomeration. Especially the provincial central city shows a significant radiation effect on land-use intensity [34]. Although the radiation effects of the provincial centers have been noticed in previous studies, the radiation effects of administrative centers of prefectural cities (i.e., municipal districts) have been neglected by most studies.

### *2.3. The Segmentation Effects of Administrative Boundaries on Built-Up Areas*

Besides the spatial radiation effects, the spatial segmentation effects across the boundary of administrative units are also significant, which are the institutional consequences of economic decentralization and promotion tournaments [8,22,35,36]. On one side, decentralization of economic governance grants local governments autonomy to make economic decisions and distribute resources within their own regions. Therefore, local governments have the incentive and responsibility to develop their local economies [22]. On the other side, the higher level government still maintains vertical control via promotion tournaments and has the authority to appoint and promote the leaders of local governments according to the performance of local economic development, which leads to fierce competition between local governments. To win the GDP-centric promotion tournament, local governments generally distort the price of the land market and use the low price of industrial land as a bargaining chip to attract investment [36]. Thus, intergovernmental competition significantly affects urban land development, demonstrating the segmentation effect across administrative boundaries [35].

Recently, Wang et al. proposed a new modeling strategy to explore how the spatial spillover effect of urban land intensity is restricted by competition among administrative units. They found that the strength of the spatial spillover effect between county-level units can be cut to half by the provincial boundary (i.e., county-level units do not belong to the same province) [16]. However, even though some studies have pointed out that the competition among prefectural-level cities has a significant effect on urban land development [35,36], few studies pay attention to the segmentation effect of prefectural boundary on the spillover effect of urban land (e.g., the radiation effect of municipal districts).

To summarize, the triple spatial effects of the administrative hierarchy on urban land have attracted extensive research attention, but these effects are investigated separately by most studies. Thus, an integrated framework is urgently needed to fully understand the

multiple effects of administrative hierarchy on urban land. Moreover, the heterogeneity characteristics between municipal districts and county-level units, the radiation effect of municipal districts on adjacent county-level units, and the segmentation effects of the prefectural boundary on the radiation effects of municipal districts are still understudied, calling for further studies to address these research gaps.

## 3. An Analytical Framework

To comprehensively investigate the effects of the Chinese administrative hierarchy on built-up areas, we propose an analytical framework to better summarize the mechanism of built-up areas' development (Figure 1).

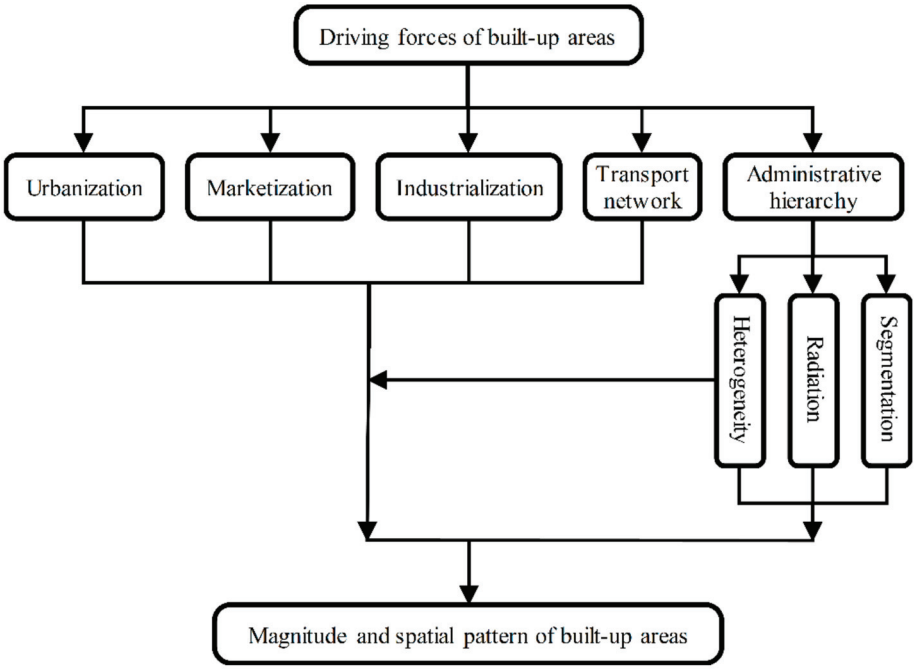



**Figure 1.** Analytical framework to examine the administrative hierarchy and built-up areas in China.

First, in the context of the Chinese socio-economic transition, urbanization, marketization, and industrialization are broadly recognized as the primary processes that affect urban land expansion [8–10]. Specifically, factors considered as significant driving forces of urban land include demographic urbanization, GDP, and enterprise development [8,10]. Moreover, many studies have stated that the transportation network also plays a key role in urban land expansion [11].

Second, the administrative hierarchy in China has triple spatial effects on built-up areas, including heterogeneity, radiation, and segmentation. From the vertical perspective, as the administrative powers and economic resources are distributed unevenly across different hierarchy levels, the magnitudes and driving forces of built-up areas tend to be sensitive to the tiered structure of the administrative hierarchy. From the horizontal perspective, local governments at the same administrative level engage in intensive cooperation and competition. The cooperation relationship leads to a spatial spillover effect between adjacent administrative units [35], and the administrative central cities demonstrate a radiation effect on nearby administrative units. At the same time, the competitive relationship induces a spatial segmentation effect between adjacent administrative units, which can restrict the radiation effect of administrative central cities across the administrative boundary.

Third, under the Chinese administrative system, the administrative territory of prefecture-level cities is divided into two categories: municipal districts and county-level units, which are the most significant levels that local government rushed to take land from the farmers and expand urban land [37,38]. However, previous studies concerned with

the effects of administrative hierarchy on urban land have mainly focused on cities at the prefectural level, and above, the effects at municipal districts and county-level units are still unexamined [9,10]. This study tries to fill this gap and investigate the triple spatial effects at relatively lower administrative levels, including the heterogeneity characteristics between municipal districts and county-level units, the radiation effects of municipal districts on nearby county-level units, and the segmentation effects of prefectural boundaries on the radiation effects of municipal districts.

To summarize, in this study, we hypothesize that the administrative hierarchy has tripe effects on built-up areas' development, including heterogeneity, radiation, and segmentation. Furthermore, we also argue that the triple effects should be investigated as a whole to fully understand the development mechanism of built-up areas, especially at the prefectural level and below, which are neglected by most previous studies.

## 4. Data and Study Area

Fujian province is situated on the southeast coast of China. It is adjacent to Zhejiang province in the northeast, bordering Jiangxi province in the northwest, and neighboring Guangdong province in the southwest. As the connection channel of the two largest and most important urban agglomerations in China (i.e., the Yangtze River Delta and the Pearl River Delta), Fujian province is a vital part of China's coastal economic belt and plays a prominent role in the national economic development layout.

Fujian province has a long history of city building. For example, Fuzhou, the capital of Fujian Province, is a famous historical and cultural city. However, until the reform and opening up, the cities in Fujian Province were relatively small. Specifically, the built-up areas of Fujian province were only 259 $km^2$ in 1990 and dramatically increased to 1335 $km^2$ in 2020 [39], with an annual growth rate of 13.4%. In terms of the spatial distribution characteristics, the built-up areas present evident heterogeneity. First, the built-up areas are mainly concentrated in two central cities, Fuzhou and Xiamen, which are the provincial capital and economic center of Fujian province, respectively. For example, the two cities accounted for 52% of Fujian province in 2015 regarding the built-up areas in municipal districts [39]. Second, the built-up areas in the west are much lower than that in the east of Fujian province, where the economy is more prosperous. For example, in terms of the built-up areas in municipal districts in 2015, the mean built-up area of three prefectural cities in the west is 45.3 $km^2$, while that of six prefectural cities in the east is 162.8 $km^2$ [39]. The significant uneven distribution indicates that administrative hierarchy and economic development profoundly affect the built-up areas.

The territory of Fujian province mainly consists of mountains and hills, accounting for more than 80% of the total area. Thus, the scarcity of available land resources has gradually limited urban expansion. Governing built-up areas' development to align economic demands with limited land resources is a challenging task for the local government. Consequently, holistically and comprehensively understanding the development mechanism of built-up areas to support sustainable land use in Fujian province is urgently needed.

In terms of administrative hierarchy, Fujian province has jurisdiction over nine prefecture-level cities. The administrative territory of prefecture-level cities is divided into two categories: municipal districts and county-level units. The municipal districts are under the direct control of prefectural governments, and county-level units include counties and county-level cities. By the end of 2015, Fujian province had a total of 44 counties and 13 county-level cities. Most of the prefectural cities have at least five county-level units, but Putian only has one county. In addition, since Tong'an county was upgraded to a municipal district in 1997, Xiamen has no county-level units. It should be pointed out that Yongding county and Jianyang city were upgraded to municipal districts in 2014 and 2015, respectively. Considering this happened at the end of the study period (i.e., 2005–2015), these two units are regarded as county-level units in this study. Finally, as Jinmen county only consists of some small islands and no evident urban built-up areas can be found there, it was removed from the study area (Figure 2).

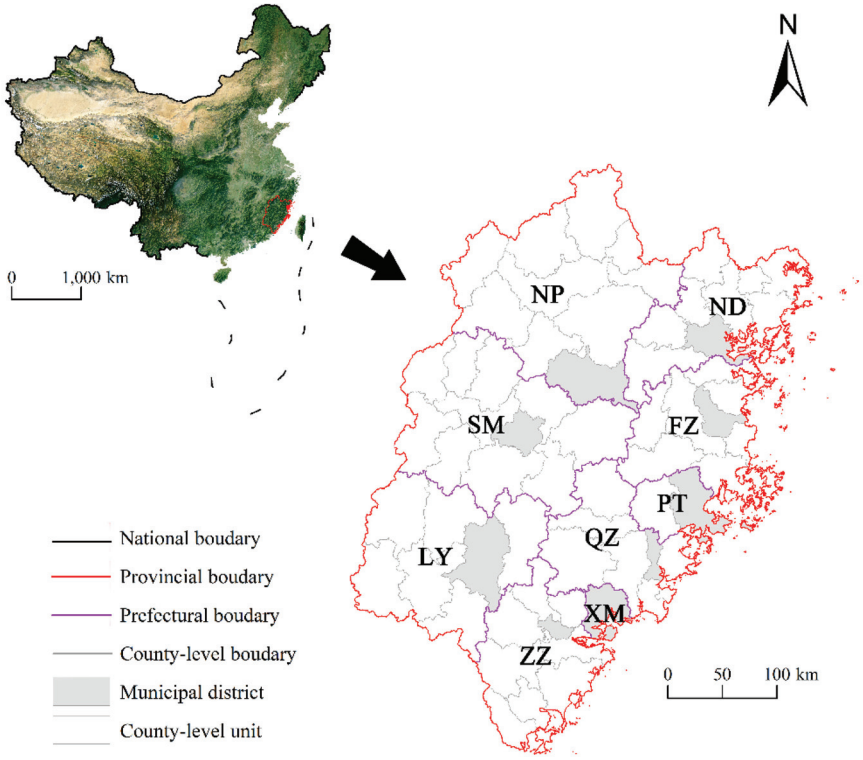



**Figure 2.** Study area. Note: Fujian province has nine prefectural cities, including Nanping (NP), Ningde (ND), Sanming (SM), Fuzhou (FZ), Putian (PT), Longyan (LY), Xiamen (XM), and Zhangzhou (ZZ).

Data used include the land use dataset with a resolution of 30 m, obtained from the Data Center of Resources and Environmental Sciences, the Chinese Academy of Sciences (http://www.resdc.cn/, accessed on 14 December 2018). This dataset is considered one of the most accurate Chinese land use datasets (e.g., the accuracy of urban land is higher than 93%) and is widely used in the empirical research of urban land in China [40]. From this dataset, we extracted the urban built-up areas of Fujian province in 2005 and 2015. The statistical data for regression analysis (e.g., population and GDP) were collected from the Fujian Statistical Yearbook (2006 and 2016).

## 5. Method

### *5.1. Descriptive Statistics*

Several descriptive statistics (i.e., minimum, median, mean, and maximum) were applied to reveal the triple spatial effects of the administrative hierarchy on built-up areas, including heterogeneity, radiation, and segmentation effects. First, the magnitudes of built-up areas of municipal districts and county-level units were compared. If the former was higher than the latter, this revealed the heterogeneity characteristics of the built-up areas, and the built-up areas coincided with the administrative hierarchy. Second, 58 county-level units of Fujian province were divided into two groups. The first group was the neighbors of municipal districts, while the second group was not. If the former was higher than the latter, this indicated the radiation effects of municipal districts on nearby county-level units. Third, 58 county-level units of Fujian province were further divided into three groups. The first group was the neighbors of municipal districts, and these county-level units and their adjacent municipal districts were in the same prefectural city. The second group was also the neighbors of municipal districts, but these county-level units and their adjacent municipal districts were in different prefectural cities. The third group was the county-level units not adjacent to municipal districts. If the built-up areas in the second group were smaller than the first group, or even comparable to the third group, this indicated

that the radiation effects of municipal districts were restricted by prefectural boundaries, representing the spatial segmentation effect of administrative hierarchy.

*5.2. Spatial Econometric Model*

Some scholars have posited that built-up areas are driven by urbanization, marketization, industrialization, and transport network [8–11]. Considering the evident impacts of the administrative hierarchy on built-up areas, two approaches were proposed to add the administrative hierarchy into the regression model to adapt to the unique institutional background of China.

In the first approach, Wei et al. examined the heterogeneity characteristics of urban land development mechanisms using the spatial regime model:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \quad (1)$$

where the subscripts 1 and 2 indicate different regimes (i.e., different administrative levels); $y_1$ and $y_2$ are vectors of observations on the dependent variable (urban land) for spatial regimes 1 and 2, respectively; $X_1$ and $X_2$ are matrices of observations on the explanatory variables; $\beta_1$ and $\beta_2$ are vectors of the regression coefficients in each regime; and $\varepsilon_1$ and $\varepsilon_2$ are vectors of error terms.

The spatial regime regression can produce two sets of comparable coefficients dedicated to each administrative level, revealing the different mechanisms of urban land expansion across cities at different administrative levels.

In the second approach, some scholars have investigated the spatial spillover and segmentation effects of the administrative hierarchy on urban land development by embedding the administrative status into the spatial weight matrix of the spatial econometric model [16,34,41].

To integrate the triple effects of the administrative hierarchy into one regression model, we combined the two approaches by employing the spatial econometric model with regimes. The spatial econometric model has two forms: the spatial lag model and the spatial error model.

In terms of the spatial lag model, spatial regime regression is extended with a spatially lagged dependent variable:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \rho W \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} + \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \quad (2)$$

the spatially lagged dependent variable is constructed with the spatial weight matrix $W$ and spatial autoregressive coefficient $\rho$. The independent variables in each regime (i.e., $y_1$ and $y_2$) are the built-up areas extracted from the land use map. Other parameters in Equation (2) are the same as in Equation (1).

In terms of the spatial error model, spatial regime regression (Equation (1)) is extended with a spatial autoregressive process in the error terms:

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} = \lambda W \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (3)$$

where $W$ is the spatial weight matrix, $\lambda$ is the spatial autoregressive parameter, $u_1$ and $u_2$ are the idiosyncratic error vectors belonging to each regime, and $\varepsilon_1$ and $\varepsilon_2$ are the same as Equation (1).

Using the spatial econometric model with regimes, spatial heterogeneity and spillover effects can be dealt with simultaneously. Specifically, regression coefficients specific to municipal districts and county-level units can be derived from the model, representing the heterogeneity effects of the administrative hierarchy. Moreover, the impact of the administrative hierarchy on the spillover effects between administrative units (including radiation

and segmentation effects) can also be examined by embedding the administrative structure into a spatial weight matrix, which is explained in Section 5.3. The regression analysis of this study uses the python software package spreg(1.2.4), the spatial econometrics module of PySAL library [42].

Moreover, several statistics were employed for regression diagnosis: (1) The Lagrange multiplier test statistics were applied as the detector for spatial dependence and the criterion to use either the spatial lag model or spatial error model. In this study, the Lagrange multiplier tests suggested that the hypothesis of no spatial spillover effects should be rejected and the spatial lag model should be adopted rather than the spatial error model. (2) Two versions (i.e., global and individual) of Chow tests were employed to see whether there was a significant difference between the coefficients across different levels of the administrative hierarchy. (3) The Anselin–Kelejian test was used to assess whether the residuals of the spatial econometric model with regimes exhibited a spatial pattern.

### *5.3. Spatial Weight Matrix Construction*

As mentioned in Section 5.2, the spatial econometric model with regimes can be applied to explore the heterogeneity characteristics of built-up development mechanisms between municipal and county-level units. The model can further reveal the impacts of administrative hierarchy on the spillover effects of built-up areas (including radiation and segmentation effects) by embedding the administrative structure into a spatial weight matrix.

Initially, the built-up areas in one administrative unit are assumed to be affected by the adjacent units, and this effect has a close connection with the administrative status. Then, based on the spatial adjacent relations across the administrative hierarchy, 3 scenarios were devised, and these spatial adjacent relations were embedded into the spatial weight matrices in spatial econometric models. Finally, the results of the spatial econometric models were used to verify this spatial effect of the administrative hierarchy on built-up areas.

As shown in the schematic diagram of administrative hierarchy (Figure 3), the administrative territory of prefecture-level cities consists of municipal districts and county-level units, and there are three types of spatial adjacent relations between municipal districts and county-level units. Adjacent type I is two county-level units that are adjacent to each other (e.g., C and D). Adjacent type II is a county-level unit adjacent to a municipal district, and they are located in the same prefectural city (e.g., C and B), indicating the interaction between different administrative levels. Adjacent type III is also a county-level unit adjacent to a municipal district, but they are located in different prefectural cities (e.g., A and B), implying the composition effect of the interaction between different administrative levels and the potential segmentation caused by prefectural boundaries.

As shown in Equation (4), these spatial adjacent types are embedded into the spatial weight matrices through parameters $\alpha$ and $\beta$: (1) The spatial weight is 0, if the administrative units i and j are not adjacent. (2) The spatial weight is 1, if the adjacent relationship of i and j is type I. (3) The spatial weight is $1 + \alpha$, if the adjacent relationship of $i$ and $j$ is type II, where $\alpha$ is the indicator reflecting the radiation effect of a higher administrative level. (4) The spatial weight is $1 + \alpha \times \beta$, if the adjacent relationship of $i$ and $j$ is type III, where $\beta$ is the indicator representing the segmentation effect of the prefectural boundary.

$$Wij = \begin{cases} 0 & i \text{ and } j \text{ are not adjacent} \\ 1 & \text{adjacent type I} \\ 1+\alpha & \text{adjacent type II} \\ 1+\alpha \times \beta & \text{adjacent type III} \end{cases} \quad (4)$$

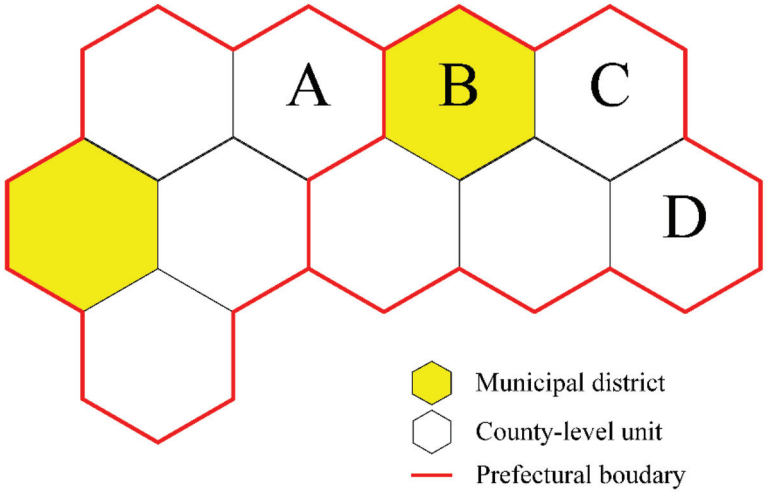



**Figure 3.** The schematic diagram of administrative hierarchy.

As a simplified example, the spatial weight matrix of $A$, $B$, $C$, and $D$ can be expressed as:

$$W_{ABCD} = \begin{array}{c} \\ A \\ B \\ C \\ D \end{array} \begin{array}{c} \begin{array}{cccc} A & B & C & D \end{array} \\ \begin{bmatrix} 0 & 1+\alpha \times \beta & 0 & 0 \\ 1+\alpha \times \beta & 0 & 1+\alpha & 0 \\ 0 & 1+\alpha & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \end{array} \quad (5)$$

By controlling the values of $\alpha$ and $\beta$, three scenarios with different spatial weight matrices were constructed for further spatial econometric modeling (Figure 4). In scenario 1, both $\alpha$ and $\beta$ were set to 0. This means that the spatial weight matrix is constructed with general queen contiguity regardless of administrative status/level. In scenario 2, $\alpha$ was set to be larger than 0, while $\beta$ was set to 0, indicating that we only consider the radiation effect of municipal districts. In scenario 3, both $\alpha$ and $\beta$ were set to be larger than 0, and $\beta$ was further restricted to a value smaller than 1. Compared with scenario 2, scenario 3 further considered the reduction in the radiation effect, which was caused by the segmentation effect of the prefectural boundary. We evaluated multiple combinations of the candidate values of $\alpha$ and $\beta$, looking for regression models that best explain the dependent variable within the context of regression diagnosis criteria, such as the Anselin–Kelejian test and the spatial pseudo R-squared. In this study, $\alpha$ was assigned a value of 1.5 and 1 in 2005 and 2015, respectively; $\beta$ was assigned a value of 0.1 and 0.8 in 2005 and 2015, respectively.

To summarize, under these scenarios, the radiation and segmentation effects of the administrative hierarchy are integrated into the spatial weight matrix by controlling parameters $\alpha$ and $\beta$. By analyzing the spatial econometric modeling under these scenarios, we can investigate the radiation effect of municipal districts and the segmentation effect of prefectural boundaries.

### *5.4. Control Variables of Regression*

In Sections 5.2 and 5.3, the dependent variable (i.e., built-up areas) and how the administrative hierarchy is embedded in the regression model are described and explained. According to our analytical framework (Figure 1), the variables that represent urbanization, marketization, industrialization, and the transport network are also included in the regression as control variables:

Urbanization: as China has undergone urbanization, millions of rural migrants have flooded into cities, which is a prominent driving force of urban expansion [8]. We selected the urbanization rate, urban population, and rural population to represent the demographic urbanization process. In addition, the literature mentioned that, along with the rural population transitioning to urban citizens, the rise in their income and consumption was

found to increase land used to meet the rising demand for housing, production, and leisure spaces [8,10]. Thus, wages and social consumption were incorporated to reflect the socioeconomic aspects of urbanization.

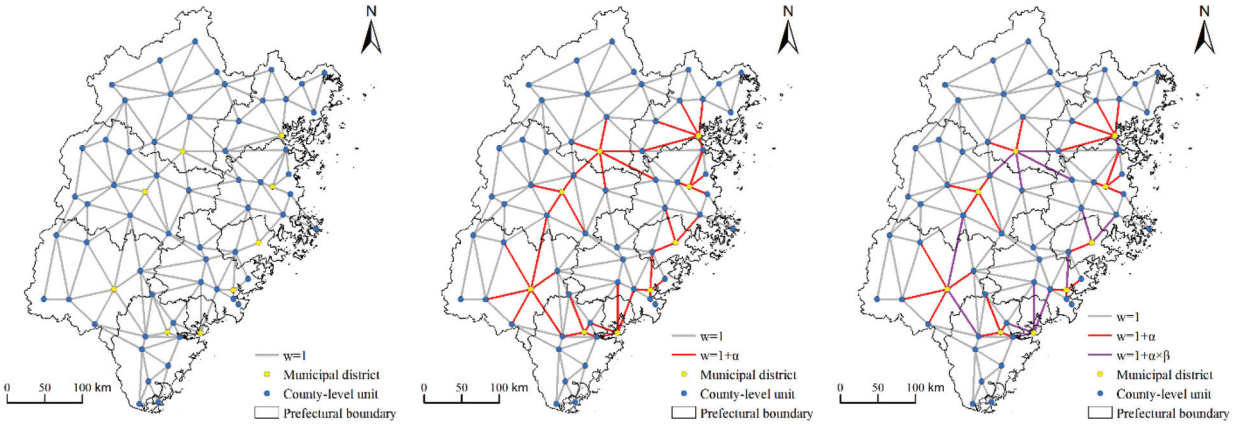



**Figure 4.** The maps of spatial weight matrices under different scenarios. (**a**) The map of spatial weight matrix under scenario 1. (**b**) The map of spatial weight matrix under scenario 2. (**c**) The map of spatial weight matrix under scenario 3.

Marketization: in the context of the marketization transition, labor and production factors have been allowed to flow freely and concentrate in cities, which has greatly promoted the urban economy. The expansion of the urban economy logically will have an impact on the growth of the urban areas [8]. We used the GDP of the secondary industry and the GDP of the tertiary industry to represent the development status of the urban economy.

Industrialization: industrialization is the main process used to boost the local economy. Local governments generally invest heavily in the industrial sector to raise GDP, leading to the expansion of industrial land. The literature contended that industrial enterprise development was closely connected with urban expansion [10]. We used the number of employees and enterprises' profits and taxes to measure the development of industrial enterprises.

Transport network: transportation land is inherently an important type of built-up land use, and transportation construction requires land. Thus, transportation development is a crucial factor in promoting urban expansion. On the other hand, the development of transport networks facilitates inter-city and intra-city interaction, which can further affect urban growth [11]. We used highway mileage to represent the development status of transport networks.

## 6. Result

### *6.1. Descriptive Statistics and Spatial Visualization Analysis*

#### 6.1.1. The Heterogeneity Characteristics of Built-Up Areas, Comparing Municipal Districts and County-Level Units

Table 1 represents the divergence of built-up areas in Fujian province by comparing municipal districts and county-level units. It shows that built-up areas of municipal districts were much larger than that of county-level units, reflected by the descriptive statistics. Specifically, the minimum built-up areas at the county level were less than 1 $km^2$ in 2005 and 2015, while the minimum values at the municipal district level were higher than 10 $km^2$ in both years. In terms of the mean of built-up areas, the values of municipal districts were nearly four times higher than that of counties in 2005 and 2015. Moreover, the medians of built-up areas at the municipal district level were 9.57 and 7.99 times as large as that at the county level in 2005 and 2015, respectively. It should be pointed out

that the maximum values of the built-up areas of county-level units were slightly higher than those of municipal districts. In both 2005 and 2015, the administrative unit with the maximum built-up areas at the county level was Jinjiang. According to its government website, Jinjiang's county-level economy has been the strongest in Fujian province for 28 consecutive years, and its competitiveness of county-level economy ranks fourth in China. Urban land expansion in China is closely related to economic growth [15]. Jinjiang is the only county-level administrative unit with more built-up areas than all the municipal districts in Fujian. To summarize, although this is a unique exception, it is evident that municipal districts occupy more built-up areas than county-level units.

**Table 1.** The descriptive statistics of built-up areas in municipal districts and county-level units.

| Year | Administrative Level | Min | Median | Mean | Max |
|---|---|---|---|---|---|
| 2005 | Municipal districts | 10.26 | 52.64 | 59.17 | 125.24 |
| | County-level units | 0.15 | 5.50 | 11.92 | 128.06 |
| 2015 | Municipal districts | 11.04 | 54.68 | 59.19 | 129.68 |
| | County-level units | 0.06 | 6.84 | 12.67 | 132.02 |

Figure 5 shows the spatial distribution of the disparity of built-up areas between municipal districts and county-level units across the prefectural cities in Fujian province. In all the prefectural cities, built-up areas of municipal districts were larger than the mean built-up areas of county-level units. This further confirmed that municipal districts had more built-up areas than county-level units. Notably, the disparity of built-up areas was more conspicuous in Fuzhou, the capital city of Fujian province. The built-up areas of the Fuzhou municipal district were 16.3 and 13.8 times as large as the mean areas of its eight county-level units in 2005 and 2015, respectively. This can be attributed to the fact that the Fuzhou municipal district is the resident of the provincial government. Thus, in terms of administrative hierarchy, the gap between municipal district and county-level units in Fuzhou is greater than that in other prefectural cities [34], which leads to a more conspicuous disparity in built-up areas.

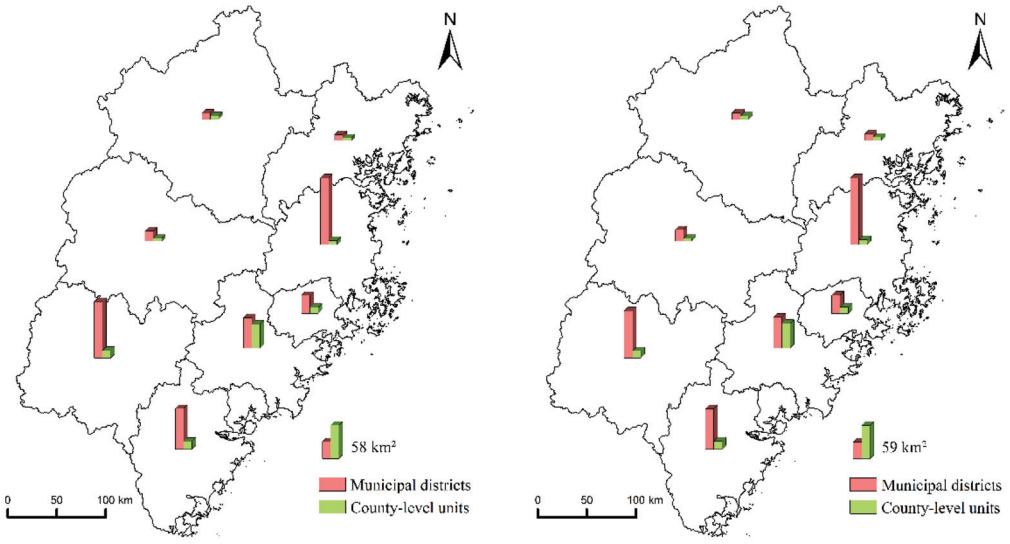



**Figure 5.** The disparity of built-up areas when comparing municipal districts and county-level units across prefectural cities. (**a**) The disparity of built-up areas when comparing municipal districts and county-level units in 2005. (**b**) The disparity of built-up areas when comparing municipal districts and county-level units in 2015.

6.1.2. The Radiation Effects of Municipal Districts on Built-Up Areas

To explore the radiation effect of municipal districts, we divided 58 county-level units of Fujian province into two groups. The counties of group A are the neighbor of municipal districts; in contrast, the counties of group B are not adjacent to municipal districts. Table 2 demonstrates the disparity of built-up areas when comparing the counties of group A and group B. It can be found that the built-up areas of group A were larger than that of group B when using descriptive statistics. Specifically, the median value of built-up areas of group A was 5.56 $km^2$, which was 0.27 $km^2$ higher than that of group B in 2005. In 2015, the difference was further expanded to 1.53 $km^2$. Notably, in both years, the means and maximums of built-up areas of group A were more than twice and five times as large as those of group B, respectively. These results demonstrate that municipal districts have strong radiation effects and greatly promote the expansion of built-up areas of their adjacent county-level units.

**Table 2.** The descriptive statistics of built-up areas in groups A and B.

| Year | Group | Min | Median | Mean | Max |
|---|---|---|---|---|---|
| 2005 | A | 0.15 | 5.56 | 15.82 | 128.06 |
| | B | 1.02 | 5.29 | 7.45 | 24.68 |
| 2015 | A | 0.06 | 9.73 | 16.62 | 132.02 |
| | B | 1.36 | 6.34 | 8.12 | 22.76 |

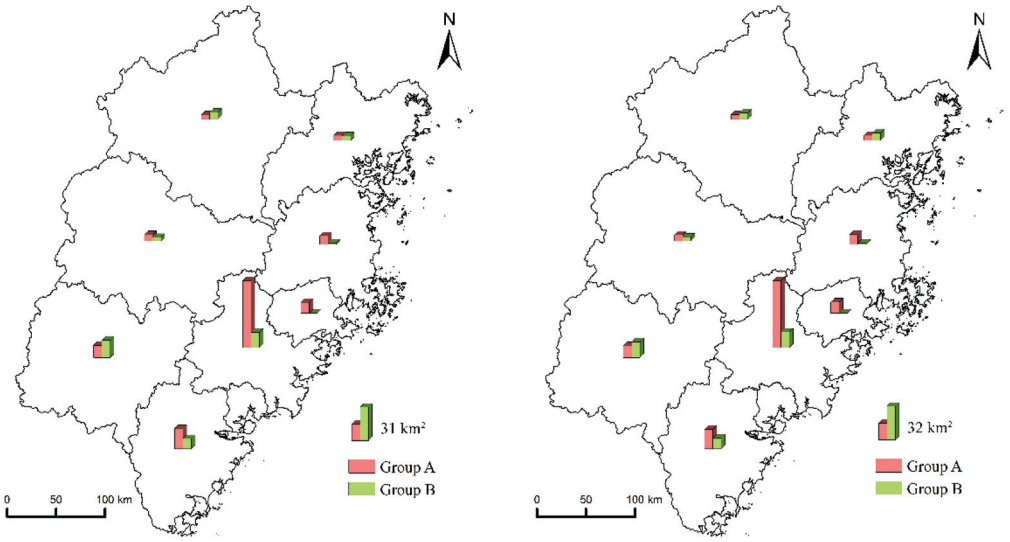
Figure 6 shows the disparity in the means of built-up areas when comparing the two groups at the prefectural level. First, in most prefectural cities, the means of built-up areas of group A were higher than that of group B. For example, in Fuzhou, the means of built-up areas of group A were 6.6 and 7.1 times as large as those of group B in 2005 and 2015, respectively. This further confirms the radiation effects of municipal districts on their adjacent counties. Second, in a few prefectural cities, the means of built-up areas of group A were lower than those of group B, including Ningde in 2015, Nanping, and Longyan in 2005 and 2015. This can be attributed to the fact that some counties not adjacent to municipal districts (e.g., Fuding in Ningde, Shaowu in Nanping, and Changting in Longyan) have abnormally large built-up areas, making the means of group B larger than group A in corresponding prefectural cities. According to official statistics, these county-level units have a greater population than surrounding units [43], which is an important impetus for urban expansion [8]. This indicates that, besides administrative hierarchy, other factors can also affect the growth of built-up areas. To summarize, although there are other factors, the radiation effect of municipal districts has a significant impact on built-up areas' development.

6.1.3. The Segmentation Effects of Prefectural Boundaries on Built-Up Areas

To identify the spatial segmentation effect across the boundaries of prefectural cities, we divided 58 county-level units of Fujian province into three groups. Groups A and B include the counties that are adjacent to municipal districts. Counties in group A and their adjacent municipal districts belong to the same prefectural city; in contrast, counties in group B and their adjacent municipal districts locate in different prefectural cities. Finally, counties in group C are not adjacent to any municipal district.

Table 3 represents the differences in built-up areas among these three groups through several descriptive statistics. First, the built-up areas of group A were much higher than groups B and C in both 2005 and 2015. Strikingly, in both years, the maximum area of group A was five times higher than the maximum of groups B and C. This indicates that a municipal district can greatly promote the land expansion of its adjacent counties within the same prefectural city. Second, although the counties of group B are adjacent to municipal districts, the built-up areas of group B are smaller than group A and even smaller than group C (e.g., the median and maximum areas in 2005 and 2015). This shows

that the municipal district does not promote the land expansion of its adjacent counties that are located in other prefectural cities. In other words, the radiation effect of municipal districts is restricted to within the prefectural city boundary, and there are evident spatial segmentation effects across the boundaries of prefectural cities.



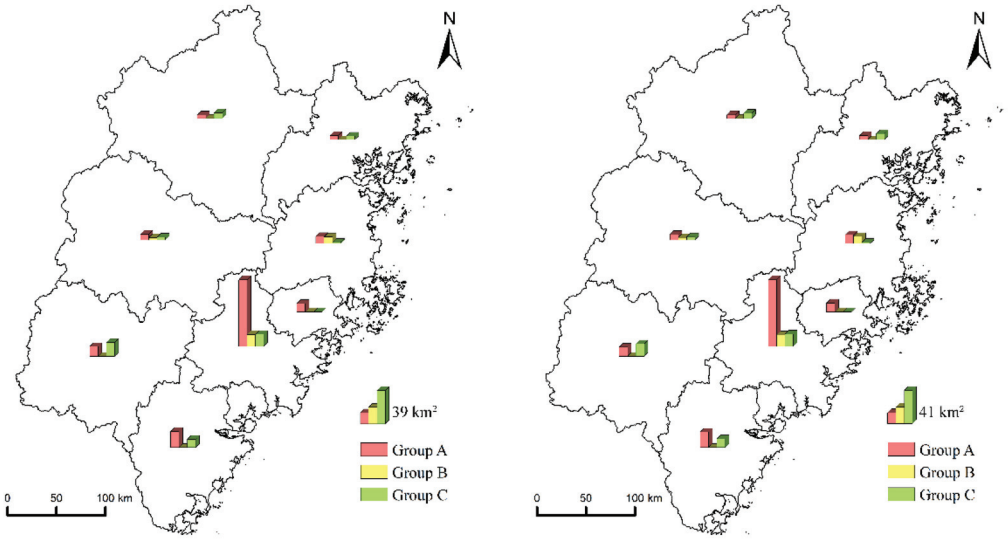

(**a**) (**b**)

**Figure 6.** The disparity of built-up areas when comparing group A and group B across prefectural cities. (**a**) The disparity of built-up areas when comparing group A and group B in 2005. (**b**) The disparity of built-up areas when comparing group A and group B in 2015.

**Table 3.** The descriptive statistics of built-up areas in groups A, B, and C.

| Year | Group | Min | Median | Mean | Max |
|---|---|---|---|---|---|
| 2005 | A | 0.15 | 6.60 | 17.35 | 128.06 |
| | B | 0.95 | 3.12 | 7.85 | 18.71 |
| | C | 1.02 | 5.29 | 7.45 | 24.68 |
| 2015 | A | 0.06 | 9.90 | 18.19 | 132.02 |
| | B | 0.95 | 4.48 | 8.45 | 19.97 |
| | C | 1.36 | 6.34 | 8.12 | 22.76 |

Figure 7 displays the means of built-up areas among the three groups across the prefectural cities in Fujian province. First, the means of built-up areas of group A were higher than those of group B in all three prefectural cities wherein the counties of group B are located. The means of built-up areas of group A were also higher than those of group C in most prefectural cities. As discussed in Section 6.1.2, due to other driving forces of built-up areas, the means of built-up areas of group A were lower than those of group C in a few prefectural cities (e.g., Naping and Longyan). Second, even though counties of group B are adjacent to municipal districts, the built-up areas of group B are smaller than group A and even smaller than group C in some prefectural cities (e.g., Quanzhou and Sanming in both 2005 and 2015). To summarize, these results indicate that the radiation effect of municipal districts only promotes the expansion of urban land of counties that are located within the same prefectural city, further confirming the spatial segmentation effects across the boundaries of prefectural cities.




(**a**) (**b**)

**Figure 7.** The disparity of built-up areas among groups A, B, and C across prefectural cities. (**a**) The disparity of built-up areas among groups A, B, and C in 2005. (**b**) The disparity of built-up areas among groups A, B, and C in 2015.

### *6.2. Spatial Econometric Modeling*

The previous section analyzes the triple spatial effects of administrative hierarchy on urban built-up areas based on descriptive statistics and spatial visualization. To explore these effects in a more rigorous multi-variant environment, we employed the spatial lag model with regimes, a technique that explicitly recognizes the heterogeneity of driving mechanisms and spillover strength across the different statuses of the administrative hierarchy.

First, the spatial lag model with regimes can produce two sets of comparable coefficients that are dedicated to each level of administrative hierarchy, reflecting the differences in driving mechanisms between municipal districts and county-level units. The result (Table 4) shows that rural population, GDP of tertiary industry, enterprises' taxes, and highway mileage were significant determinants of built-up areas in 2005 and 2015, echoing the previous findings that urbanization, marketization, industrialization, and transport networks are the key driving forces of built-up areas [8–11]. It is important to note that the coefficients of these driving forces varied across different administrative levels, and the global Chow tests provided strong evidence of the overall significant differences between coefficients in municipal districts and those in county-level units in both 2005 and 2015.

Moreover, individual Chow tests show that several individual coefficients differed significantly between the two administrative levels in 2005 and 2015, such as highway mileage, the GDP of tertiary industry, and the rural population. Specifically, in 2005, the coefficients of highway mileage were statistically significant at both administrative levels, but the coefficient in municipal districts was significantly higher than in county-level units. In contrast, in 2015, the coefficients of tertiary industry GDP were statistically significant at both administrative levels, but the coefficient in municipal districts was significantly lower than in county-level units. Interestingly, the coefficients of the rural population were statistically significant only in municipal districts and exhibited significant differences between municipal districts and county-level units in 2005; however, the coefficients of the rural population were statistically significant in both administrative levels and showed no significant difference. This is consistent with Chinese urbanization; the floating population is first concentrated in higher-level cities and spreads to lower-level cities in later years [29].

**Table 4.** The regression result of the spatial lag model with regimes under scenario 3.

| Variables | 2005 | | | 2015 | | |
|---|---|---|---|---|---|---|
| | **Municipal Districts** | **County-Level Units** | **Chow Test** | **Municipal Districts** | **County-Level Units** | **Chow Test** |
| Intercept | −331.51 | 2.58 | 0.3 | 421.7 ** | 40.87 ** | 8.62 ** |
| Rural population | −60.63 * | −3.07 | 3.86 * | −21.64 * | −3.75 * | 2.6 |
| Wages | −36.36 | −2.91 ** | 1.86 | −5.41 ** | −0.67 * | 5.23 * |
| Social consumption | 0.34 ** | 0.25 | 0.18 | | | |
| GDP of tertiary industry | | | | 1.01 ** | 2.07 ** | 6.14 * |
| Number of employees | | | | −0.77 ** | 0.04 | 20.14 ** |
| Enterprises' taxes | 1.12 | 1.35 ** | 0.03 | | | |
| Highway mileage | 122.15 * | 4.87 ** | 5.53 * | 0.24 | 0.03 | 0.02 |
| Spatial lag (ρ) | 0.04 * | | | 0.03 * | | |
| Global Chow test | 69.34 ** | | | 86.70 ** | | |
| Anselin-Kelejian Test | 0.19 | | | 0.24 | | |
| Spatial pseudo R-squared | 0.59 | | | 0.86 | | |

Note: ** $p$ value < 0.01; * $p$ value < 0.05.

Second, the spatial autoregressive coefficients of the spatial lag model with regimes were highly significant, and the Anselin–Kelejian test was not significant in both 2005 and 2015 (Table 4). This suggests that there is little evidence of any remaining spatial error autocorrelation, and the specification of the spatial weight matrix is sufficient to address the spatial dependence in the regression model. In other words, the results further confirm that: (1) the spatial interactions between municipal districts and their adjacent county-level units are stronger than those between two county-level units, indicating the radiation effect of municipal districts; (2) the radiation effect of municipal districts are restricted to within the boundaries of prefectural cities, reflecting the segmentation effects of the administrative hierarchy.

Third, the spatial weight matrixes under scenarios 1 and 2 (Tables 5 and 6) were employed in spatial lag models with regimes to further explore the institutional influence on built-up areas. In these models, the coefficient of determination (i.e., spatial pseudo R-squared) and spatial lag coefficient (ρ) varied significantly under different scenarios, reflecting the radiation and segmentation effects of the administrative hierarchy. As specified in Section 5.3, scenario 1 embraces the spatial weight matrix with general queen contiguity regardless of the administrative status/level, and scenario 2 enhances the spillover strengths between the municipal district and county-level units. Compared with scenario 2, scenario 3 further restricts the enhancement of spillover strengths within the boundaries of prefecture cities. In Tables 4–6, it can be found that, except for the only exception (scenario 2 in 2005), the spatial pseudo R-squared of scenario 3 (Table 4) was much higher than other scenarios in both 2005 and 2015. In addition, except for scenario 3, all of the spatial lag coefficients were not significant, indicating that scenarios 1 and 2 cannot catch the spatial interaction among the administrative units. These results indicate that the spatial weight matrixes of scenario 3 are better than others to fit and capture the spatial structure of built-up areas, further confirming the radiation effect of municipal districts on nearby county-level units and that the radiation effect is restricted to within the boundaries of prefecture cities since the spatial segmentation effect among prefecture cities.

**Table 5.** The regression result of the spatial lag model with regimes under scenario 1.

| Variables | 2005 | | | 2015 | | |
|---|---|---|---|---|---|---|
| | Municipal Districts | County-Level Units | Chow Test | Municipal Districts | County-Level Units | Chow Test |
| Intercept | −612.05 | −10.04 | 0.09 | −3068.57 | 34.75 * | 0.22 |
| Rural population | 52.33 | −1.06 | 0.08 | 120.96 | −3.46 | 0.27 |
| Wages | 69.05 | −2.43 ** | 0.1 | 45.01 | −0.57 * | 0.23 |
| Social consumption | −0.15 | 0.2 | 0.12 | | | |
| GDP of tertiary industry | | | | −2.55 | 2.14 ** | 0.53 |
| Number of employees | | | | 4.09 | 0.04 | 0.22 |
| Enterprises' taxes | −1.55 | 1.49 ** | 0.22 | | | |
| Highway mileage | −70.86 | 5.14 * | 0.09 | −1.53 | 0.14 | 0.05 |
| Spatial lag (ρ) | −0.01 | | | 0.02 | | |
| Global Chow test | 37.20 ** | | | 13.95 * | | |
| Anselin-Kelejian Test | 0.05 | | | 0.03 | | |
| Spatial pseudo R-squared | 0.44 | | | 0.31 | | |

Note: ** $p$ value < 0.01; * $p$ value < 0.05.

**Table 6.** The regression result of the spatial lag model with regimes under scenario 2.

| Variables | 2005 | | | 2015 | | |
|---|---|---|---|---|---|---|
| | Municipal Districts | County-Level Units | Chow Test | Municipal Districts | County-Level Units | Chow Test |
| Intercept | 6.93 | −5.33 | 0 | −3064.03 | 35.38 * | 0.22 |
| Rural population | −72 | −1.69 | 1.62 | 120.67 | −3.49 * | 0.27 |
| Wages | −45 | −2.55 ** | 1.18 | 44.95 | −0.58 * | 0.23 |
| Social consumption | 0.29 | 0.21 | 0.09 | | | |
| GDP of tertiary industry | | | | −2.55 | 2.16 ** | 0.53 |
| Number of employees | | | | 4.08 | 0.04 | 0.22 |
| Enterprises' taxes | 1.69 | 1.46 ** | 0.03 | | | |
| Highway mileage | 107 | 4.94 ** | 1.41 | −1.52 | 0.16 | 0.05 |
| Spatial lag (ρ) | 0.01 | | | 0.01 | | |
| Global Chow test | 271.12 ** | | | 15.27 * | | |
| Anselin-Kelejian Test | 0.81 | | | 0.04 | | |
| Spatial pseudo R-squared | 0.66 | | | 0.31 | | |

Note: ** $p$ value < 0.01; * $p$ value < 0.05.

## 7. Discussion

The administrative hierarchy is one of the most salient influencing factors of urbanization; its triple spatial effects (heterogeneity, radiation, and segmentation) have been broadly used to explain the spatial pattern and expansion mechanism of urban built-up areas [9,16,34]. Using descriptive statistics, spatial visualization, and spatial econometric model, we comprehensively explored and quantified the triple spatial effects of administrative hierarchy on built-up areas in Fujian province, China. In terms of theory, this study advances the understanding of the triple spatial effects of the administrative hierarchy on built-up areas at the prefectural level and below. In terms of methodology, this study provides a comprehensive modeling framework to integrate the triple spatial effects into a single spatial econometric model.

### *7.1. The Further Understanding of the Triple Spatial Effects of the Administrative Hierarchy on Built-Up Areas at the Prefectural Level and below*

First, in terms of the heterogeneity effect, we found that built-up areas of municipal districts were much larger than those of county-level units, and the driving forces of built-up areas were also sensitive to the two different levels of the administrative hierarchy. Previous studies found that, with a higher administrative level, municipalities directly under the

Central Government and provincial capitals had a higher speed of urban expansion than prefectural cities [3]. Li et al. further presented that the driving forces of built-up areas have different influences on cities at the prefectural level and above [9]. In short, previous studies have focused on the divergences between prefectural cities and cities above prefectural level. However, few studies have paid attention to the divergence of built-up areas between municipal districts and county-level units, even though many studies have conducted in-depth historical and institutional analyses of the tense relations and obvious differences between the two levels of the administrative hierarchy [13,21,31]. This study fills this gap and points out that, not only in terms of the spatial areas but also in terms of the driving mechanisms of built-up areas, the heterogeneity of built-up areas is evident across the municipal districts and county-level units in Fujian province.

Second, in terms of the radiation effect, we found that the built-up areas of county-level units were larger if these units were adjacent to municipal districts, reflecting the radiation effect of municipal districts, which is the administrative center of prefectural cities. Previous studies have shown that administrative centers play a vitally important role in urban land expansion and have qualitatively depicted the downward trend of built-up areas intensity from provincial administrative centers to peripheral areas through spatial visualization [17], indicating the radiation effect of provincial administrative centers on nearby administrative units. In recent years, Zeng et al. argued that the adjacency status of administrative units (e.g., whether or not the two adjacent units are at the same level of administrative hierarchy) has an evident spatial effect on urban land development and proposed a quantitative framework to verify that a provincial center has a significant radiation effect on nearby administrative units [34]. To summarize, using qualitative and quantitative methods, previous studies have shown the radiation effects of administrative centers at the provincial level. However, the radiation effect of administrative centers below the provincial level has not received enough attention. We filled this research gap and further revealed that municipal districts also have radiation effects on nearby county-level units, showing the radiation effects of administrative centers on built-up areas below the provincial level.

Third, besides the radiation effect of municipal districts on county-level units, we further found that the radiation effect was restricted to within the boundary of prefectural cities, reflecting the spatial segmentation effect at the prefectural level. Although a rich body of literature has discussed the spatial segmentation between administrative units in China [35,36], very few studies have investigated the spatial segmentation effects of administrative boundaries on the spillover effects of urban land. Until recently, Wang et al. employed spatial econometric modeling and found that the strengths of the spillover effect were reduced by 50% when two adjacent administrative units belonged to different provinces, indicating the spatial segmentation effect caused by mutual competition between provinces [16]. Surprisingly, although many studies have discussed the severe competition between prefecture cities and pointed out that this competition has a salient impact on urban land development [35,36], studies investigating the spatial segmentation effects between prefecture cities have been rare. This study fills this gap and demonstrates that the radiation effect of municipal districts on nearby county-level units will be reduced if they do not belong to the same prefectural city, reflecting the spatial segmentation effects of the prefectural boundary.

To summarize, this study furthers the understanding of the triple spatial effects of the administrative hierarchy on built-up areas (i.e., heterogeneity, radiation, and segmentation) at the prefectural level and below, which are relatively low administrative levels that have not received enough attention in previous research. Specifically, we revealed the heterogeneity characteristics of municipal districts and county-level units. In addition, we demonstrated the radiation effect of municipal districts on nearby county-level units, and the radiation effect is restricted to within the administrative boundary of prefectural cities, reflecting the segmentation effects of the administrative hierarchy.

### *7.2. The Comprehensive Approach to Integrating the Triple Spatial Effects into a Single Regression Model*

We proposed a comprehensive modeling approach to integrate the triple spatial effects into a single spatial econometric model.

On the one hand, we integrated the heterogeneity and spillover effects of administrative hierarchy on built-up areas into the regression model. The regression results show both evident heterogeneity characteristics between municipal districts and county-level units and significant spillover effects between administrative units. In previous studies, the heterogeneity and spillover effects of administrative hierarchy on built-up areas have been widely discussed [3,14,17,33], but heterogeneity and spillover effects are handled separately. More specifically, Li et al. investigated the divergence between cities at prefectural level and above but did not consider the spillover effect [9]. Li and Xiong identified strong spillover effects in urban land expansion but neglected the heterogeneity characteristics of different administrative levels [12]. This study points out a new subject for further studies on urban land in China: heterogeneity and spillover effects of administrative hierarchy should be integrated. If one of the two is missing, the study may lead to biased results.

On the other hand, we integrated the radiation and segmentation effects of the administrative hierarchy on built-up areas into the spatial weight matrix of spatial econometric regression. The results showed that municipal districts had evident radiation effects on nearby county-level units, but the radiation effects were reduced by the boundary of prefectural cities, indicating the spatial segmentation effects between prefectural cities. In previous studies, the radiation effects of the higher-level administrative units and the spatial segmentation effects of administrative boundaries have been discussed [16,17,34], but spillover and segmentation effects have always been investigated separately. More specifically, Zeng et al. demonstrated the radiation effect of the provincial administrative center but did not consider the segmentation effect [34]. Wang et al. examined the segmentation effect of provincial boundaries on urban land development but neglected the radiation effect [16]. This study proposes a new approach to consider the radiation and segmentation effects simultaneously, which can support the better fitting of the regression model and better handling of the spatial autocorrelation problem.

To summarize, the triple impacts of the administrative hierarchy have effects on built-up areas simultaneously and should be integrated into a comprehensive modeling approach. Otherwise, biased conclusions may be drawn. The modeling approach we proposed integrates the triple effects into a single spatial lag model with regimes, which can delineate the heterogeneity effect by spatial regimes and embed the radiation and segmentation effects into the spatial weight matrix. This new modeling approach is transferable to other regions to shed further light on urban land expansion in China.

## 8. Conclusions

Due to rapid urbanization in the last four decades, Chinese cities have experienced dramatic land expansion. Under the land use system in China, local governments are the sole legitimate providers of newly increased urban land [12]. More importantly, in the process of tax-sharing reform and marketization transition, urban land has been regarded as a unique and very significant resource for local revenue, and it has become the most important instrument of local government to promote economic growth and urban construction [9]. Thus, urban land development has not been purely driven by market forces, and local governments have been playing a proactive role in this process. Since the organization of local governments is characterized by tiered political and economic power structures in a national hierarchy system, many studies have investigated the effects of administrative hierarchy on urban land expansion, such as heterogeneity, radiation, and segmentation. However, these studies mainly have focused on only one of these effects. As a result, these parallel and distinct studies have created a limited understanding that can result in partial and potentially misleading conclusions about urban land expansion in China. Contrary to previous literature, this study proposes a comprehensive theoretic and

modeling framework to investigate the triple spatial effects of the administrative hierarchy as a whole. Furthermore, we focus on the relatively low levels of the administrative hierarchy (i.e., the prefectural level and below). These are the levels that have experienced much more intense land development [37,38] but have not received enough attention from previous studies.

This study advances the understanding of the triple spatial effects of administrative hierarchy (i.e., heterogeneity, radiation, and segmentation) on built-up areas by using a new comprehensive modeling approach to integrate the triple spatial effects as a whole.

From a theoretical perspective, we advance the understanding of the tripe effects of administrative hierarchy at the prefectural level and below. First, we revealed the heterogeneity characteristics of built-up areas by comparing municipal districts and county-level units, not only in terms of the magnitude but also in terms of the strengths of the driving forces. Moreover, we also discerned the radiation effect of municipal districts: a county-level unit would have more built-up areas if it is adjacent to a municipal district. Therefore, we further the understanding of the heterogeneity and radiation effect of the administrative hierarchy at the levels below prefectural cities, while previous studies have only focused on the prefectural level and above. Finally, we identified the segmentation effect of the prefectural boundary: the radiation effects of municipal districts on nearby county-level units are reduced if the county-level units are located in another prefectural city. Thus, we advance the understanding of the segmentation of administrative hierarchy at the prefectural level, while previous studies have only shown the administrative barriers to the spatial spillover of built-up areas at the provincial level. To summarize, compared with previous studies, we further verify that the triple effects of the administrative hierarchy are evident at the prefectural level and below, which have experienced more intensive land urbanization [37,38] but have not received enough attention from previous researchers.

From a modeling perspective, we propose a new approach to integrating the triple effects of administrative hierarchy on built-up areas into a single spatial lag model with regimes. Specifically, we handle the heterogeneity effect using spatial regimes and embed the radiation and segmentation effects into the spatial weight matrix through two parameters, $\alpha$ and $\beta$. Therefore, we improve the modeling method and can investigate the triple effects of administrative hierarchy simultaneously, while previous studies have merely focused on a single effect. As shown in Section 6.2, if one or more effects are neglected, biased or even misleading regression results would be obtained. Thus, leveraging the new transferable modeling approach proposed in this study, the multiple facets of the administrative hierarchy effects can be handled as a whole and deserve more attention from those who care about the urbanization process in China. Such attention will lead to a thorough understanding of the mechanism of urban land expansion and enlighten the policy debates on better land use under China's unique institutional environment.

From the perspective of international comparison regarding the connection between administrative hierarchy and urban development, Chinese and foreign scholars focused on different urban elements. Chinese scholars were mainly concerned with the built-up areas, while foreign scholars paid more attention to the population. For example, Heider et al. stated that administrative status significantly impacts urban growth [23]. Unlike many Chinese case studies, they chose population as the indicator of urban growth. Furthermore, some scholars from the USA and the Netherlands investigated the differences in the migration patterns of different ages across different levels of administrative hierarchy [24,25]. In the case study of the Netherlands, de Jong et al. found that the "75 and older" age cohort is oriented towards smaller towns and rural areas, while the "65–74" age cohort is increasingly oriented toward urban areas [25]. Considering the potential heterogeneity characteristics of built-up areas across the different levels of urban hierarchy, we argue that the effects of administrative hierarchy on urban land can be a new subject for foreign scholars.

The results of this study indicate that the effects of the administrative hierarchy result in divergence between different administrative levels and segregation across administrative

boundaries. From the policy point of view, we argue for a reform and better design of the administrative arrangement to achieve balanced and integrated urban land development. Vertically speaking, the magnitudes and strengths of driving forces of built-up areas coincide with the administrative levels. The heterogeneity effect tends to reinforce the imbalances in land development and cause greater tensions between different levels of cities. We suggest reforming local land administrative rights and changing the constraint structures of local governments in the hierarchical system. Horizontally speaking, the radiation effect of municipal districts can promote the urban land expansion of nearby county-level units and helps alleviate the divergence of built-up areas between them. However, the segmentation effect of prefectural boundaries restricts the radiation effect and is a barrier to integrated urban land development. Therefore, breaking through the administrative barriers should be the next focus to optimize the structure of land use and improve the synergy of land development.

Foreign scholars also reported similar problems that stemmed from the inappropriate power arrangement of administrative hierarchy. For example, in a case study of Uyo (a midsized city in Nigeria), Etido found a lack of continuity in commitment to urban infrastructural development projects, which will hamper sustainable urbanization [44]. He attributed the problem to fiscal management across the administrative hierarchy. Specifically, Uyo follows a system of disbursing funds from the state to the local governments, which limits local governments' financial independence. Thus, regardless of Chinese and foreign countries, better design of the administrative arrangement is crucially important to achieve balanced and sustainable urban development.

China can learn from Germany and Japan, where a multi-tier government system has been widely used. In these countries, broader functions such as environmental protection and education can be managed by a higher level government, while decisions for the economy and people's livelihood can be made by local governments. As Gu et al. stated, this design can enhance the cooperation between governmental power and city management [45].

Finally, this study can be improved by considering more inter-city relationships that can affect urban land development. For instance, Zeng et al. argued that, besides the administrative hierarchy, spatial accessibility and social network should be integrated to provide a reference for urban policymakers [41]. Integrating more inter-city relationships into our proposed approach may have the potential to further improve our understanding. Furthermore, we have only focused on the prefecture and county levels because our study area is only one province. Considering the province is another primary administrative level in China, we will explore the differences and interactions between these levels and the provincial level in our future research.

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# Simulation and Analysis of Land-Use Change Based on the PLUS Model in the Fuxian Lake Basin (Yunnan–Guizhou Plateau, China)

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**Abstract:** It is essential to study the characteristics of land use change in the Fuxian Lake basin, a plateau lake in Yunnan Province, and to predict the basin's future trend of land use change for sustaining the key carriers of current national major strategies such as ecological civilization, green development, and rural revitalization. This study used the Fuxian Lake basin as the subject and based on the seven periods of historical land use data, added six driving factors including human and natural factors, applied patches to generate the land-use simulation model (PLUS), and forecasted and analyzed the characteristics of land-use change in the basin in 2048 under the three scenarios of natural trend development, ecological protection, and production protection. The results showed that: (1) the overall simulation accuracy of the model was 79.14%, Kappa index was 0.73, FOM value was 0.29, and the model's consistency was high. The model can be used to simulate future land-use changes in the Fuxian Lake basin. (2) In the natural development scenario, land-use development and the driving factors in the basin have the following relationship: rainfall and trunk road distance significantly impacted the types of land that emphasize ecological conservation and product development. Elevation and soil distribution characteristics had a significant impact on land types focused mainly on water zones and ecological protection. The land types mainly focused on urban construction were greatly affected by elevation, trunk road distance, GDP per capita, and other factors. (3) The main direction of land-use change in the watershed is the mutual conversion between farmland and forest land, with the continuous expansion of construction land. In the production protection scenario, the area of farmland increased by 44.79 $hm^2$. In the ecological protection scenario, the area of arbor forest land increased by 37.85 $hm^2$ and the area of shrub forest land decreased by 62.37 $hm^2$. (4) From the perspective of spatial distribution patterns, the regional hotspot change blocks are mainly concentrated in the north of the basin, along the coast of the north of Fuxian Lake, and the southern land. In general, the PLUS model had good applicability in this study. The simulation results of the different scenarios were in line with the land development in the Fuxian Lake basin and can provide scientific reference for land-space planning, ecological and production land constraints, and coordination of development in the Fuxian Lake basin.

**Keywords:** land-use change; PLUS model; simulation and prediction; Fuxian Lake basin

## 1. Introduction

Land-use/land-cover (LULC) changes are closely associated with the interaction of human production space, living space, and ecological space [1–3]. LULC change research focuses on simulating and exploring their spatial–temporal evolution at the regional or global scale, analyzing the dynamic mechanisms of its development, and modeling its dynamic trends [4]. In general, cities have production, living, and ecological functions

in any area [5,6]. Among these, ecological functions are essential, and the optimization of urban ecological functions provides support for human production and life. Some researchers found that forest land, grassland, and water area account for a large proportion of ecological space, and the evolution of the ecological space is a dynamic evolutionary relationship between living space, ecological space, and production space, as well as the various land types within them [7]. Previous land-use simulation models were linear and numerical and all the processes of land-use change could not be integrated [8,9].

Cellular automata (CA) can represent the complex LULC system and is widely used in land-use simulations and predictions [10,11]. CA models have been applied to simulate land-use changes, and the results have the advantages of strong dynamic simulation ability, limited data, simple calibration, and can reproduce different land-cover and complicated patterns [12]. Among the various models, the CA model can dynamically reflect the complex structure of an urban system. An extended version of this model has been widely used in the simulation of urban growth, such as the SLEUTH model [13], CLUE-S model [14,15], CLUMondo model [16,17], and the Multi-Agent System (MAS) model [18,19]. However, in the conversion process of most models, the competition and mutual influence between the different land types are usually ignored. The PLUS model is derived from the CA model and proposes an adaptive, inertial competition mechanism in the random forest classification algorithm for bi-state decision making. The PLUS model is an improved cellular automata model, which focuses on the nonlinear relationship between land use and underlying cover, and can tap the driving factors of land expansion and landscape change with the ability to reflect the landscape evolution of patches and the use potential for policy formulation. Compared with other models, PLUS models can obtain higher simulation accuracy and more similar landscapes, and can further explore potential land-use conversion rules [20] to identify the drivers of land expansion and project landscape dynamics [21,22]. However, the cellular automata model for land-use change has insufficient accuracy [23]. In order to improve the accuracy of land-use simulation and reduce errors, scholars have improved the original cellular automata model from different perspectives. For example, Verburg et al. [24] proposed the CLUE-S model based on systems theory, and the FLUS model proposed by Liu et al. [25] transformed and upgraded the original cellular automata model by establishing self-adaptive inertia and a competition mechanism to process the complex competitions and interactions between the various land-use types. The PLUS model has been widely used to investigate the evolution of land-use spatial patterns and the driving factors affecting land-use change. The PLUS model simulated the land-use pattern of key mountain development areas [26]. The PLUS model explored the spatiotemporal change characteristics of land use in the Weihe River basin [27]. The PLUS, Future Land-Use Simulation (FLUS), and Markov models were used to simulate and predict the land-use status quo in the western Beijing ecological reserve in 2020 under two management scenarios [28]. The results showed that the PLUS model's prediction accuracy was high. The PLUS model simulated future land-use changes in Xi'an [29]. The PLUS model forecasted and analyzed future land-use changes in the middle reaches of the Yangtze River basin [30]. The PLUS model simulated the land-use data of Nanjing in 2025 [31]. Under different land-use constraints, the development direction and the evolution of land-use spatial patterns are also different. The PLUS model simulates land-use change under different land-use application scenarios [32–35], such as natural tendency development, ecological land protection, ecological and economic balance, economic development scenarios, rural development, and commercial circumstances.

At present, land-use change scholars utilizing these models have mainly concentrated on urban areas [36–38] and rarely on Ecological Conservation Areas [39]. Moreover, as a newly proposed land-use model, there are few studies incorporating the PLUS model. The Fuxian Lake, as a typical large deep-water plateau lakes in China, has outstanding representativeness in facing regional ecological problems such as ecological environment and ecological space. While verifying the accuracy of the PLUS model in simulating the land-use of the basin in the future, this study sought to understand the evolution

of the spatial pattern of land use in the basin through the comparison of multi-scenario simulations including predictions of ecological protection, production protection, and natural trend development of the basin, effectively highlighted the land hotspots and key areas in the basin. Our model also provides methods for future land-use simulation in the basin, and regional land-use planning, land conversion constraints, and a scientific reference for the layout of production space and living space. Cloud content and data accuracy were involved in the selection of remote sensing image data. The forecast period conformed to the domestic national economic planning guidelines and the period of land, forestry, and other relevant thematic planning. Due to the constraints of the actual situation, this study chose 2018 as the starting year of the prediction and selected 2048 as the forecast year, according to the planning habit of adopting integer years in most of China.

## 2. Materials and Methods

### *2.1. Study Area*

The Fuxian Lake basin (24°21′–24°38′ N and 102°49′–102°57′ E) [40] with an area of 68,725 $hm^2$, is located in Yuxi City, Yunnan province, in the central Yunnan basin. The Fuxian Lake basin has a typical subtropical subhumid monsoon climate, with an average annual temperature of 15.5 °C and spans across the Jiangchuan, Huaning, and Chengjiang counties/districts (Figure 1). It is dominated by plateaus and hilly landforms. In the basin, there are primarily four types of soil: red soil, brown soil, purple soil, and paddy soil. The rural economy in the basin is dominated by the planting industry and the tourism industry has developed rapidly. Fuxian Lake is a north–south tectonic depression belonging to Nanpanjiang River system and is the largest deep-water freshwater lake in China. The elevation of Fuxian Lake is about 1723.35 m a.s.l. with an area of 216.6 $km^2$, average depth of 95.2 m, and capacity of $10^8$ $m^3$.

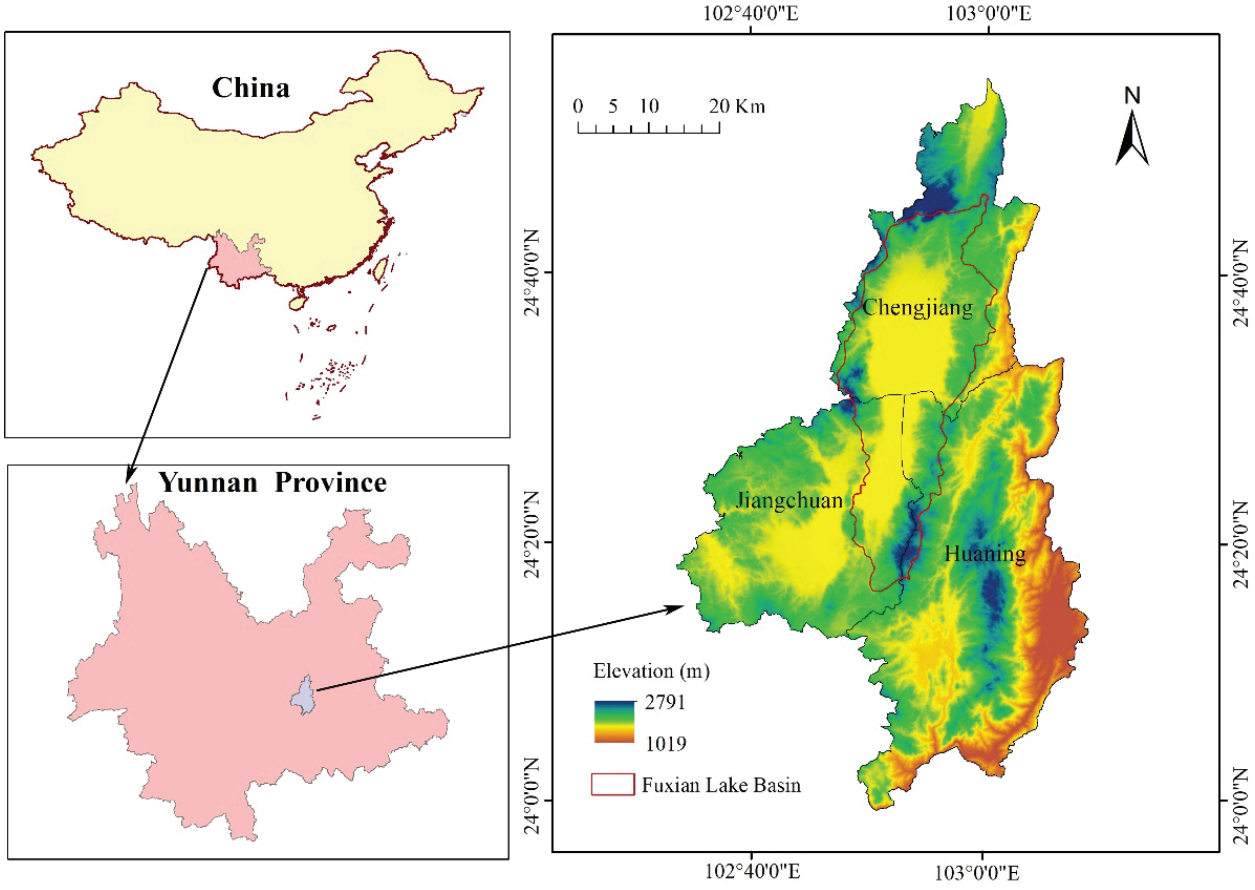


**Figure 1.** The map of the Fuxian Lake watershed.

*2.2. Data Source and Processing*

The data classification in the Fuxian Lake basin are the Land-sat series data from 1990, 1995, 2000, 2005, 2010, 2015, and 2018 with a data resolution of 30 m × 30 m. The ENVI5.2 software was used to process the filtered images with multi-band synthesis, atmospheric correction, geometric correction, image mosaic, clipping, enhancement, etc. After radiation correction, the spectral curve of the sample point is relatively consistent with that of the standard ground objects [41,42]. Based on field investigation and the data collected, the interpretation signs of remote sensing were established. Visual interpretation and classification of remote sensing images were carried out on the basis of land resource classification, forest land classification, and other systems. Finally, combined with site verification, land-use types in the Fuxian Lake basin were classified into Fuxian Lake basin farmland, arbor forest land, shrubbery land, other forest land, urban and rural residential construction land, swamp wetland, other construction land, industrial and mining construction land, other grassland, artificial wetland, and lake and transportation land. Six factors, including per capita GDP, population density, average annual rainfall, distance from main trunk roads (referred to as "trunk road distance"), and soil distribution and elevation, were comprehensively selected as the driving factors affecting land-use change, based on the consideration of economic development, community coordination, natural protection, and other factors in the Fuxian Lake basin. The projection conversion, resampling, mask, and the other tools of ArcGIS 10.2 software were used to process the spatial accuracy of the data for consistent driving factors and land-use type data with a set resolution of 30 m × 30 m, projected as WGS_ 1984 grid data.

*2.3. Research Method*

2.3.1. PLUS Model and Operation Mechanism

(1) PLUS model mechanism

The PLUS model comprises the cellular automata (CA) module, the multi-type patch strategy, and the rule mining method based on the land expansion analysis strategy with a better interpretation of the influencing factors of various land-use changes and a higher precision for the simulation results [9]. By evaluating and selecting the parts of various types of land expansion in the previous and subsequent land data and combining the spatial characteristics of the driving factors, the PLUS model uses a random forest method to determine the probability of development of various types of land. The Markov chain estimates the quantity of future land use as the constraint condition of land use. Then, random patches are generated based on the CARS module and other relevant parameter settings. Finally, combined with the land transfer cost matrix and threshold decline mechanism, the spatial pattern of future land use in the Fuxian Lake basin was simulated and predicted.

(2) Prediction of land-use demand

In the PLUS model, the Markov chain and linear regression methods were integrated to determine future land-use demand, which was predicted based on historical data. The general linear regression method is a static model, that can be used to predict the land area that will be used in the future. It cannot be used for visual simulation of land-use spatial structure [43]. The Markov chain estimates the total amount of future land-use demand through highly efficient and effective predictions of the probability of conversion between land-use types [44]. In this study, the Markov chain method was mainly used to predict the land-use cover in 2048 and then used to analyze the land-use change in the Fuxian Lake basin. The land-use cover predicted by the linear regression method in 2048 was only used to assist the hotspot analysis of land-use changes in areas used by subsequent analyses.

(3) Land-use simulation process

The land-use simulation process of the Fuxian Lake basin was divided into three parts: (1) the PLUS model was used to simulate the land-use data in 2018, and the accuracy and consistency were compared with the real data of 2018, based on the land-use data and driving factors in 1990 and 2018; (2) on the premise that the overall accuracy and

consistency of the model is satisfied, different rules were set for the transformation of land-use types, and the land-use data in 2048, generated by the Markov chain method and linear regression method as the constraint, were used to simulate the spatial pattern distribution of land use in the Fuxian Lake basin in 2048 based on the historical data and the land-use data in 2018 as the prediction starting point; and (3) we extracted the hotspots of land-use change in the watershed (e.g., the spots that change and change consistently in the future under the prediction of different methods).

#### 2.3.2. Calculation of Land-Use Dynamic Degree

The dynamic degree of land use can be quantitatively calculated through the land quantity change model, which can directly reflect land resource changes [45]. In this study, the change degree of land-use types of different land types [46] and the dynamic degree of the comprehensive land use of the study area [47] in different change periods were calculated by using the land quantity change model to assist in exploring the characteristics of land-use change in the Fuxian Lake basin from 1990 to 2018. The formula is as follows:

$$LC = \frac{LU_j - LU_i}{LU_i \times T} \times 100\% \quad (1)$$

$$ZLC = \left[\frac{\sum_m^n \Delta LU_{m-k}}{2 \times \sum_m^n LU_m}\right] \times \frac{1}{T} \times 100\% \quad (2)$$

In the above formula, $LC$ is the dynamic degree of a single land-use type; $T$ is the research period; $LU_i$ and $LU_j$ are the areas of a land type at the beginning and end of the research period, respectively; $ZLC$ is the dynamic degree of comprehensive land use; n is the total number of land-use types in the Fuxian Lake basin; $\Delta LU_{m\text{-}k}$ is the absolute value of the area of type m land-use converted to type $k$ land-use type in the study period; and $LU_m$ is the area of type m land-use at the start of the study.

#### 2.3.3. Rules for Conversion of Land-Use Types

The regional land development demands determine the development orientation of land space to a certain extent. Combining the current land-use situation in the Fuxian Lake basin with the requirements of national policies on land, the simulation of future land use should include land conversion constraints that meet the relevant planning criteria. These can provide certain decision-making references for sustainable economic development and ecological protection, and assist in the formulation of scientific and reasonable land-use planning and environmental protection planning to optimize the spatial layout of regional land use.

In this study, the land transfer matrix in the PLUS model was configured to define three different land-use type transformation rules and simulate the spatial layout of land use under three scenarios. In the transfer matrix, the "0" value indicates that conversion is not allowed, and the "1" value indicates that conversion is allowed. Under the natural trend development scenario, all the land transfer matrices were set as "1" values, indicating that all land types may be transferred out or transferred in from other land types. Under the production protection scenario, land-use transformation focuses on ensuring that farmland does not change excessively and limiting the quantity and direction of its transfer. Under the ecological protection scenario, land-use transformation mainly considers the protection of forests, waters, wetlands, and other ecologically sensitive areas in the Fuxian Lake basin.

### *2.4. Precision Inspection*

In this study, the Kappa coefficient and FoM (Figure of Merit) value were applied to evaluate the accuracy of the PLUS model simulation results. The closer the Kappa coefficient value is to 1, the better the simulation accuracy is. When the Kappa coefficient is higher than 0.7, it indicates that the simulation accuracy of the model is statistically satisfactory [48]. The FoM value is generally small, ranging from 0 to 1. The higher the

value, the higher the consistency between the model prediction results and the actual values [49]. It can be used to identify the accuracy of the area where changes occur between the whole land and the simulation results.

## 3. Results

### *3.1. Analysis of Land-Use Characteristics in the River Basin*

#### 3.1.1. Analysis of Quantity and Structure Characteristics

In the Fuxian Lake basin, arbor forest land, farmland, shrub forest land, and other forest land were the dominant land types. Urban and rural residential construction land, swamp wetlands, grasslands, artificial wetlands, other construction land, industrial and mining construction land, and transportation land occupied a relatively low proportion in the Fuxian Lake basin. The area of lakes has not changed much over time. Arbor forest land, farmland, other forest land, grassland, urban and rural residential construction land, other construction land, and transportation land showed a significant growth trend, while shrub forest land area decreased annually, with the largest change range among all the land types. In summary, ecological and production protection are the main land-use development strategies in the studied region. With the continuous development of urban construction, the population in the basin is increasing, and the demand for food and construction land is increasing every year. The expansion of the majority of land types has occupied the original shrub forest land, leading to the continuous reduction of its area (Figure 2).

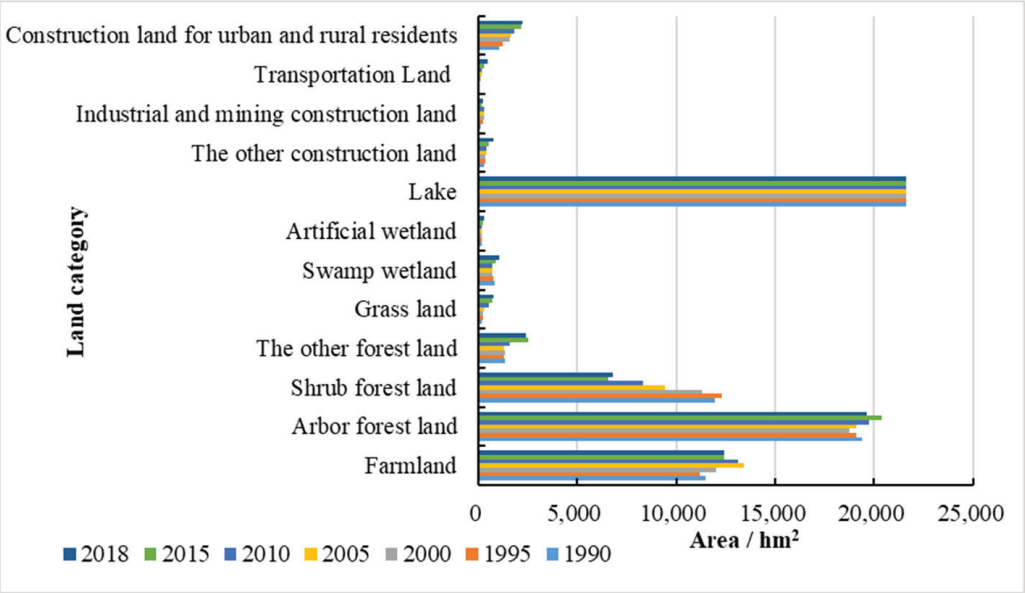


**Figure 2.** Changes in the number of different categories in the Fuxian Lake basin from 1990 to 2018.

#### 3.1.2. Analysis of the Dynamic Degree of Land Use

Using Formula (1), the dynamic degree of change of land use of the 12 land types in the Fuxian Lake basin in five periods from 1990 to 2018 was calculated. In the basin, the change rate of land for transportation was the fastest, and construction land reached the maximum growth rate from 1995 to 2000. The other construction land, industrial and mining construction land, urban and rural residents' construction land, and artificial wetlands increased to a certain extent from 2010 to 2018 with the development of regional urban construction. Since the total amount of farmland and arbor forest land is large, the dynamic degree of land use is small compared with other land types in the historical period and Fuxian Lake has basically remained unchanged. During each study period, the shrub forest land showed a negative growth rate, indicating that the degradation of shrub forest in this region was relatively severe. However, the area of the other forest lands, grasslands and swamp wetlands were relatively small. The annual average change rate was relatively

high, with noticeable changes from 2005 to 2018 (Table 1). According to Formula (2), the comprehensive land-use dynamic degree of change of the whole Fuxian Lake basin during the five study periods from 1990 to 1995, 1995 to 2000, 2000 to 2005, 2005 to 2010, and 2010 to 2018 were 0.22, 0.40, 0.57, 0.42, and 0.45, respectively. The land use in the basin has changed to different degrees at different times. The comprehensive land use dynamic showed a trend of increasing initially, then slowing down before increasing again. The degree of land change is more intense after 2005, which is consistent with a single type of land-use dynamic change.

**Table 1.** Relative annual change rate of various land-use types in the Fuxian Lake basin.

| Study Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1990–1995 | 3.76 | −0.49 | 13.47 | 0.54 | 0.00 | 3.94 | 3.16 | 3.68 | −0.94 | −0.35 | 2.13 | −1.35 |
| 1995–2000 | 5.15 | 1.47 | 5.37 | −1.56 | 0.00 | 31.61 | −0.25 | 0.56 | 0.53 | −0.33 | 0.17 | −1.95 |
| 2000–2005 | 0.66 | 2.32 | −0.25 | −3.34 | −0.01 | 7.60 | 5.02 | 2.86 | −0.70 | 0.37 | −0.17 | −0.35 |
| 2005–2010 | 2.18 | −0.46 | 0.99 | −2.32 | 0.00 | 0.05 | 16.63 | −0.29 | 4.77 | 0.69 | −2.77 | 0.40 |
| 2010–2018 | 2.90 | −0.69 | −2.62 | −2.32 | 0.00 | 14.86 | 4.49 | 9.93 | 6.16 | −0.10 | 8.00 | 6.17 |

Note: 1—Construction land for urban and rural residents; 2—Farmland; 3—Industrial and mining construction land; 4—Shrub forest land; 5—Lake; 6—Transportation Land; 7—Grassland; 8—Other construction land; 9—Other forest land; 10—Arbor forest land; 11—Artificial wetland; 12—Swamp wetland.

Based on the comprehensive analysis of the single land type and the dynamic degree of extensive land use in the whole region, it can be seen that there are small land types in the Fuxian Lake basin with a large degree of change, such as land for transportation, other construction land, artificial wetlands and other human factors, which have a significant impact on the dynamic degree of land use in the whole region, reflecting that with the continuous improvement of urbanization level, human activities have a more significant impact on farmland and a potential large disturbance to forest land.

### *3.2. PLUS Model Accuracy Verification*

Based on land-use data from 1990, the relevant parameters were inputted into the model to simulate the spatial distribution of land use in the Fuxian Lake basin in 2018, and the simulation results were tested using current land-use data from 2018. The results showed that the overall simulation accuracy of the model was 79.14%, the Kappa index was 0.73, and the FOM value was 0.29. These results show that the model has good applicability in this study. In addition, the PLUS model can be used to simulate the future land-use development of the Fuxian Lake basin.

### *3.3. Driver Contribution Analysis*

When investigating the relationship between the expansion of land-use types from 1990 to 2018 and the driving factors, the labels and the extracted values of multiple driving factors at exact locations were used to reconstruct the training dataset, so as to calculate the contribution of the driving factors to the development and change of each category (Figure 3). The analysis in Figure 3 shows that the influence of different driving factors on land-type changes was different. Farmland and the other forest land were mainly driven by rainfall and trunk road distance, with rainfall also being the main driving factor affecting grassland changes. Soil distribution was the main driving factor affecting the change in swamp wetlands and transportation land. The change in swamp wetlands, transportation land, and artificial wetlands was mainly driven by elevation. The change in industrial and mining construction land was primarily driven by per capita GDP. The change of the other construction land, arbor forest land, and industrial and mining construction land was mainly driven by the distance between main roads. The driving force of elevation and population density dramatically influenced the change in urban and rural residential construction land. The number of shrub forest land continued the trend of decreasing over time, which was greatly influenced by elevation and population density, indicating that the

disturbance to this land type in the Fuxian Lake basin was sustainable and conformed to the actual situation of urban construction site selection and economic development occupation in the Fuxian Lake basin. However, the driving effect of the PLUS model on lake area changes cannot be simulated. The reason is that the net change of the lake was small, and the area change was less than 7 $hm^2$ from 1990 to 2018, which is almost unchanged compared with other land types.

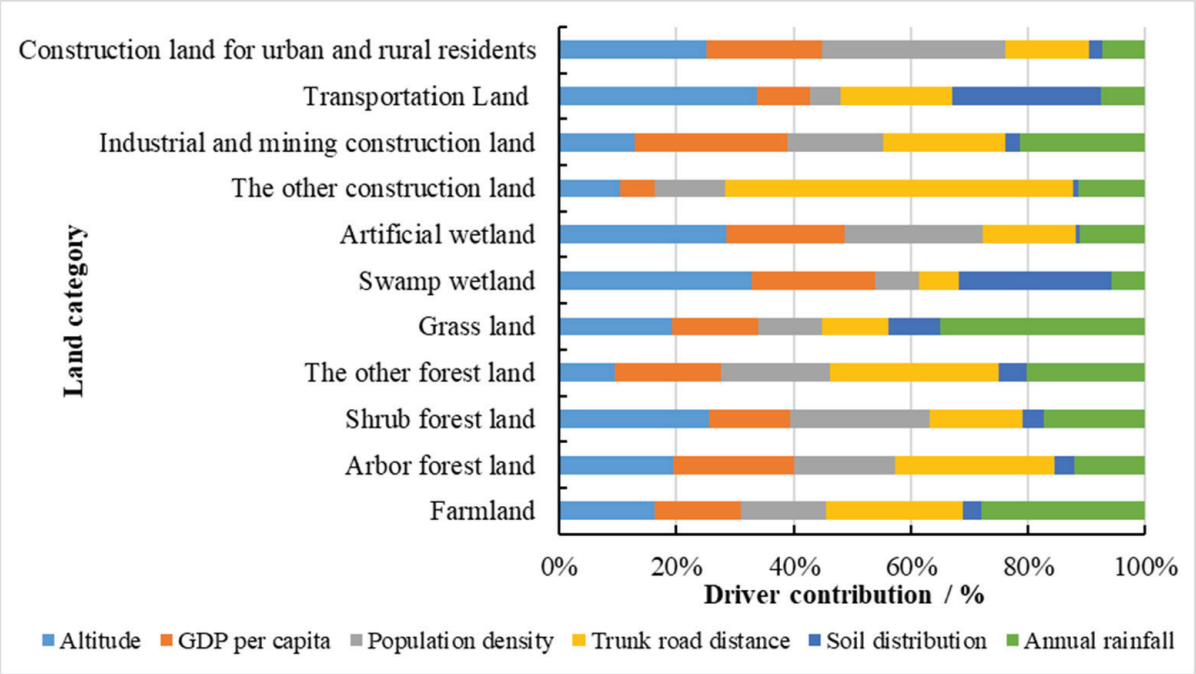


**Figure 3.** Contribution of driving factors to changes in various categories of land use.

### *3.4. Land-Use Prediction Results under Multiple Scenarios*

The PLUS model was used to simulate the changes in land use under three different scenarios, driven by the demand for future land use to obtain land-use predictions for the Fuxian Lake basin in 2048. According to the analysis of the land-use type transfer matrix table (Table 2), the spatial distribution of predicted land-use types in 2048 (Figure 4), and the percentage of predicted changes in land use under three scenarios (Figure 5), it can be concluded that in the natural trend development scenario, the demand for food from urban construction development and population growth occupied forest land by a large margin, whereas construction land, farmland, and grasslands increased by a large margin. Specifically, the area of arbor forest land that was converted to other construction land and farmland was 190.55 $hm^2$, 474.23 $hm^2$, and 2286.99 $hm^2$, respectively. Shrub forest land was degraded to grassland. In the production protection scenario, less farmland was converted to other types of land. The traffic and transportation land used to assist agricultural production activities increased, while forest land was still decreased. The area of arbor forest land converted to farmland was 434.55 $hm^2$, and the area of shrub forest land and urban and rural residential land converted to traffic and transportation land was 210.43 $hm^2$ and 133.21 $hm^2$, respectively. In the ecological protection scenario, the development of shrub forest land and arbor forest land increased compared with the natural trend. Urban construction and development were based on farmland expansion to reduce the occupation of arbor forest land and shrubbery forest land. Specifically, the area of farmland and grasslands that were converted to arbor forest were 383.04 $hm^2$ and 102.19 $hm^2$, respectively, while shrub forest land was rarely converted to other land types. The predicted land-type distribution of the lake surface of Fuxian Lake and the swamp wetland area distributed around it under the three scenarios was basically unchanged,

which was consistent with the minimal changes of lake surface area and water volume in Fuxian Lake during the historical period. In general, the land-type changes in the Fuxian Lake basin had different land-use type transformation directions under different land-use management and control measures. Among them, farmland, arbor forest land, shrub forest land, urban and rural residential construction land, and transportation land were subject to frequent expansion and changes and were vulnerable to human control and management. The distribution law of production space was related to artificial land surface distribution space. At the same time, attention should be paid to the dynamic changes in ecological space types and structures caused by continuous urbanization.

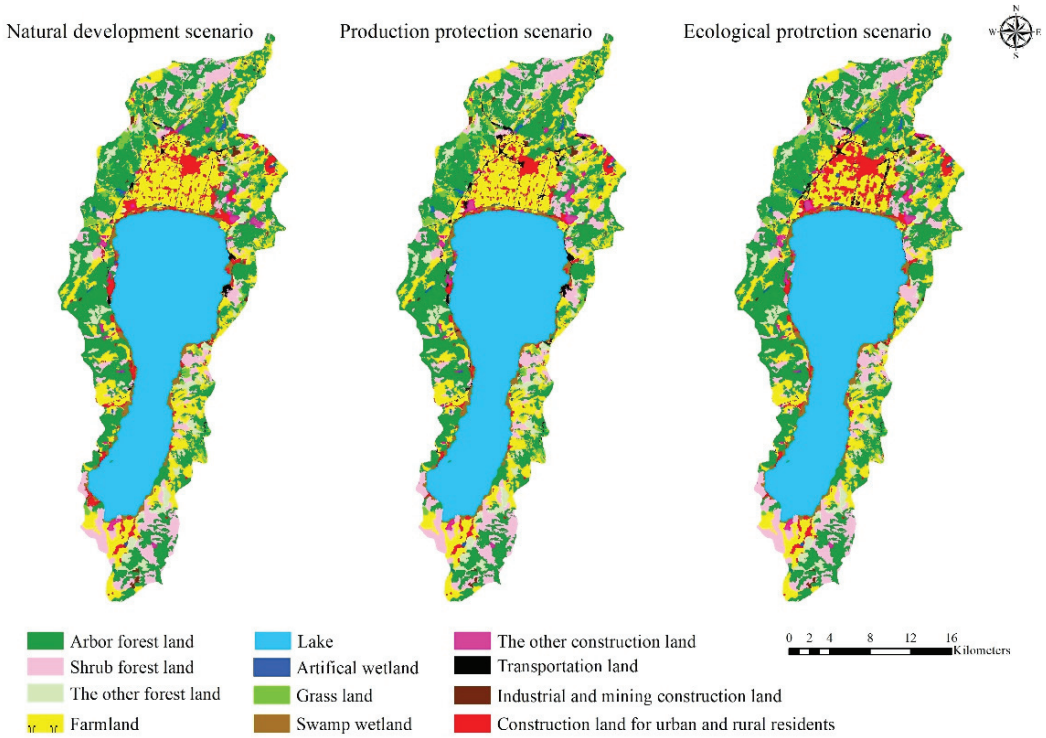


**Figure 4.** Spatial distribution map of land-use types in 2048. The forecast performed according to the three scenarios.

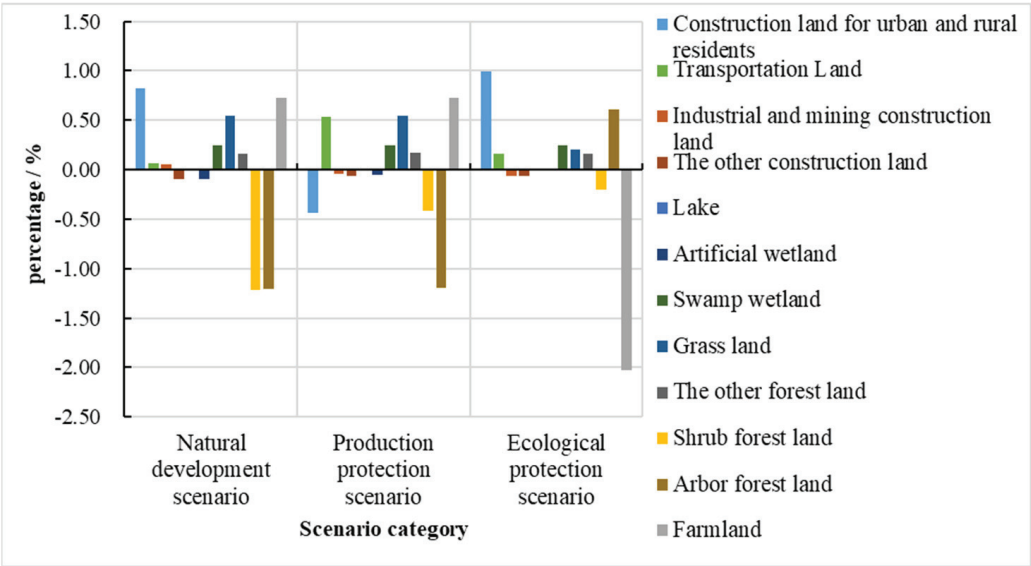


**Figure 5.** Percentage of predicted land−use changes under different scenarios.

**Table 2.** Land-use type transfer matrix from 2018 to 2048.

| Scenario Type | Land Category in 2018 | Land Category in 2048 | | | | | | | | | | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | |
| Production protection scenario | Construction land for urban and rural residents | 1892.38 | 9.80 | | 25.21 | 1.72 | 133.21 | 11.85 | 69.31 | 1.03 | 20.94 | 14.79 | 64.64 | 2244.88 |
| | Farmland | 6.81 | 12,352.94 | 0.44 | 7.30 | | 8.13 | 3.09 | 1.15 | 0.89 | 27.40 | 1.19 | 1.35 | 12,410.69 |
| | Industrial and mining construction land | | 0.99 | 200.47 | 4.39 | | 7.21 | 8.05 | | 0.31 | 16.40 | | | 237.81 |
| | Shrub forest land | 0.81 | 90.58 | 0.48 | 5808.31 | 0.56 | 210.43 | 203.88 | 0.59 | 36.06 | 390.39 | 5.31 | 56.50 | 6803.90 |
| | Lake | 0.56 | | | 0.41 | 21,623.80 | 0.65 | | 0.19 | | 0.25 | 0.03 | 11.36 | 21,637.26 |
| | Transportation Land | 25.93 | 7.28 | 6.08 | 2.33 | 0.99 | 357.38 | 7.81 | 8.51 | 0.24 | 16.39 | 2.39 | 16.77 | 452.09 |
| | Grassland | 0.03 | 5.43 | 0.18 | 10.72 | | 5.85 | 654.16 | 0.09 | 0.92 | 70.38 | 0.99 | 1.11 | 749.85 |
| | Other construction land | 10.61 | 2.29 | | 16.73 | 0.11 | 62.00 | 1.60 | 654.39 | 0.32 | 25.75 | 2.90 | 7.73 | 784.45 |
| | Other forest land | 0.64 | 1.86 | 0.12 | 3.19 | | 0.13 | 1.23 | 0.13 | 2380.08 | 12.11 | 0.02 | 0.14 | 2399.64 |
| | Arbor forest land | 3.24 | 434.55 | 4.90 | 610.73 | 0.17 | 28.30 | 222.13 | 3.19 | 95.24 | 18,162.93 | 36.81 | 27.91 | 19,630.08 |
| | Artificial wetland | 0.04 | 1.78 | | 28.86 | | 0.24 | 8.84 | 0.13 | | 60.03 | 193.18 | 2.16 | 295.25 |
| | Swamp wetland | 2.96 | 0.89 | | 2.09 | 4.45 | 6.69 | 0.01 | 0.23 | 0.11 | 3.59 | 0.05 | 1058.01 | 1079.07 |
| | Total | 1944.00 | 12,908.40 | 212.66 | 6520.26 | 21,631.80 | 820.22 | 1122.63 | 737.91 | 2515.20 | 18,806.56 | 257.66 | 1247.67 | 68,724.96 |
| Natural development scenario | Construction land for urban and rural residents | 2071.95 | 18.21 | | 10.52 | 1.50 | 2.41 | 15.82 | 7.68 | 0.80 | 9.31 | 13.76 | 92.93 | 2244.88 |
| | Farmland | 51.76 | 12,280.73 | 1.49 | 8.10 | | 11.58 | 4.83 | 3.24 | 3.82 | 40.89 | 2.05 | 2.21 | 12,410.69 |
| | Industrial and mining construction land | | 2.04 | 225.36 | 0.49 | | 0.45 | 0.18 | 0.07 | 0.54 | 8.67 | | | 237.81 |
| | Shrub forest land | 246.62 | 98.07 | 18.26 | 5546.92 | 0.83 | 151.83 | 286.99 | 100.89 | 35.12 | 235.15 | 5.34 | 77.87 | 6803.89 |
| | Lake | 2.28 | | | 0.69 | 21,622.20 | 0.45 | | 0.47 | 0.06 | 0.23 | 0.03 | 10.91 | 21,637.31 |
| | Transportation Land | 88.29 | 14.53 | 0.37 | 2.34 | 1.07 | 290.02 | 11.69 | 10.77 | 0.26 | 14.07 | 2.16 | 16.54 | 452.09 |
| | Grassland | 1.94 | 9.75 | 4.62 | 7.96 | | 5.06 | 666.72 | 3.56 | 1.09 | 47.00 | 1.15 | 1.00 | 749.85 |
| | Other construction land | 190.55 | 4.08 | | 10.58 | 0.49 | 12.52 | 1.94 | 528.63 | 0.48 | 19.09 | 2.50 | 13.59 | 784.45 |
| | Other forest land | 1.03 | 3.47 | 0.16 | 3.41 | | 0.09 | 1.45 | 0.30 | 2376.47 | 13.12 | 0.00 | 0.14 | 2399.64 |
| | Arbor forest land | 87.91 | 474.23 | 22.07 | 351.56 | 0.26 | 21.15 | 121.63 | 31.45 | 95.31 | 18,381.60 | 17.79 | 25.10 | 19,630.06 |
| | Artificial wetland | 10.66 | 2.54 | | 24.74 | | 0.97 | 11.02 | 30.08 | | 27.06 | 183.31 | 4.86 | 295.25 |
| | Swamp wetland | 57.31 | 1.25 | | 1.99 | 5.21 | 3.71 | 0.05 | 3.28 | 0.23 | 3.55 | 0.02 | 1002.48 | 1079.07 |
| | Total | 2810.27 | 12,908.90 | 272.34 | 5969.31 | 21,631.55 | 500.24 | 1122.32 | 720.41 | 2514.18 | 18,799.73 | 228.12 | 1247.62 | 68,724.99 |

**Table 2.** *Cont.*

| Scenario Type | Land Category in 2018 | Land Category in 2048 | | | | | | | | | | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | |
| Ecological protection scenario | Construction land for urban and rural residents | 1999.61 | 115.40 | | 9.86 | 0.76 | 19.10 | 3.90 | 11.88 | 0.53 | 28.29 | 2.18 | 53.39 | 2244.88 |
| | Farmland | 850.99 | 10,741.43 | 4.77 | 57.81 | 0.13 | 216.62 | 51.82 | 46.72 | 2.30 | 383.04 | 33.59 | 21.44 | 12,410.68 |
| | Industrial and mining construction land | | 23.43 | 188.93 | 2.13 | | 0.66 | 1.56 | 0.06 | 0.35 | 20.69 | | | 237.81 |
| | Shrub forest land | 1.28 | 7.18 | 0.54 | 6163.20 | 0.41 | 1.00 | 40.57 | 0.83 | 35.52 | 499.31 | 0.46 | 53.60 | 6803.90 |
| | Lake | 0.32 | 0.20 | | 0.36 | 21,624.10 | 0.22 | | 0.08 | | 0.25 | | 11.74 | 21,637.27 |
| | Transportation Land | 45.41 | 45.27 | 0.67 | 3.27 | 0.54 | 306.39 | 2.07 | 6.96 | 0.04 | 23.18 | 1.27 | 17.01 | 452.09 |
| | Grass land | 0.25 | 4.87 | 0.21 | 14.50 | | 0.83 | 624.55 | 0.13 | 1.00 | 102.19 | 0.60 | 0.70 | 749.85 |
| | Other construction land | 21.58 | 34.55 | | 3.96 | 0.14 | 15.23 | 0.17 | 667.95 | 0.27 | 33.81 | 0.71 | 6.08 | 784.45 |
| | Other forest land | 0.51 | 1.42 | 0.10 | 2.97 | | 0.00 | 1.00 | 0.07 | 2383.64 | 9.70 | 0.00 | 0.22 | 2399.64 |
| | Arbor forest land | 5.74 | 39.68 | 0.96 | 399.10 | 0.09 | 2.67 | 159.13 | 2.99 | 89.68 | 18,884.61 | 25.45 | 19.95 | 19,630.05 |
| | Artificial wetland | 0.20 | 0.85 | | 3.01 | | 0.04 | 2.05 | 0.31 | | 61.32 | 225.55 | 1.92 | 295.25 |
| | Swamp wetland | 3.42 | 1.11 | | 2.12 | 4.15 | 0.67 | 0.05 | 0.34 | 0.23 | 4.09 | 0.01 | 1062.88 | 1079.07 |
| | Total | 2929.30 | 11,015.40 | 196.19 | 6662.28 | 21,630.34 | 563.43 | 886.88 | 738.32 | 2513.56 | 20,050.49 | 289.82 | 1248.92 | 68,724.94 |

Note: 1—Construction land for urban and rural residents; 2—Farmland; 3—Industrial and mining construction land; 4—Shrub forest land; 5—Lake; 6—Transportation Land; 7—Grassland; 8—Other construction land; 9—Other forest land; 10—Arbor forest land; 11—Artificial wetland; 12—Swamp wetland.

### *3.5. Analysis of Land-Use Change Hotspots in the Study Area*

Figure 6 shows the comparison of land types in critical areas with respect to land-use changes under the three scenarios. Figure 7 shows the spatial distribution of hotspots of land-use changes. In terms of land use, the number of hotspots in the ecological protection scenario was the largest, with an area of 2369.34 $hm^2$. The number of hotspots under the production protection scenario was second, with an area of 1498.41 $hm^2$. Farmland and forest land were the hotspots in the Fuxian Lake basin. The growth of farmland space was mainly at the cost of reducing the spatial development of urban and rural residential construction land. The number of hotspots under the natural trend development scenario was the least, with an area of only 1086.21 $hm^2$. Farmland, arbor forest land, urban and rural residential construction land, and grasslands were all hotspots in the Fuxian Lake basin. The development of farmland and forest land was relatively strong, and there was a contradiction between squeezing and occupying land space.

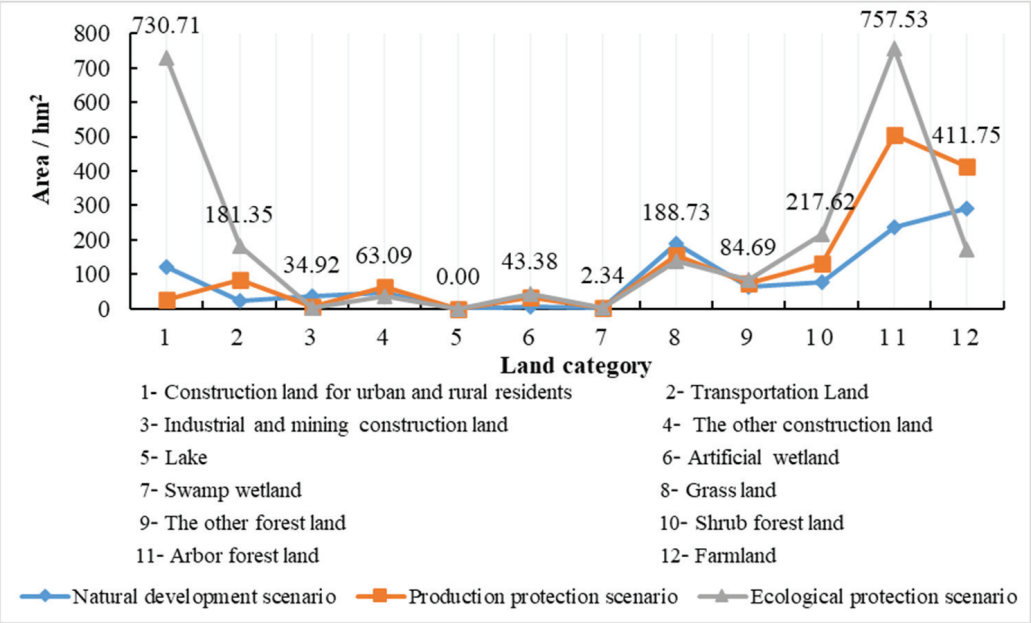


**Figure 6.** Comparison of land type area in hotspots.

In geographical space, the northern part of the study area consisting of the coast of the north Fuxian Lake and the southern land, was the hotspot of land-use changes. Under the ecological protection scenario, compared with the other two scenarios, shrubland had the smallest reduction and east of the northern bank of Fuxian Lake, the area with an average elevation of about 1800 m showed expansion. On the land north of Fuxian Lake, a large number of contiguous forest land showed a large number of infiltration expansions around the road. The land for construction and transportation of urban and rural residents was only dispersed and expanded from the original area. The reason is that this area was originally residential land and farmland, with gentle terrain and surrounded by forest land on three sides. In this situation, the development of forest land restricted the conversion of construction land outside the ecological space under the natural trend development scenario. The other forest land showed simultaneous expansion with forest land and shrub forest land on the south bank of the study area and west of the northern bank of Fuxian Lake; grassland, which had a reciprocal transformation relationship with arbor forest, expanded the most in this scenario. These results indicate that the conversion potential of the other forest land is very large and flexible, which can be used as the first consideration for the construction and occupation of the forest lands. At the same time, attention should be paid to the grassland to prevent the potential degradation of forest land into grassland. In the production protection scenario, the farmland in the northern part of the region with

the highest annual rainfall presented a large and concentrated development trend. At the same time, artificial wetlands such as reservoirs and ditches, which are helpful for irrigation and auxiliary uses, and transportation land have a certain growth distribution along with the expanded cultivated land. It shows that regional production development is closely related to transportation land and artificial wetland, and it is important to consider the development of such land in land planning in regards to the development of production.

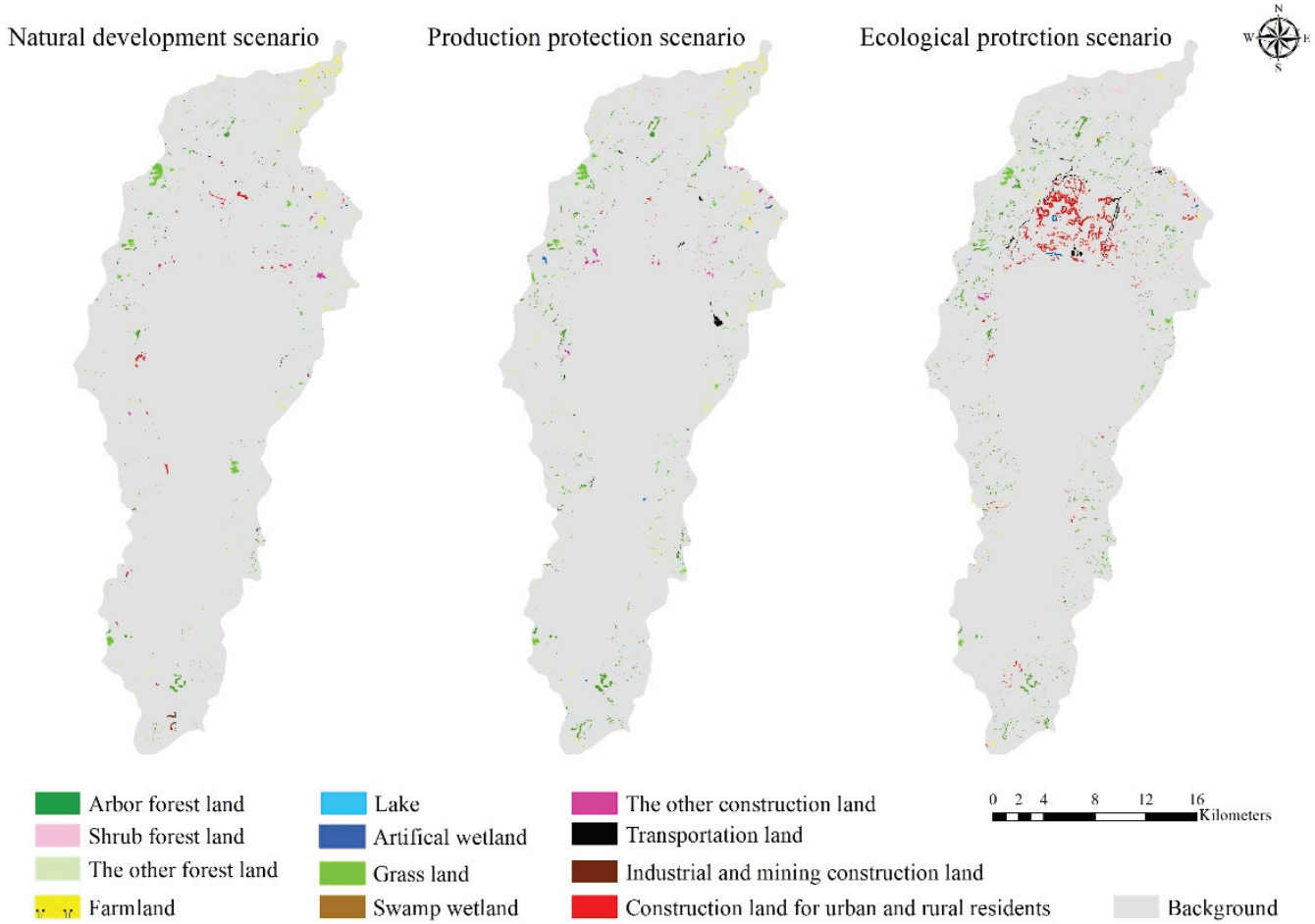


**Figure 7.** Spatial distribution map of land types in hotspots of land-use changes.

## 4. Discussion

### *4.1. Driving Forces and Suggestions for Land-Use Change*

In this study, the PLUS model was used to explain the influence of driving factors on land use and land cover from a qualitative perspective. In the Fuxian Lake basin, the land type mainly involved in terrestrial ecological protection, such as arbor forest land, other forest land, and grassland, and the land type most suitable for product development, such as farmland, were greatly affected by the human factor of the distance between the main roads and the natural factor of rainfall. Natural factors such as elevation and soil distribution had a great influence on the wetlands, such as swamp wetlands and artificial wetlands. The land types mainly used for urban construction, such as transportation land, urban and rural residents' construction land, other construction land, and industrial and mining construction land, were greatly affected by natural factors such as elevation and soil distribution, and human factors such as trunk road distance, per capita GDP, and population density. Based on the driving effects of land-use changes, the conflict between production development and ecological protection should be fully considered in the Fuxian Lake Basin [50] so as to reasonably update the main driving factors of land-use changes. In the future process of land-use development and protection, we can refer to the main driving

factors of land-use changes in this study, and give the driving factors greater influence in planning, project construction site selection, and ecological service improvement.

### *4.2. Land Change Trends and Benefits in Different Scenarios*

The predicted land-use types in the Fuxian Lake basin have continued the historical change trend since 1990. Lakes, arbor forests, farmland, and shrub forests are still the dominant land types in the Fuxian Lake basin. The lake area is relatively stable, and the artificial surface area is slightly growing. The land-use development changes are still dominated by ecological protection and production protection measures. Three land-use scenarios were adopted for simulation and prediction based on the characteristics of land-use development in the Fuxian Lake basin. The results of the multi-scenario simulation showed that the forecast direction of land-use change is quite different in different land-use control scenarios. The results of the multi-scenario simulations showed that under the natural trend development scenario, farmland took over a lot of arbor forests, shrubbery turned into grassland, and the construction land of urban and rural residents developed on farmland, swamp wetlands, and other types of land; under the production protection scenario, farmland expanded. Under the ecological protection scenario, arbor forest land expanded. Under the production protection scenario, farmland expanded. By predicting future land-use changes, the direction of regional land-use development can be mastered, which is helpful for decision makers to evaluate and plan regional land-use development modes and optimize land-use structure in future constructions [51]. The results of our simulations and predictions are also consistent with the current regional development pattern. Our model is a valuable reference for policies for future land-use space control, governance, and even restoration in the Fuxian Lake basin.

### *4.3. Fuxian Lake Basin Hotspot Changes and Land-Use Suggestions*

Our results can provide a theoretical basis and methodological support for land-use prediction and future ecosystem service value calculation under different development constraints. The main direction of land-use change in the Fuxian Lake basin is the conversion between farmland and forest land and the continuous expansion of construction land. From the perspective of spatial distribution patterns, the hotspot change plots are mainly concentrated in the northern part of the basin and along the northern coast of Fuxian Lake. The analysis of the development direction of the different land types and the hotspots of land types in different scenarios helps provide theoretical support for land-use planning, ecological governance and restoration, and agricultural development and protection in the Fuxian Lake basin. The reduction of cultivable land will have an impact on food security. The red line of cultivated land protection should be strictly observed, the production efficiency of cultivated land should be improved, and existing cultivated land should be intensively used. Shrub forest land and forest land are the main types of forest land transfer, so attention should be paid to the protection and restoration of forest land in key ecological areas [52], and the direction of land-use conversion between ecological space and production space should be adjusted. Considering the current characteristics of regional urbanization development, on the one hand, the transfer of cultivated land should be restricted, and on the other, the transfer of forest land should be controlled to ensure that there will be no drastic changes in the ecosystem in urbanized areas [42] and effectively mitigate the continuous crowding out of ecological and production space by artificial surface expansion.

### *4.4. Consideration of Simulation Accuracy of Land-Use Change Based on PLUS Model*

The overall simulation accuracy of land-use prediction in this study is slightly lower than that simulated by other researchers using the PLUS model. On the one hand, the historical data used in the study spans about 30 years, and the data resolution is not high enough due to the impact of data quality and technological development, which is an inevitable objective factor. On the other hand, although the influence of climate change,

human activities, and other factors were comprehensively considered in the process of formulating the simulation rules, six driving factors, including natural and human factors, were extracted to improve the accuracy of the model as much as possible. However, due to the limitations of acquisition of some data, there are still some factors (such as settlement distribution data [53], mean annual temperature data [54], and soil organic carbon data [55]) that cannot be fully considered. In future studies, efforts will be made to collect higher-resolution land classification data and incorporating more drivers that include both natural and human factors. To improve its accuracy, the simulation of land-use changes may be made more scientific, reasonable, and pertinent. Thus, it may more effectively encourage the preservation, repair, and enhancement of land resources and contribute to the region's sustainable development.

## 5. Conclusions

This study used the PLUS model to analyze the spatiotemporal evolution of land use/land cover and the driving factors of land-type change in the Fuxian Lake basin from 1990 to 2018. The present study predicted land-use quantity, spatial distribution characteristics, and change trends in three scenarios in 2048. Specifically, this study showed:

1. The land types in the Fuxian Lake basin, which mainly focused on land ecological protection and production development, were greatly affected by the natural factor of rainfall and the human factor of the distance from the trunk road. The land type dominated by urban construction was greatly affected by the natural factors of elevation and soil distribution, and human factors of trunk road distance, per capita GDP, and population density.

2. The predicted land-use types in the Fuxian Lake basin have continued the historical change trend since 1990. Lakes, arbor forests, farmland, and shrub forests are still the dominant land types in the Fuxian Lake basin. The lake area is relatively stable, and the artificial surface area is slightly growing. The land-use development type is still dominated by ecological and production protections.

3. The results of a multi-scenario simulation showed that under the natural trend development scenario, farmland occupied a large number of arbor forests, the shrub forest land largely degenerated into grassland, and the urban and rural residents' construction land expanded onto farmland, swamp wetlands, and other land types. Farmland showed an increasing trend under the production protection scenario. Under the ecological protection scenario, the arbor forest land showed positive growth, while the negative growth rate of shrub forest land decreased. In the Fuxian Lake basin, the main direction of land-use changes is the exchange of farmland and forest land, as well as the constant growth of construction land.

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# Analysis of Spatiotemporal Interaction Characteristics and Decoupling Effects of Urban Expansion in the Central Plains Urban Agglomeration

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**Abstract:** In recent years, the rapid improvement in the urbanization level of the Central Plains urban agglomeration is bound to bring about significant changes in urban land expansion and economic development. However, at present, there is little attention paid to the research on the spatiotemporal interaction characteristics of urban expansion and the interaction between urban expansion and economic development in this region, and existing research lacks a geographical analysis perspective. This study uses spatial autocorrelation, hot spot analysis, LISA time path, and standard deviation ellipse models to analyze the spatiotemporal interaction characteristics of urban expansion in the Central Plains urban agglomeration from 1990 to 2020, and it uses bilateral spatial autocorrelation and decoupling models to analyze the spatial correlation and decoupling effects of urban expansion and economic development. The results show that (1) the urban built-up area of the Central Plains urban agglomeration as a whole is growing in a "J" shape, and the expansion rate has increased rapidly in the past 10 years. (2) The spatial expansion of the city is mainly in the direction of "northwest–southeast"; the directionality has been gradually strengthened in the past 10 years, mainly in the direction of several prefecture-level cities under the jurisdiction of Anhui Province, and the spatial center of gravity of the city has shifted significantly to the south. (3) The spatial agglomeration characteristics of urban expansion in the Central Plains urban agglomeration are not obvious; local hot spots are concentrated in Jiaozuo and its surrounding areas, and urban expansion has local spatial structural instability. (4) During the 2005–2020 period, the risk of uncoordinated urban expansion and economic growth in the Central Plains urban agglomeration increased. This study is of great significance for the rational control of regional development, providing empirical reference for the formulation of the development planning of the Central Plains urban agglomeration, as well as providing a reference for research ideas and methods related to urbanization.

**Keywords:** urban expansion; spatiotemporal interaction; decoupling effect; Central Plains urban agglomeration

## 1. Introduction

The improvement of urbanization level is the main driving force for regional economic development [1], and it is also an important symbol of population non-agriculturalization and the progress of human civilization. According to the "World Cities Report 2020", the world will further urbanize in the next decade, and the proportion of global urban population is expected to reach 60.4% by 2030 [2]; population urbanization is bound to promote the further development of urban expansion [3]. China is in a period of rapid urbanization, with the disorderly expansion of cities causing waste of land resources [4,5], with some cities experiencing aggressive "incremental" expansion, and the phenomenon of "ghost cities" has emerged. Extensive urban expansion can exacerbate urban displacement

and affect quality of life [6]. Relevant research indicators should pay more attention to the improvement of housing quality, as well as the improvement of urban housing quantity [7]. With the development of technology, especially the development of the digital economy, the economic growth of cities is not at the cost of consuming land resources. Urban expansion is the most intuitive manifestation of urbanization. Therefore, the exploration of the characteristics of urban expansion and the analysis of the relationship between urban expansion and economic growth have become research fields of concern to scholars.

At present, there are many related studies on urban expansion in academic circles. From the perspective of the research content, it mainly includes the following aspects: First, there is research on urban expansion based on mathematical statistics. The commonly used evaluation perspectives include urban expansion intensity, expansion speed, expansion direction, urban compactness, etc. [8–10]. Second, there are studies about the spatiotemporal pattern characteristics of urban expansion: more scholars analyze the spatial agglomeration characteristics of urban expansion and landscape pattern characteristics, and the common methods include spatial statistical analysis and landscape pattern index in landscape ecology [11,12]. Third is the study of drivers of urban expansion [13,14], and fourth is the study of simulation and prediction of urban expansion [15–17], in which meta-automata are often used to simulate urban expansion. Fifth, there is the study of the interaction between urban expansion and transportation, ecological environment, and peri-urban agriculture [18–20]. Statistical data, remote sensing image interpretation data, and nighttime lighting data are often used to calculate the area of urban built-up areas in different periods [9,13,21]. The above research contents, methods and data sources can reflect the spatiotemporal characteristics of urban expansion and its impacts from different aspects, which have important academic values. However, the analysis of spatiotemporal patterns of urban expansion mostly separates time and space, ignoring the study of the spatial and temporal interaction characteristics of the urban expansion process.

Urbanization in China has led to accelerated urban expansion, and urban expansion is significantly correlated with gross domestic product (GDP) per capita [22]. Studies have shown that economic development affects the process of urban expansion, but in the long run, economic development also inhibits urban expansion, and urbanization and economic development have a positive impact on environmental degradation [23,24]. The growth of China's urban economy is influenced by the land factor [25], and moderate urban sprawl has a significant positive impact on economic development, while excessive urban sprawl has a significant negative impact on economic development [26]. China's urban expansion is highly uneven between provinces and municipalities, and the "core–periphery" growth pattern of cities has exacerbated economic disparities between Chinese provinces and municipalities [27]. At present, different scholars have studied the relationship between urban expansion and economic development from different perspectives. One category is to measure the correlation between urban sprawl and economic development [28]; Zhang analyzed the relationship between urban sprawl and economic development using regression analysis. The results show that the level of economic development of a city is positively correlated with urban land expansion [29]. Xie explored whether there is an inevitable link between urban construction land expansion and economic growth using 108 prefecture-level cities in the Yangtze River Economic Belt, and the results show that urban expansion in the Yangtze River Economic Belt has a catalytic effect on its own economic development, as well as the development of its surroundings [30]. Another type of analysis is related to the perspective of the coupling and coordination of urban land use changes with population, land finance, economic growth, and ecological changes in the urbanization process [31–33]. Previous research is of great significance to recognize the relationship between urban expansion and economic growth, but the analysis perspective seldom considers the degree of separation between urban expansion and its own economic development and the spatial correlation with the economic development of surrounding regions.

China has a vast territory and significant regional differences, with different levels of urbanization in various regions [34–36]. As the fourth growth pole of China's economy, the Central Plains urban agglomeration has a medium level of urbanization in the country, and there is significant room for improvement in its urbanization level. Urban agglomeration is a spatial organization form of urban development, with closely related internal functions. Therefore, at the critical stage of its urbanization process, it is necessary to recognize the spatiotemporal evolution characteristics of urban expansion in the Central Plains urban agglomeration. Given the two-way causal relationship between urban expansion and economic development [37], it is of important practical significance to recognize the regional difference pattern of the correlation between urban expansion and economic development in order to promote high-quality urbanization and narrow the gap between urban expansion and economic development. Therefore, this study is based on vector data of urban built-up area scope, and the ESTDA model is used to explore the spatiotemporal interaction characteristics of urban expansion from both temporal and spatial dimensions in the Central Plains urban agglomeration. After that, using bivariate spatial autocorrelation and decoupling models, this paper explores the correlation between urban expansion and surrounding economic development in the Central Plains urban agglomeration, as well as the coordination with its own economic development. The results of this study have important theoretical and practical significance for clarifying the development and control objectives of urban expansion in the Central Plains urban agglomeration, providing important reference significance for formulating reasonable regional development policies for the Central Plains urban agglomeration, as well as providing new research perspectives and methods for the analysis and evaluation of the process of urban expansion in the academic community.

## 2. Materials and Methods

### *2.1. Study Area*

The Central Plains urban agglomeration is one of the seven major urban agglomerations in China, located in the central-eastern part of China. According to the "Central Plains Urban Agglomeration Development Plan" released by the State Council in 2016, the Central Plains urban agglomeration includes 30 prefecture-level cities in 5 provinces, including Henan Province, Shanxi Province, Hebei Province, Shandong Province, and Anhui Province, as shown in Figure 1; among them, Zhengzhou City is the center and Luoyang is the subcenter. The total area is 287,000 square kilometers, the total population is about 158 million people, and the total GDP was about CNY 8 trillion and 100 billion in 2020. There is good natural endowment, the advantages of both the north and south, and the terrain is mainly plains and hills, with climate conditions in the transition zone of the north and south that constitute a good human living environment. The Central Plains urban agglomeration, with a lower level of economic development than the Yangtze River Delta Urban Agglomeration, the Pearl River Delta Urban Agglomeration, and the Beijing–Tianjin–Hebei Urban Agglomeration, is the fourth growth pole and an important power source of China's economic growth, with a good industrial base. According to the 2017 annual development report of the Central Plains urban agglomeration, the urbanization rate of the permanent population is 49.6%. According to the recent goal of the "Central Plains Urban Agglomeration Development Plan", the urbanization rate of the permanent population will exceed 56% by 2020. In terms of transportation, it is a must-go road to carry east and west and connect north and south. The Central Plains urban agglomeration is of strategic importance to the Central China and even the whole country in promoting urbanization and widening the space for economic development.

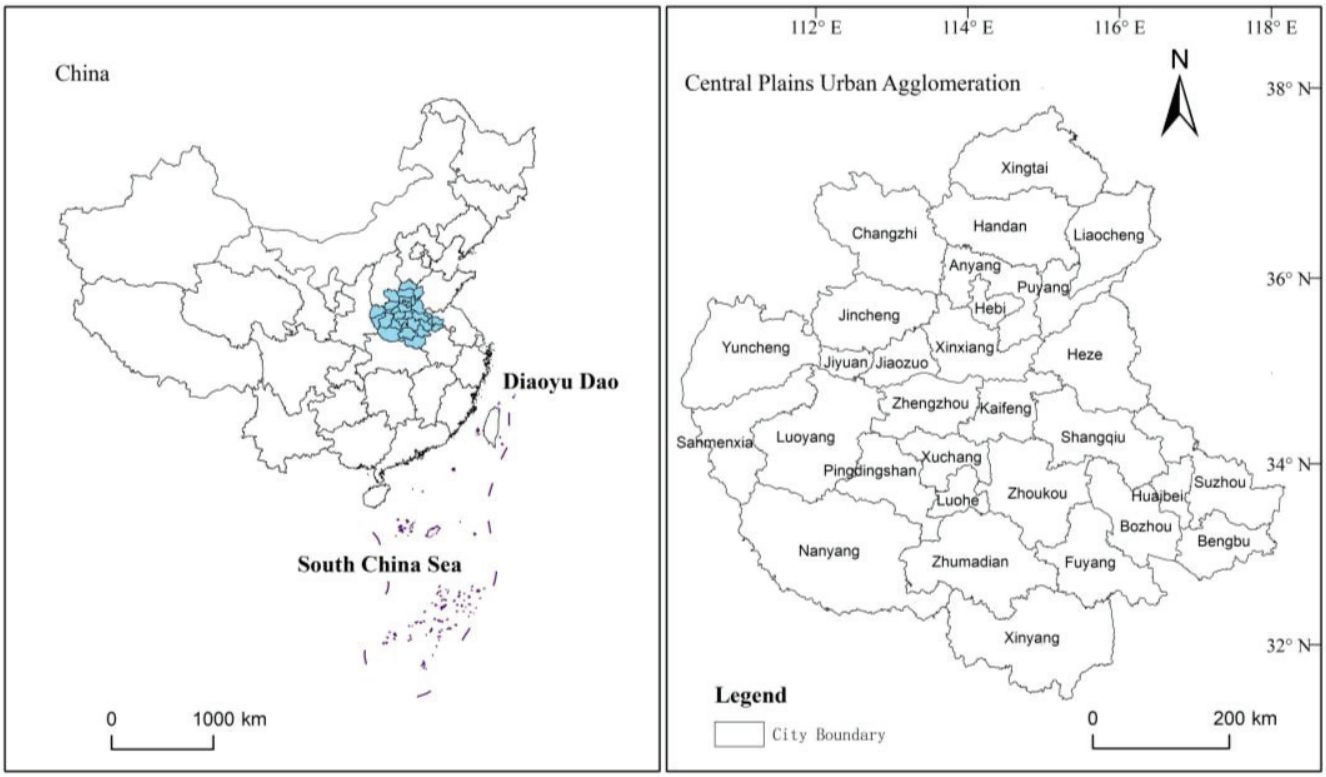


**Figure 1.** Location and study area: Central Plains urban agglomeration.

### *2.2. Data Sources*

Most studies have used raster data or statistical yearbook data as the data source to analyze urban expansion. Given the limitations of the accuracy of these two types of data, vector data can portray the spatial pattern and actual area of urban built-up areas with higher accuracy. Therefore, this paper selects "A standardized dataset of built-up areas of China's cities with populations over 300,000 for the period 1990–2015 (https://www.doi.org/10.11922/sciencedb.j00076.00004 (accessed on 1 August 2022))" [38], as well as "A dataset of built-up areas of Chinese cities in 2020 (https://doi.org/10.11922/sciencedb.j00001.00332 (accessed on 1 August 2022))" [39]. This dataset is the vector data of urban built-up areas published by Science Data Bank and the Chinese urban dataset, developed with reference to the United Nations built-up area standard. It is produced with high-precision data sources, and the data products are highly accurate, with an average overall accuracy and kappa coefficient of 92% or more, meeting the current requirements of urban sustainable development research. As a result, they can be of greater use in applications such as urban expansion analysis and environmental assessment. Using the 2020 administrative division range as the standard, the original data were cropped and merged to form the vector data of the urban built-up area range of the Central Plains urban agglomeration for six periods. In order to maintain the accuracy of the area, the original data projection is uniformly converted to a Lambert equal area projection. Administrative division map vector data were obtained from the standard map service website (http://bzdt.ch.mnr.gov.cn/ (accessed on 1 August 2022)). GDP data for municipal districts for each year were obtained from the China City Statistical Yearbook for each year and were adjusted according to the administrative divisions in 2020. The GDP data of municipal districts in each year were obtained from the China City Statistical Yearbook of each year, and were grouped and adjusted according to the administrative divisions in 2020. In order to ensure the comparability of GDP in different years, it was uniformly adjusted to the real GDP, with 2005 as the base period, by calculating the GDP deflator.

### *2.3. Methods*

#### 2.3.1. Expansion Intensity Index

Expansion intensity is the ratio of urban built-up area expansion to the land area of a region within a certain time span, and it is often used to compare the strength, speed, and trend of urban built-up area expansion within a region in different periods [40]. The formula is

$$I = \Delta U / (\Delta t * TA) * 100\% \quad (1)$$

where I is the expansion intensity; TA is the total urban land area in the study area; ΔU is the expansion area of urban built-up area in different periods; and Δt is the time interval. The larger I is, the greater the expansion intensity of urban built-up area in the characterized region; I can be used to compare the spatial differences of urban expansion in different spatial units.

#### 2.3.2. Exploratory Spatiotemporal Data Analysis

Exploratory spatiotemporal data analysis (ESTDA) is a collection of spatial data analysis methods. It includes global spatial autocorrelation, local spatial autocorrelation, LISA spatiotemporal path, LISA spatiotemporal leap, etc. It is mainly used to analyze the spatial and temporal attribute data of geographic feature datasets and is a key research field of geographic information science (GIS) [41]. The ESTDA analysis will take into account spatial relevance based on geographical perspectives, as well as temporal factors. It overcomes the defect that traditional exploratory spatial analysis (ESDA) ignores the temporal element.

The Global Moran's I index was selected to identify the overall spatial pattern characteristics of the study area's urban sprawl with statistical significance [42]. The Global Moran's I index takes values between $-1$ and 1, with values less than 0 indicating negative spatial correlation, i.e., a spatial unit and its neighbors have similar "low–low" attributes clustered together, values equal to 0 indicating no correlation, i.e., an attribute value of a spatial unit is randomly distributed in space, and values greater than 0 indicating positive spatial correlation. In other words, the spatial unit and its neighbors have similar "high–high" attributes clustered together; the closer its value is to 0, the less concentrated the spatial distribution of a certain attribute of the spatial unit, and the closer its absolute value is to 1, the more obvious the spatial clustering of a certain attribute of the spatial unit.

In order to measure the local spatial correlation pattern, the local Getis–Ord Gi* index was selected in this study to identify urban sprawl hot and cold spots with statistical significance [43], i.e., it is used to identify the correlation degree of spatial location i, within a distance of d, with other spatial locations j. When the Z value is positive and statistically significant, it represents that the value within the region of distance d around cell i is greater than the regionwide expected value, presenting high value clustering, i.e., hot spot region; when the Z value is negative and passes the significance test, it represents that the value within the distance d region around cell i is less than the expected value of the whole region for low-value spatial clustering, i.e., cold spot region.

In order to explore the spatial correlation between the expansion of urban space and economic development, this study selects bivariate spatial autocorrelation to measure the spatial correlation between the two [44]. The global bivariate Moran's I can analyze the spatial correlation of the two attributes in the whole study area. If the bivariate autocorrelation coefficient is significantly positive, it indicates that the two attributes are spatially positively correlated and tend to be global; if the bivariate autocorrelation coefficient is significantly negative, it indicates that the two attributes are spatially negatively correlated and tend to be globally dispersed. Bivariate local Moran's I can analyze the local spatial correlation of the two attributes. If the local bivariate autocorrelation coefficient is significantly positive, it indicates that the two attributes are spatially positively correlated at spatial cell i. If the local bivariate autocorrelation coefficient is significantly negative, it indicates that the two attributes are spatially positively correlated at spatial unit I, which then indicates that the two attributes are spatially negatively correlated at spatial unit i.

LISA time path analysis, by calculating the geometric characteristics of coordinate movement trajectories of spatial units in Moran scatter diagrams, analyzes the spatially and temporally dependent interactive change characteristics of urban expansion intensity at local scales in a certain period, thus transforming spatially dependent characteristics into dynamic expressions. The main measures of LISA time path include relative length and curvature, which are calculated as follows [45]:

(1) Relative length of LISA time path

$$Len_i = \frac{n * \sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}{\sum_{i=1}^{n} \sum_{t=1}^{T=1} d(L_{i,t}, L_{i,t+1})} \quad (2)$$

where $n$ is the number of research units; T is the annual time interval; $L_{i,t}$ is the LISA coordinate of the research unit in year $t$; and $d(L_{i,t}, L_{i,t+1})$ is the moving distance of research unit $i$ from year $t$ to year $t + 1$. The larger the $d$, the stronger the dynamic of the local spatial structure; $d > 1$ represents that the moving distance of research unit $i$ is greater than the average of the moving distance of research units.

(2) LISA time path curvature

$$C_i = \frac{\sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}{d(L_{i,1}, L_{i,\mathrm{T}})} \quad (3)$$

where $d(L_{i,1}, L_{i,t})$ is the moving distance of research unit $i$ from the first year to the last year. The larger $C_i$ is, the more curved the LISA time path is, and the more tortuous local spatial structure fluctuations are. If $C_i > 1$, it indicates that the moving tortuosity of research unit $i$ is higher than the average.

2.3.3. Standard Deviation Ellipse

The Standard Deviational Ellipse (SDE) model is a method for measuring the characteristics of the directional distribution of spatial data [46,47]. In the standard deviation ellipse, the long semiaxis represents the directional characteristics of the distribution of the data, and the short axis represents the range of the distribution of the data; the larger the difference between the long and short semiaxes, the more significant the directional distribution characteristics of the data, and the shorter the short semiaxis, the more pronounced the centripetal force of the data [48]. This study uses the standard deviation ellipse model to analyze the spatial party evolution characteristics of urban expansion in the Central Plains urban agglomeration in different periods, as well as the spatial distribution pattern characteristics. The three parameters of the standard deviation ellipse are the center of the circle, the angle of rotation, and the length of the $X$- and $Y$-axis, which are calculated as follows [49]:

(1) Center of ellipse:

$$SDE_x = \sqrt{\frac{\sum_{i=1}^{n} (\mathrm{x_i} - \bar{x})^2}{n}}$$
$$SDE_y = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{n}} \quad (4)$$

(2) Rotation angle:

$$\tan\theta = \frac{(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2) + \sqrt{(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2)^2 + 4(\sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i)^2}}{2\sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i} \quad (5)$$

(3) Standard deviation of *X*-axis and *Y*-axis:

$$\sigma^x = \sqrt{\frac{\sum_{i=1}^{n} (\widetilde{x}_i \cos\theta - \widetilde{y}_i \sin\theta)^2}{n}}$$
$$\sigma^y = \sqrt{\frac{\sum_{i=1}^{n} (\widetilde{x}_i \sin\theta - \widetilde{y}_i \cos\theta)^2}{n}} \quad (6)$$

where $x_i$ and $y_i$ represent the spatial coordinates of each element; $\overline{x}$ and $\overline{y}$ are the arithmetic mean center; $\widetilde{x}$ and $\widetilde{y}$ are the deviation of the $x$ and $y$ coordinates from the mean center; and $n$ is the total number of elements.

2.3.4. Decoupling Model

The Tapio decoupling model is based on the decoupling elasticity to construct evaluation indicators; it was widely used because it was not affected by the error caused by the choice of the base period [50,51]. This paper constructs a decoupling elasticity model of urban expansion and economic growth based on the Tapio model to comprehensively analyze the disengagement of the relationship between urban spatial expansion and economic growth, where the urban built-up area change is used to denote the urban spatial expansion variable and the municipal GDP is used as the economic variable to construct the following decoupling model:

$$e = \frac{\Delta A / A}{\Delta GDP / GDP} \quad (7)$$

where e is the decoupling elasticity, and ΔA and ΔGDP are the amount of change in the built-up area of the municipal area and GDP at the beginning and end of the study, respectively. Based on the magnitude of the e value, with reference to the decoupling state set by Tapio, the decoupling state is specifically divided into three states and eight levels, and the specific classification criteria are listed in the following Table 1.

**Table 1.** Criteria for delineating the degree of decoupling between urban expansion and economic growth.

| Decoupling Type | | ΔA | ΔGDP | Decoupling Elasticity (e) |
|---|---|---|---|---|
| Negative decoupling | Growth negative decoupling | >0 | >0 | e > 1.2 |
| | Strong negative decoupling | >0 | <0 | e < 0 |
| | Weak negative decoupling | <0 | <0 | 0 < e < 0.8 |
| Decoupling | Weak decoupling | >0 | >0 | 0 < e < 0.8 |
| | Strong decoupling | <0 | >0 | e < 0 |
| | Recession decoupling | <0 | <0 | e > 1.2 |
| Connections | Growth Links | >0 | >0 | 0.8 < e < 1.2 |
| | Recession Link | <0 | <0 | 0.8 < e < 1.2 |

## 3. Results

### *3.1. Analysis of Urbanization Scale Change Characteristics*

From 1990 to 2020, the urban built-up area of the Central Plains urban agglomeration expanded by 3159.06 km$^2$, with an average annual expansion of 105.3 km$^2$. As shown in Table 2, the total area of urban expansion in different periods showed a gentle "J"-type exponential growth, indicating that the urban expansion of the Central Plains urban

agglomeration showed a gradual upward trend and a state of active expansion. The total expansion area in the 2010–2015 and 2015–2020 periods exceeded 800 km$^2$, with a total expansion area of 1670.18 km$^2$, accounting for one half of the total expansion area. The expansion speed in both periods exceeded 160 km/a, a significant increase compared with 53.72 km/a in the 1990–1995 period, indicating that urban construction efforts have been significant in the past 10 years, with a significant expansion of the urban scope, and the overall regional urban construction is less subject to government regulation and control.

**Table 2.** Change in urban built-up area in Central Plains urban agglomeration.

| Index | 1990–1995 | 1995–2000 | 2000–2005 | 2005–2010 | 2010–2015 | 2015–2020 |
|---|---|---|---|---|---|---|
| Area growth (km$^2$) | 268.63 | 303.72 | 344.24 | 572.29 | 816.45 | 853.73 |
| Average annual expansion (km$^2$/year) | 53.726 | 60.744 | 68.848 | 114.458 | 163.29 | 170.746 |

The intensity of the expansion varies from different periods and shows clear phase-by-phase characteristics. As shown in Figure 2, it can be roughly divided into three stages, of which the 1990–2005 period is the first stage, during which the regional urban sprawl index grew more slowly, indicating that during this 15 years period, the whole area of the region grew more evenly and maintained a stable development trend. The period of 2005–2015 is the second stage, with a steep linear rise in the expansion intensity index, also reflecting the dramatic increase in the volume and rate of area growth during this period, during which the urbanization process accelerated. In the third stage in the 2015–2020 period, the expansion intensity still maintained an upward trend, but the increment slowed down. In recent years, the country has attached great importance to the construction of ecological civilization and urban human settlements, and it is not pursuing increments in urban expansion.

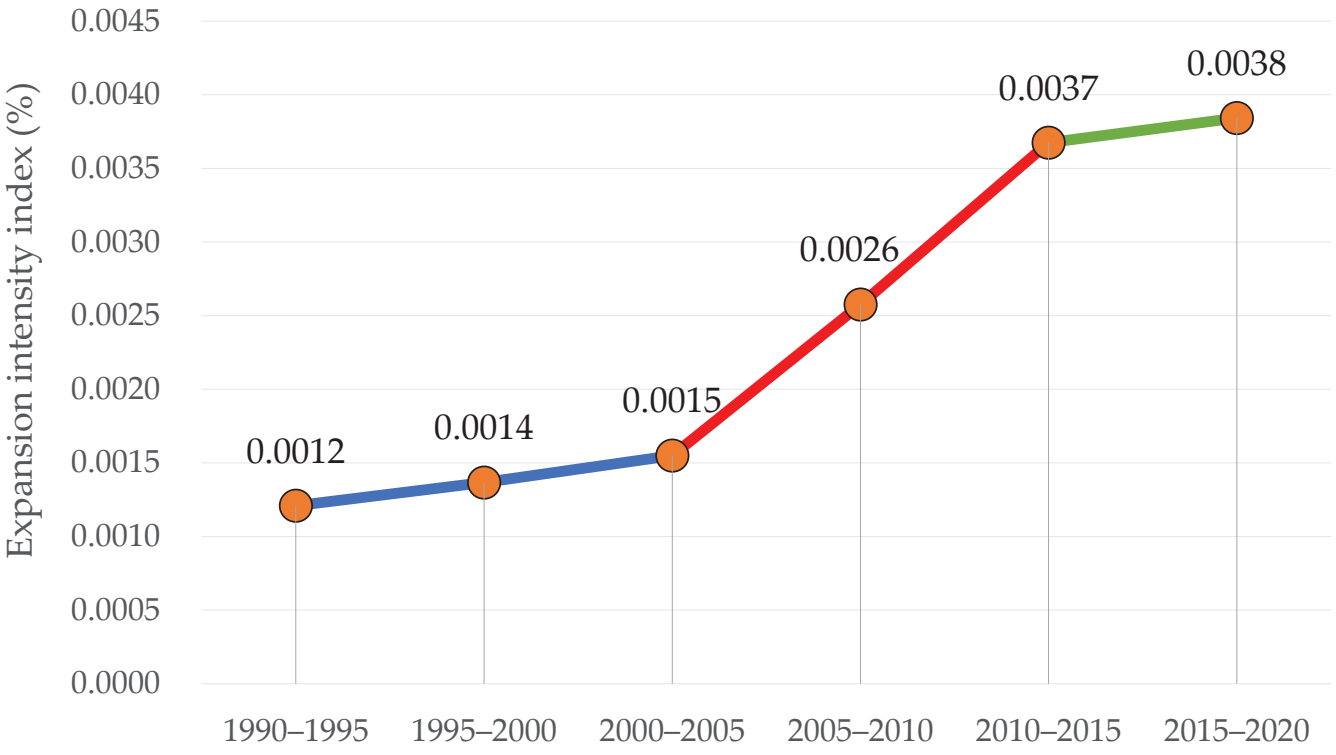


**Figure 2.** Expansion intensity Central Plains urban agglomeration in different periods.

As shown in Figure 3, from the city scale, the expansion intensity of Zhengzhou is increasing year by year, which reflects that the urbanization development of Zhengzhou, as

the core city of the Central Plains urban agglomeration, has been accelerating, and the level of urban expansion has been increasing. The regional development strategy of Zhengzhou of "expanding to the east, expanding to the west, extending to the south and linking to the north", as well as the planning of many new areas around Zhengzhou, have made the urban built-up area of Zhengzhou expand continuously. As a municipality directly under the central government of Henan Province, the intensity of urban expansion in Ji yuan has been at a high level compared with other cities. The built-up area of the city has increased from 3.67 $km^2$ in 1990 to 48.21 $km^2$ in 2020. Ji yuan has been adhering to the strategy of strengthening the city through industry in recent years. The development of industry has made considerable progress, which has led to employment, population concentration, and urban expansion. Luoyang, Anyang, Xinxiang, Pingdingshan, Jiaozuo Zhumadian, Puyang, and Jincheng have a moderate level of urban expansion. The rest of the cities have lower levels of expansion intensity, among which Xinyang, Sanmenxia, Changzhi, and Suzhou had the weakest expansion intensity during 30a, indicating that the urban expansion process in these regions is slower than other regions, and the regional development is at a lower level in the region.

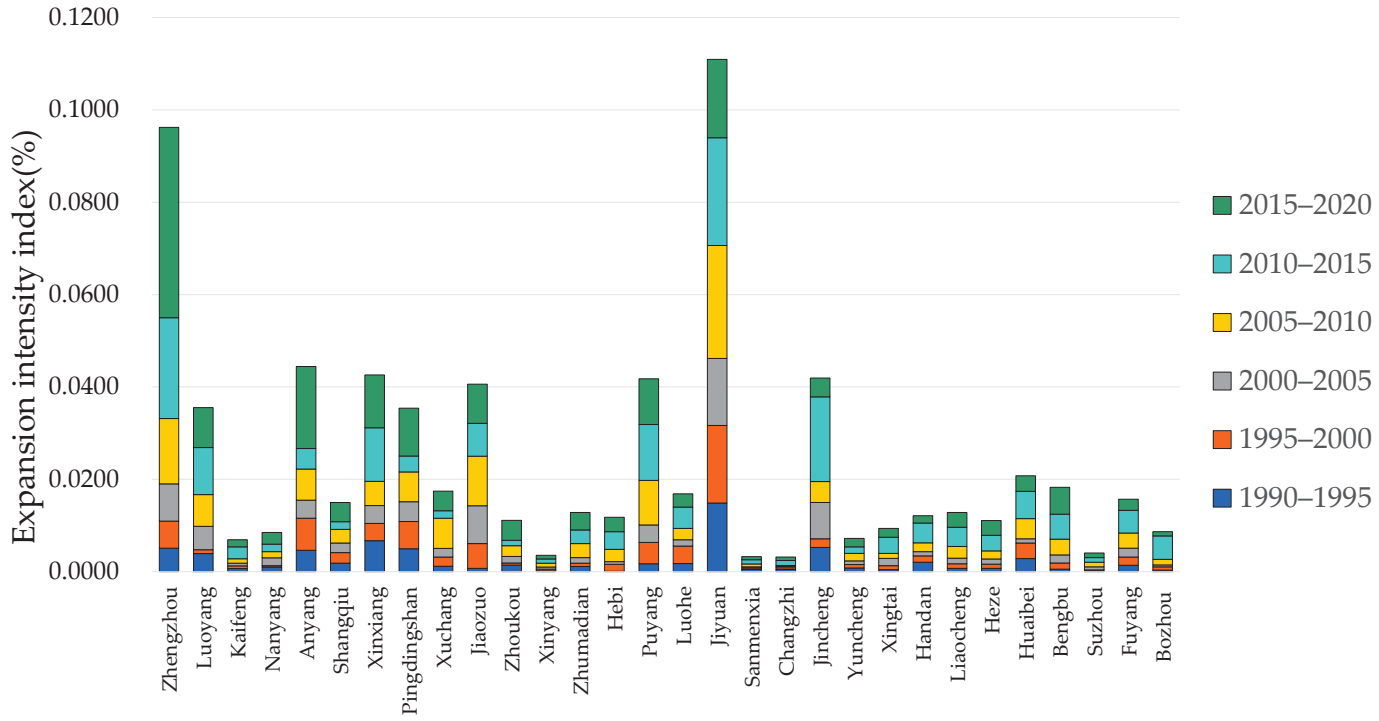


**Figure 3.** Expansion intensity of different cities in different periods.

### *3.2. Analysis on the Evolution Characteristics of Urbanization Direction*

The standard deviation ellipse of urban built-up areas in each period was calculated by using the directional distribution tool in ArcGIS software to measure the directional distribution characteristics of urban areas in different periods. The calculation results are shown in Table 3 and Figure 4. Overall, the urban space of the Central Plains urban agglomeration has been mainly in the direction of "northwest–southeast" in the past 30 years. From 2010 to 2020, the elliptical azimuth angle changed from 148.93° to 125.5°; the direction of urban expansion is advancing eastward. After 2010, with the continuous optimization and upgrading of the internal structure of the urban system, resources have been used efficiently, and the economy, society, and environment of urban agglomerations have developed in a coordinated manner. Some cities will step into the new development stage, mainly present in the east extension and driven by Zhengzhou and Luoyang. From the perspective of ellipse oblateness, the ellipse oblateness gradually decreased from 0.25 to

0.16 from 1990 to 2010, and the directionality of urban space expansion became weaker and weaker. During this period, all regions are in a period of urgent need for development. Due to the gradual reduction in directionality brought by external forces, urban construction mainly assumes a regional "natural" growth. From 2010 to 2020, the oblateness rate gradually increased, from 0.16 to 0.35, and the direction gradually strengthened, mainly extending to Anhui Province. From 1990 to 2015, the total area of the ellipse gradually decreased from 1.23 to 0.98, indicating that the centripetal force of urban development was obvious during this period; the expansion of urban space was mainly in the form of "filling", and the urban land space was relatively concentrated. From 2015 to 2020, it increased slightly, showing the trend of "extension" in urban expansion.

**Table 3.** Standard deviation ellipse parameters of different periods.

| Year | 1990 | 1995 | 2000 | 2005 | 2010 | 2015 | 2020 |
|---|---|---|---|---|---|---|---|
| Area ($km^2$) | 1.23 | 1.12 | 1.06 | 1.05 | 1.06 | 0.98 | 1.10 |
| Elliptical azimuth | 125.3° | 136° | 141.30 | 143.31 | 148.93 | 119.96 | 125.50 |
| Elliptical oblateness | 0.25 | 0.18 | 0.20 | 0.17 | 0.16 | 0.20 | 0.35 |

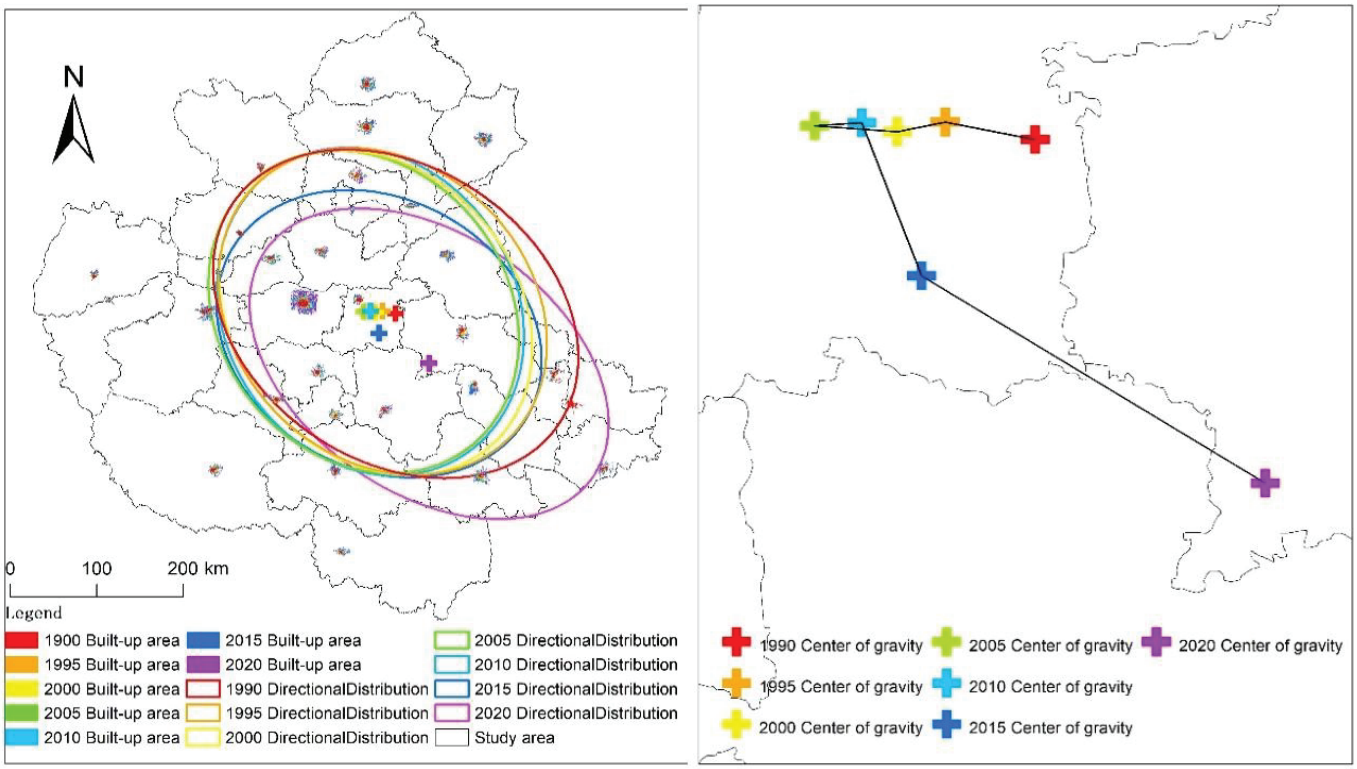


**Figure 4.** Standard deviation ellipse of urban built-up area and distribution of urban center of gravity.

Using the average center tool in ArcGIS 10.7 (ESRI Inc., Redlands, CA, USA), the urban center of gravity of the Central Plains urban agglomeration in each period was calculated, and the results are shown in Figure 4. From the perspective of the distribution of the center of gravity of the urban space, the center of gravity of the entire region hovered in Kaifeng from 1990 to 2010. Since 2010, the urban center of gravity has continuously moved in a southeast direction, and by 2020, the urban spatial center of gravity moved to Shangqiu. The direction of movement of the center of gravity of the city is relatively consistent with the development strategy of the entire region, i.e., "expansion to the east" and "extension to the south", which also reflects the effect of the regional development strategy.

### *3.3. Analysis of Spatiotemporal Interaction Characteristics of Urbanization*

#### 3.3.1. Analysis of Spatial Agglomeration Characteristics

The expansion intensity index I is selected as the measurement index, and the spatial agglomeration characteristics of urban expansion in the study area are measured with the help of the Global Moran's I index. The results show that the Moran's I index for the 1990–1995 and 1995–2000 periods were 0.03 and 0.02, respectively, and the *p* value was greater than 0.05, indicating that the level of urban expansion in these two periods was characterized by a random spatial distribution, and the development interaction between cities was relatively small. In the 2000–2005, 2005–2010, and 2010–2015 periods, the Moran's I indexes were 0.34, 0.18, and 0.17, respectively, and the significance levels were 0.1, 0.5, and 0.5, respectively, reflecting that the intensity of urban expansion during this period was characterized by spatial agglomeration, and the agglomeration characteristics reflected a gradually decreasing trend, indicating that the development of the city in this period was influenced by the neighboring cities. The Moran's I index from 2015 to 2020 is about 0.01, and it has not passed the significance test. The intensity of urban expansion is randomly distributed in space.

Taking the intensity of urban expansion in different periods as the measurement index, with the help of spatial statistical analysis tools provided by Geoda software, the Ge-tis–Ord Gi* index for six periods was calculated, and the evolution map of urban expansion hotspots of the Central Plains urban agglomeration in different periods was drawn. As shown in Figure 5, the spatial distribution of hot spots is relatively stable in different periods of time, mainly in Jiaozuo and surrounding cities, showing a clustering trend. Zhengzhou, Luoyang, Kaifeng, Jiyuan, Xinxiang, and other cities around Jiaozuo have developed rapidly in recent years, with large-scale urban expansion, and the urban area increment is at a relatively high level in the region, Showing obvious "high–high" agglomeration characteristics, it has always been a hot spot of urban expansion in the Central Plains urban agglomeration. The spatial distribution of cold spots is characterized by instability. Since 1995, cold spot areas have appeared, among which Shangqiu has been in the cold spot area. It reflects the characteristics of the "low–low" agglomeration of the expansion intensity of Shangqiu and surrounding cities. On the whole, the distribution of cold and hot spots is generally characterized by a punctiform distribution of "hot in the northwest and cold in the southeast", but there are differences in the distribution form and number of hot and cold spots in different periods. Zhengzhou and Luoyang, as the center and subcenter of the urban agglomeration in the Central Plains, have obvious radiating effects on the surrounding areas, and the urban expansion level of the surrounding cities is relatively high. Although cities such as Shangqiu, Huaibei, Bozhou, Suzhou, and Bengbu in the southeast have maintained a trend of increasing urban expansion in recent years, the rate of increase has not been large. These cities are far from central cities such as Hefei, Zhengzhou, and Wuhan in the central region. Therefore, they mainly rely on their own internal development, and they are less affected by the surrounding areas. The level of urban expansion is relatively low in the region. During the study period, the number of hot and cold spots also fluctuated, with no obvious trend characteristics. From the perspective of changes in hot and cold spots, Jiaozuo was always in the hot spot during the study period, and Shangqiu has been in the cold spot since 1995.

#### 3.3.2. Spatiotemporal Interaction Feature Analysis

Based on the above, the period from 1990 to 2020 is divided into a period of five years with a total of six periods, corresponding to the national economic and social development planning from the "Eighth Five-Year Plan" to the "Thirteenth Five-Year Plan". The Moran scatter diagram of the urban expansion index in the first and sixth periods was calculated with the help of Geoda software, and the spatial coordinates of each research unit in the Moran scatter diagram in different periods was obtained. The LISA time path length, curvature, and path movement direction were calculated according to Formula (2) and

Formula (3), and the local spatiotemporal interaction characteristics of the urban expansion intensity of the Central Plains urban agglomeration were analyzed.

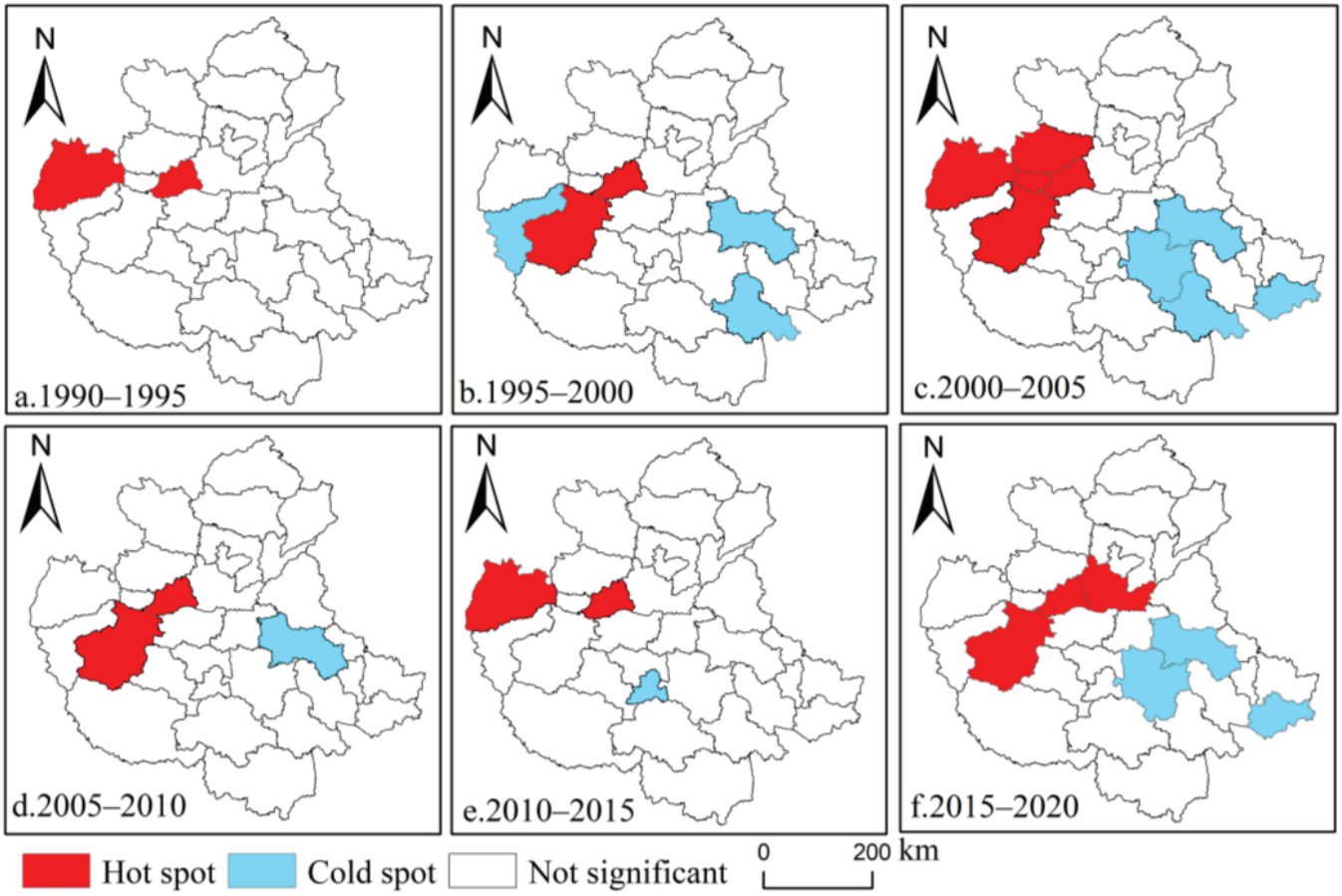


**Figure 5.** Evolution of hot and cold spots of urban spatial expansion. (**a**) 1990–1995 hot and cold spots of urban spatial expansion; (**b**) 1995–2000 hot and cold spots of urban spatial expansion; (**c**) 2000–2005 hot and cold spots of urban spatial expansion; (**d**) 2005–2010 hot and cold spots of urban spatial expansion; (**e**) 2010–2015 hot and cold spots of urban spatial expansion; (**f**) 2015–2020 hot and cold spots of urban spatial expansion.

The relative length of the LISA time path can reveal the local spatial dependencies and the spatiotemporal evolution characteristics of the spatial structure. The relative path length is divided into five levels by using the natural breakpoint method, and the results are shown in Figure 6. The relative length of urban expansion intensity in the Central Plains urban agglomeration generally presents a spatial distribution characteristic of low in the northwest and high in the southeast. This indicates that urban expansion in the northwest region has a more stable local spatial structure, while urban expansion in the southeast region has a more dynamic local spatial structure. The regions with relatively large lengths mainly include Xuchang, Jincheng, Liaocheng, Puyang, Fuyang, and Bengbu, indicating that these regions have a more dynamic spatial structure, and regional development policies should focus on steadily promoting the process of urban expansion.

The curvature of the LISA time path can reflect the size of the regional urban expansion affected by the neighborhood. Using the natural breakpoint method, the curvature is divided into five levels. The curvature in general presents a spatial distribution characteristic of high in the middle and low in the surrounding area, with an average value greater than 1, indicating that the urban expansion of the Central Plains urban agglomeration has a strong spatial dependence. Cities with larger curvature include Zhumadian, Pingdingshan, Luoyang, Anyang, Hebi, Xinxiang, Kaifeng, and Bengbu, indicating that

these cities have greater fluctuations in spatial dependence and are greatly affected by neighborhoods; except for the Bengbu accident, the rest of the cities are distributed on both sides of Zhengzhou, which also shows that the central megacities have a significant effect on the surrounding cities. Therefore, these cities need to strengthen their own development, enhance the resilience of urban development, and gradually form a relatively stable spatial relationship with the surrounding areas.

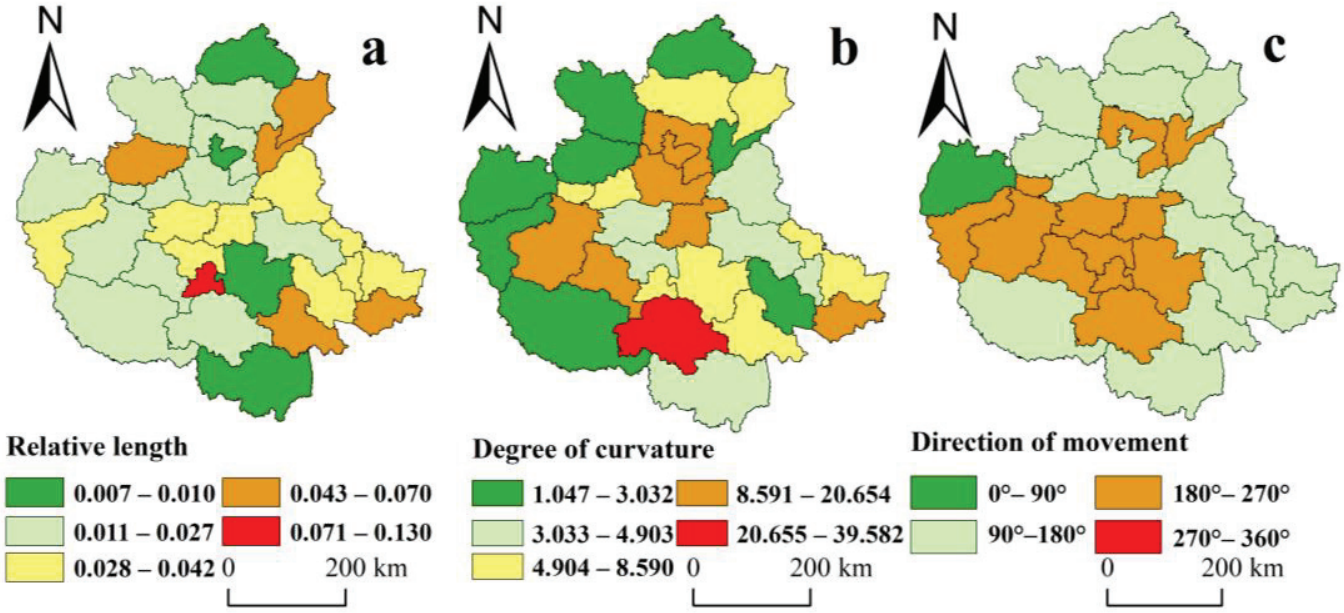


**Figure 6.** Schematic diagram of LISA time path analysis results. (**a**) Relative length of LISA time path; (**b**) LISA time path curvature; (**c**) LISA time path moving direction.

According to the coordinate position and moving trajectory of the urban expansion intensity of different cities in different periods in the Moran's I scatter diagram, the migration direction of the LISA path is calculated, and the moving direction of the LISA coordinates of the research unit is divided into four quadrants. The first quadrant is 0–90°, indicating that the research unit and the neighborhood show a "high–high" growth trend; 90~180° is the second quadrant, indicating that the research unit and its neighborhood are in a "low–high" growth trend, the research unit itself has a low growth rate, and the neighborhood has a high growth rate; 180~270° is the third quadrant, showing a "low–low" growth trend. In a "low–low" growth trend, the research unit and its neighbors show a negative synergistic growth. The fourth quadrant is 270~360°, which is a "high–low" growth trend: the urban area unit and its neighboring cities show a reverse growth, and the research unit itself has a high growth rate, indicating neighborhood low growth. As shown in Figure 5, there are 12 cities showing a "low–high" growth trend, accounting for 40%, and they are mainly distributed in the northwest and southeast directions centered on Xuchang in space, showing a state of spatial agglomeration. There are 17 cities showing a "low–low" growth trend, accounting for 57%, and the spatial distribution has the characteristics of agglomeration, concentrated in the periphery of the Central Plains urban agglomeration.

### *3.4. Analysis of the Correlation between Urban Spatial Expansion and Economic Development*

#### 3.4.1. Analysis of the Correlation between Urban Expansion and Peripheral Economic Development

According to the above, the urban expansion speed and expansion intensity of the Central Plains urban agglomeration have greatly increased since 2005 and have entered a stage of rapid development. The three periods of "2005–2010", "2010–2015", and "2015–2020" discuss the spatial coordination between rapid urban expansion and economic development. GDP is an important indicator of a region's economic development, and it represents

the level of regional economy to a certain extent. Therefore, this paper uses the GDP of municipal districts to represent the economic development level of different research units. According to the bivariate global autocorrelation model, the change rate of urban built-up area in different stages is selected as the first variable and the change rate of GDP is the second variable, and the spatial agglomeration characteristics of urban expansion and economic development of the Central Plains urban agglomeration in different periods are analyzed with the help of Geoda software. The results show that the global Moran's I index of the two variables in the three stages is negative and has not passed the significance test, indicating that from a global perspective, urban expansion and the economic development of surrounding cities do not exhibit spatial agglomeration characteristics.

This study uses the local bivariate Moran's I index to further explore the spatial agglomeration degree and agglomeration area of urban expansion and economic development in the Central Plains urban agglomeration. As shown in Figure 7, four aggregation types are divided, namely "high–high", "high–low", "low–high", and "low–low". It can be seen from Figure 7 that the local clustering types of the two variables are different in different periods, and the local clustering characteristics are not significant in most regions. The "high–high" agglomeration feature only appeared in Kaifeng from 2010 to 2015. This indicates that the high level of urban expansion in this region and the high level of economic development in the surrounding cities have gathered, and that urban expansion and economic development in the surrounding cities have shown coordinated growth. The "low–low" type of agglomeration area indicates that there is a positive correlation between low urban expansion and the low economic development level of surrounding cities. This type of area occurred in Handan from the 2005–2010 to 2015–2020 periods, indicating that the low change rate of urban area in Handan and the low level of economic development in the surrounding areas appeared as an agglomeration phenomenon during these two periods. However, from 2010 to 2015, Handan was characterized by "high–low" agglomeration, indicating that the urban construction of Handan was accelerating during this period, but the speed of economic development in the surrounding area was low, and the factors of urban expansion came more from its own government intervention; it was less affected by the surrounding economic development. During the "Eleventh Five-Year Plan" and "Twelfth Five-Year Plan" periods, Liaocheng was in a "high–low" agglomeration type, indicating that its own urban construction was not in harmony with the surrounding economic development. The "low–high" agglomeration areas appeared in Shangqiu from 2010 to 2015, and in Yuncheng and Huaibei from 2015 to 2020, indicating that the urban areas in these areas had a low increase in urban area, but the surrounding economic development has greatly improved. The two positively correlated agglomeration types of "high–high" and "low–low" in each period appeared less and did not show an increasing trend, indicating that the urban expansion of the Central Plains urban agglomeration has a low correlation with the economic development of surrounding cities.

#### 3.4.2. Analysis of Decoupling between Urban Expansion and Its Own Economic Development

Using the Tapio decoupling model, the decoupling index of 30 prefecture-level cities in the Central Plains urban agglomeration was calculated. Due to the spatial lag effect of urban expansion and economic growth, the three periods of 2005–2010, 2010–2015, and 2015–2020 were selected for decoupling calculations. According to the classification criteria of decoupling types, the decoupling elasticity of urban expansion and economic development in different stages was discussed, as shown in Figure 8. The types of decoupling between urban expansion and economic growth of the Central Plains urban agglomeration mainly appear in three stages: negative growth decoupling, weak decoupling, and growth connection, but the decoupling types show obvious changes in quantity and spatial distribution in different periods. The number of cities with growth negative decoupling and growth connection decoupling has increased, and they are clustered towards the

regional center. Weak decoupling is the main type of decoupling at each stage, but there is a tendency to gradually decrease.

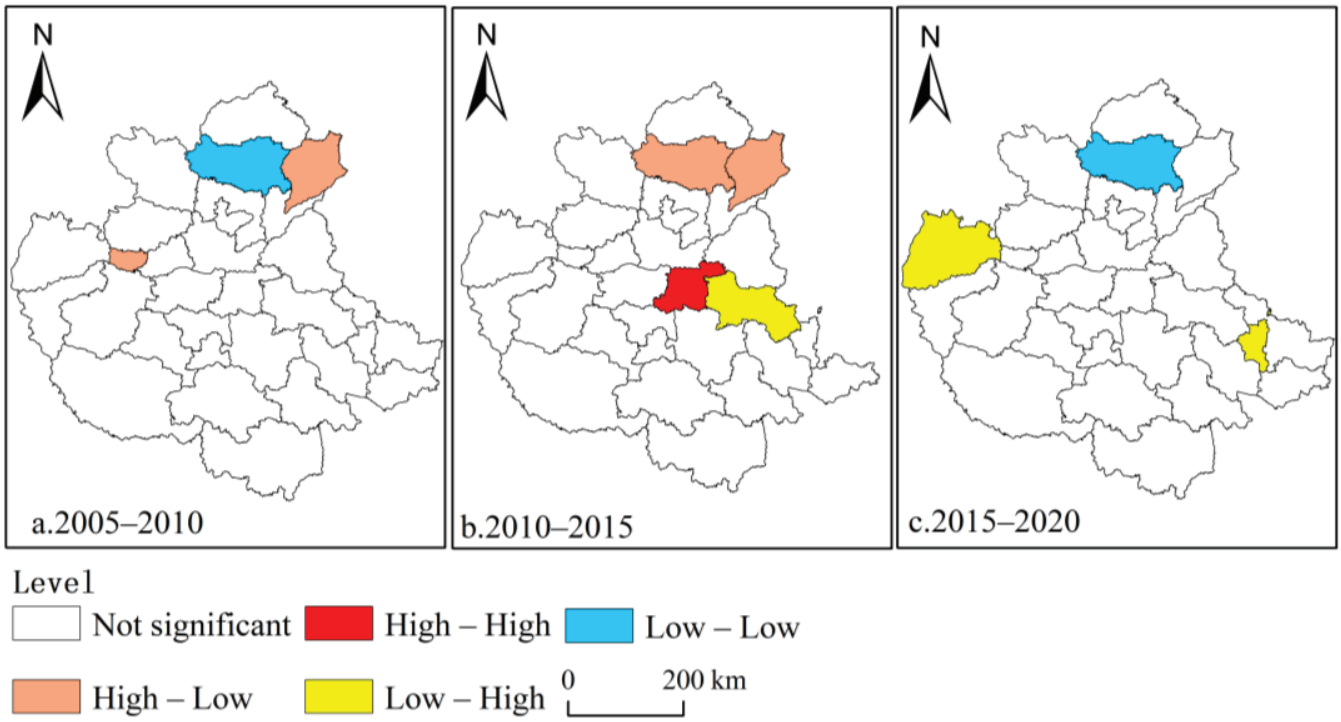


**Figure 7.** Spatial correlation between urban expansion and economic growth. (**a**) 2005–2010 Local bivariate spatial autocorrelation; (**b**) 2010–2015 Local bivariate spatial autocorrelation; (**c**) 2015–2020 Local bivariate spatial autocorrelation.

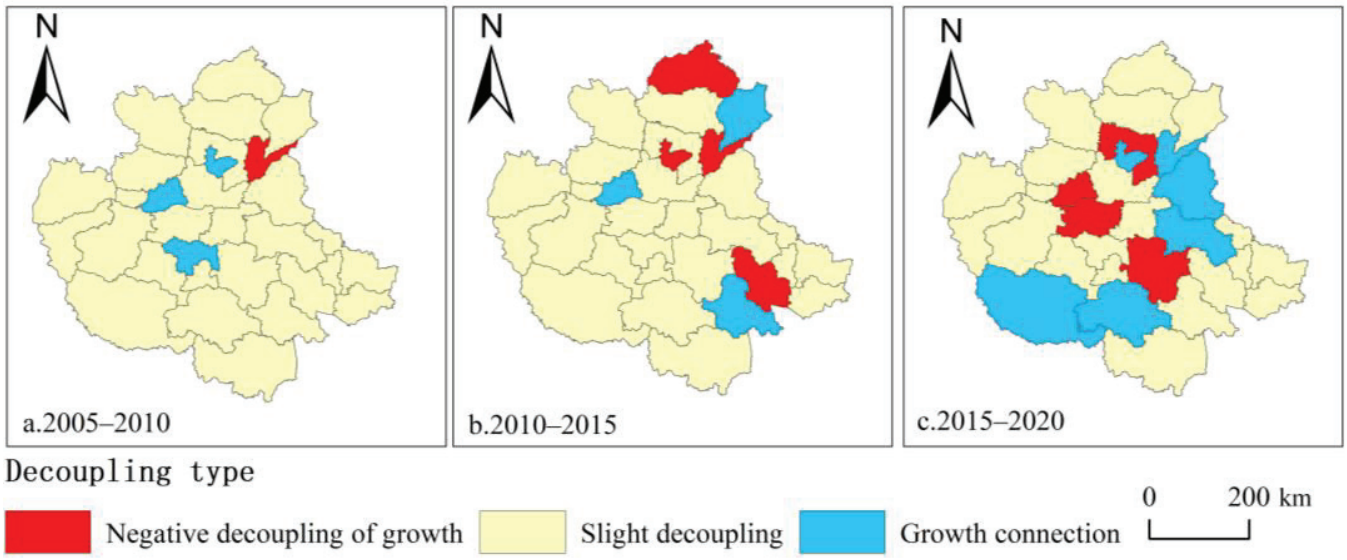


**Figure 8.** Types of decoupling between urban expansion and economic growth. (**a**) 2005–2010 Decoupling type; (**b**) 2010–2015 Decoupling type; (**c**) 2015–2020 Decoupling type.

Specifically, there was only one negative decoupling of growth in the first stage, which appeared in Puyang, and three types of growth connections appeared in Hebi, Jiaozuo, and Xuchang. The negative decoupling of growth and the connection of growth reflect the imperfect coupling between the expansion of these cities and economic development; that is, the expansion of cities does not bring about corresponding economic growth. The rest of

the cities are all weakly decoupled, accounting for 86.7% of the research samples (Table 4), reflecting a slight inconsistency between the expansion of these cities and economic development. There is a certain degree of dependence between economic development and land consumption, but the degree of dependence is not high. In the second stage, negative growth decoupling increased, accounting for 13%, the proportion of weak decoupling decreased by 10%, and the proportion of growth connections remained unchanged. The cities with negative growth decoupling in terms of spatial distribution included Puyang, Hebi, Xingtai, and Bozhou, and growth connections appeared in Jiaozuo, Fuyang, and Liaocheng. The proportion of negative growth decoupling in the third stage has not changed compared with the previous stage. The proportion of weak decoupling continues to decrease by 10%, and the proportion of growth connection increases by 10%. The spatial distribution shows a big change. Among them, cities with negative growth decoupling include Anyang, Jiaozuo, Zhengzhou, and Zhoukou, and cities with growth connections include Hebi, Puyang, Heze, Shangqiu, Zhumadian, and Nanyang.

**Table 4.** Number (pcs) and proportion of different decoupling types in each period.

| Stage | Growth Negative Decoupling | Weak Decoupling | Growth Connection |
|---|---|---|---|
| First (2005–2010) | 1/3.3% | 26/86.7% | 3/10% |
| Second (2010–2015) | 4/13.3% | 23/76.67% | 3/10% |
| Third (2015–2020) | 4/13.3% | 20/66.67% | 6/20% |

Overall, weak decoupling is the main feature of the relationship between urban expansion and economic growth in the three periods, but it also shows a trend of increasing from weak decoupling to negative growth decoupling and growth linkage. Although the urban expansion and economic development of the Central Plains urban agglomeration have been greatly improved from the "Eleventh Five-Year Plan" to the "Thirteenth Five-Year Plan", the uncoordinated trend between urban expansion and economic growth will continue in the future. During the "Fourteenth Five-Year Plan" period, more stringent requirements were put forward for coordinating the relationship between urban expansion and economic development, and this incoordination appeared to gather around Zhoukou in the southeast. According to the above, in recent years, the direction and center of urban expansion in the Central Plains urban agglomeration have migrated to the southeast. Therefore, relevant departments should pay attention to the process of urban expansion and should also focus on the coordination of economic growth and land resource consumption to avoid the phenomenon of uneconomical consumption of land resources occurring in the middle of the country, so that the regional urban construction and economic development can be coordinated and steadily advanced. The slowdown in the expansion of construction land and the steady and healthy development of economic growth are the essence of decoupling performance.

## 4. Discussion

Traditionally, the analysis of spatiotemporal characteristics of urban expansion mainly uses statistical data on urban construction land or uses single remote sensing image data to interpret the scope of the built-up area. Although using these two types of data has certain feasibility, there are also certain limitations. Statistical data often have large errors and lack spatial location information, which can only be analyzed from the perspective of mathematical statistics. Using remote sensing image interpretation by researchers, it is difficult to obtain high-precision remote sensing images, and obtaining long urban built-up area range time series data while ensuring accuracy is a significant workload. This study adopts the vector data of high-accuracy and long time series of urban built-up areas published by scholars, providing convenience and data accuracy for this study. With the progress of science and technology, more and more scholars are trying to explore the study of urban using multisource data [52,53]. The further exploration direction of this study is to comprehensively identify the inherent laws and characteristics of urban development from

different aspects using multisource data. In terms of research perspective, traditionally, the measurement perspective of urban expansion mainly focuses on the characteristics of expansion scale and spatial pattern. The analysis of its evolution characteristics over time often separates time and space, ignoring the analysis of spatiotemporal interaction characteristics. This study introduces the LISA time path analysis method, which dynamically analyzes the spatiotemporal pattern interaction characteristics of urban expansion process and has certain innovations. Traditionally, analyzing the relationship between urban expansion and economic growth has focused only on the correlation analysis between urban expansion and its own economic growth, ignoring the linkage analysis between urban expansion and surrounding economic development. This study applies the bivariate spatial autocorrelation analysis method to the spatial correlation analysis between urban expansion and surrounding economic growth, which has certain applicability. In considering the coordination between urban expansion and its own economic development, this study introduces a decoupling model to analyze the decoupling effect of urban expansion and economic growth more intuitively. However, in terms of horizontal economic development level, only GDP statistics were used. In subsequent studies, objective data such as nighttime lighting should be added to comprehensively measure economic development [54], making the evaluation of economic development more objective. Due to the interaction between urban expansion and ecological environment, industrial development, and population agglomeration [5,32,55–57], in subsequent research, the decoupling effect analysis between ecological effects, industrial development, population flow, and urban expansion will be considered, and the driving mechanism of urban expansion will be further analyzed to provide scientific suggestions for regional urban expansion and economic development, as well as improve the research results system of urban geography.

## 5. Conclusions

The urbanization level of the Central Plains urban agglomeration is currently in a rapid improvement stage, with urban expansion being an important component of urbanization. All economic and social development relies on land. In order to avoid the related negative impact of urban sprawl in the Central Plains urban agglomeration, it is necessary to explore the characteristics and laws of urban expansion in the Central Plains urban agglomeration in a timely manner. Currently, research on urban expansion in the Central Plains urban agglomeration ignores the discussion of spatiotemporal interaction characteristics. This study analyzes the scale characteristics, direction characteristics, and spatiotemporal interaction characteristics of urban expansion in the Central Plains urban agglomeration in the past 30 years based on more accurate long-term urban built-up area vector data, and it analyzes the spatial correlation and decoupling effect between the two in combination with economic statistics. This study provides a reference for relevant government management departments to judge the macro pattern of regional development and formulate policies, and it provides new ideas and methods for the study of urban expansion. The specific conclusions are as follows:

(1) The total area of urban built-up areas in the Central Plains urban agglomeration has shown a trend of increasing year by year, and the total expansion area in the past 10 years accounts for half of the total expansion area. The expansion intensity showed an "S"-shaped growth trend, with a slow increase in expansion intensity from 1990 to 2005, a rapid increase in expansion intensity from 2005 to 2015, and a steady trend in urban expansion intensity from 2015 to 2020. There are significant differences in expansion intensity among different cities. Zhengzhou has maintained a high intensity of expansion; cities with moderate expansion intensity are mostly located in Henan Province and are mostly distributed around Zhengzhou. Xinyang, Sanmenxia, Changzhi, and Suzhou had the lowest expansion intensity during the past 30 years. Therefore, in the process of urbanization, the Central Plains urban agglomeration should pay more attention to the problems caused by the strong expansion of Zhengzhou and its surrounding cities, and

at the same time, strengthen the cities with weak urban construction efforts to achieve coordinated regional development and narrow the gap.

(2) From 1990 to 2020, the urban spatial expansion of the Central Plains urban agglomeration mainly presented a "northwest–southeast" trend. The directionality of urban expansion first decreased and then increased, mainly extending towards Anhui Province. Urban space has shifted from primarily "infill" expansion in the early stage to primarily "extensional" expansion. From 2010 to 2020, the center of gravity of urban space shifted significantly to the southeast, moving from Kaifeng to Shangqiu. Due to the influence of the natural geographical environment, the development space in the west and southwest of the Central Plains Urban Agglomeration is limited. Driven by the radiation centered around Zhengzhou, due to superior terrain conditions, convenient transportation, and good industrial foundation, the southeast cities have continuously expanded their urban spatial scope in recent years, making the urban center of the Central Plains Urban Agglomeration constantly move towards the southeast. Kaifeng, Xuchang, and Shangqiu have become an important gateway for the urbanization of the Central Plains urban agglomeration to the southeast.

(3) The spatial agglomeration characteristics of urban expansion in the Central Plains urban agglomeration are weak. The hot spots for urban expansion mainly change in Jiaozuo and surrounding areas. Urban expansion in the Central Plains urban agglomeration has a strong spatial dependence, and cities in the southeast region have a more dynamic spatial structure. Urban expansion in the Central Plains urban agglomeration mainly reflects the coordinated low growth of peripheral cities.

(4) From 2005 to 2020, the spatial correlation between urban expansion of the Central Plains urban agglomeration and surrounding economic development was not significant, and there was a risk of decoupling between urban spatial expansion and its own economic growth. It is suggested that the urban expansion of the Central Plains urban agglomeration is mainly influenced by its own development policies and is less driven by the development of its surrounding areas. Moreover, there is a trend of increasing the risk of uncoordinated urban expansion and economic growth. It is recommended that the formulation of future regional development strategies should consider the coordination between urban expansion and economic growth, avoid blind expansion, and focus on the driving role of cities with high urbanization levels in the development of low urbanization levels.

In summary, this study analyzes the laws of urban expansion in the Central Plains urban agglomeration from the perspective of spatiotemporal dynamics, and it analyzes the correlation between urban expansion and internal and external economic growth, which better explains the spatiotemporal characteristics of urban expansion in the Central Plains urban agglomeration in the past 30 years, based on the decoupling risk of economic development. These results can provide reference for the future development planning of the Central Plains urban agglomeration. However, this study does not explain the mechanism of the spatiotemporal characteristics of urbanization in Central Plains urban agglomeration. In the future, further analyzing the driving factors that generate the spatiotemporal characteristics of urbanization in Central Plains urban agglomeration in combination with multisource data will be considered.

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**Data Availability Statement:** The urban built-up area dataset from 1990 to 2015 is available at (http://www.doi.org/10.11922/sciencedb.j00076.00004), accessed on 1 August 2022. The urban built-up area dataset from 2020 is available at (https://doi.org/10.11922/sciencedb.j00001.00332),

accessed on 1 August 2022. The rest of the data presented in this study are available on request from the corresponding author.

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# Monitoring House Vacancy Dynamics in The Pearl River Delta Region: A Method Based on NPP-VIIRS Night-Time Light Remote Sensing Images

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**Abstract:** Urban spatial interaction integrates cities into closely related urban network systems in continuous urban regions. However, it also brings differentiation and has mutual negative impacts between each location. Unbalanced development is one such impacts and needs closely monitoring. The housing vacancy rate (HVR) in a continuous urban region is an important index in the unbalanced development of a continuous urban region since it indicates the uneven distribution of population and investment across cities. This study uses NPP-VIIRS NTL data and Landsat 8 OLT images to estimate HVRs at the district level. Additionally, this study tracks the spatial–temporal dynamics of HVR distributions in the Pearl River Delta (PRD) region. The comparison between the sampled HVRs and estimated HVRs verifies the effectiveness of the estimated HVRs in identifying dynamic changes in HVRs. This study has found that although overall decreasing HVRs are observed in the PRD, speculations and irrational real estate investment exist in cities on the west bank of the Pearl River Estuary and in some isolated districts in other cities. Furthermore, increasing proportions of vacant pixels in most cities indicate rising real estate development, requiring further supervision. This study suggests that more precise data and advanced techniques could help to improve the accuracy of the estimation techniques.

**Keywords:** house vacancy rate; NPP-VIIRS; the Pearl River Delta; built-up area extraction

## 1. Introduction

The housing vacancy rate (HVR) is the percentage of all available units in the real estate market that are unoccupied or vacant at a particular time and is an important index of housing oversupply or real estate speculation [1]. Widespread housing vacancies may indicate a structural crisis due to either property abandonment or real estate speculation, phenomena which might hurt the economy severely [2]. Recently, the distribution of HVRs in a continuous urban region and the changes over time have drawn the attention of scholars since they indicate the uneven distribution of population and investments across cities [3]. On the one hand, urban spatial interaction integrates cities into closely related urban network systems [4] with stronger population, capital and resource aggregation capabilities [5]. On the other, with the strengthening of spatial interaction, there will be differences in agglomeration between cities, inevitably leading to unbalanced development [6]. Especially in China, where the local governments have proved their powerful influence on defining urban development and have caused a remarkable scale of uneven development across and within cities [7]. Additionally, links between cities have also

become increasingly influential in the real HVRs due to the fast-developing joint plans. Overall, monitoring the dynamics of HVR distribution in a continuous urban region is a very important tool for correcting erroneous development decisions and promoting balanced regional development. In view of this, this research aims to propose an updated and inexpensive method to use to monitor the dynamics of HVR distribution in a continuous urban region. With the monitoring of unbalanced regional development as the target, the most critical issue here is not the accuracy of the vacancy situation of housing units, but the judgment of the overall vacancy rate dynamics throughout the continuous urban region with the district as the units.

However, the monitoring of HVR has long been hampered by the difficulty of collecting housing vacancy information. Multiple evaluation methods have been derived to evaluate HVRs based on single or mixed data. Survey data with huge survey samples and reliable methods, such as that derived from the CPS/HVS (Current Population Survey/Housing Vacancy Survey) and AHS (American Housing Survey) in the US, constitute the main sources of information used in these tasks [8]. Power data [9], building data and tax data [10] can also be applied to evaluate HVRs. However, these methods are either costly, time-consuming or have a high barrier to acquisition [11,12]. Scholars have reported the difficulty of obtaining reliable information using survey-based methods [13], and the lack of historical data make it difficult to track changes in HVR [11]. The housing vacancy problem is considered severe across China [14], but China lacks transparent HVR statistics with which to show the real estate market situation. There are urgent needs for both a data source with historical accumulation and timely updates and for a method to apply it with for HVR estimation in China.

Fortunately, night-time light (NTL) data, which have been available since 2013, have become widely acknowledged as objectively reflecting the changes in urban development. NTL data are indirect manifestations of human activities. They have been widely used in population density simulation [9], electricity and energy consumption [15], GDP estimation [16], the assessment of poverty [17], as well as in HVR studies [18] to substitute traditional survey-taking methods. This generally requires a mixed use of NTL and other big data. For instance, Wang et al. [19] combined NTL data with OpenStreetMap data, and Zhang et al. [20] and Yang and Pan [21] used urban POI data and NTL data to extract the urban built-up area and evaluate HVRs. Yue et al. [22] proposed a method of estimating HVRs based on the image of the appearance of a house. However, the existing city-based HVR analysis is not precise enough for use in the analysis of the interaction of urban development across cities. This is because the spillover of investment in one city might only affect one to two districts in another city. The study of district-level HVRs would be theoretically significant for studying the dynamics of HVR distribution in a continuous urban region as it shows the areas of interaction between cities more precisely. Although a district that generally covers over 100 $km^2$ is large enough for HVR estimation with NTL data, no studies elaborating this have yet been carried out.

In response to the abovementioned gaps in the research, this study applies NPP-VIIRS NTL data and Landsat 8 OLT images to the estimation of HVRs in the Pearl River Delta (PRD) region at the district level. It tracks the spatial–temporal dynamics of HVR distributions in order to evaluate the interaction of urban development across cities. The following sections have been included. The second section introduces the choice of the study area, data processing, and the calculation of HVRs and the verification of the method The results are presented in the third section, showing the distribution of different HVRs across districts and the change in HVRs over time, specifically in 2013, 2016, and 2019. Section 4 concludes the research and discusses future studies.

## 2. Materials and Methods

### *2.1. Study Area*

In this study, the study area chosen is the region of the Pearl River Delta (PRD). It is located in the southern coastal area of China and is one of the three most productive

economic regions of China [23,24], contributing up to 8689.9 billion yuan to GDP in China, which makes up around 80% of the total GDP in Guangdong Province in 2019 (National Statistics Bureau of Guangzhou 2020).

As shown in Figure 1, nine cities have been included in the PRD: Guangzhou, Foshan, Shenzhen, Dongguan, Zhongshan, Zhuhai, Jiangmen, Zhaoqing, and Huizhou. The PRD is one of China's most developed and prosperous areas has a significant population. According to the 2019 Guangdong Province Statistical Yearbook, the PRD has a population of around 63 million people. Additionally, the PDR covers an area of 4173.15 km$^2$ in terms of built-up area. This situation boosts the demand as well as supply for housing. New buildings have sprung up like mushrooms in the PRD due to urban development. The unregulated growth of real estate development has resulted in an increasing number of empty housing units and may have harmed the local economy [14]. Therefore, implementing rational planning for urban housing development, in addition to accurately estimating HVRs of the region and their distribution, is extremely important.

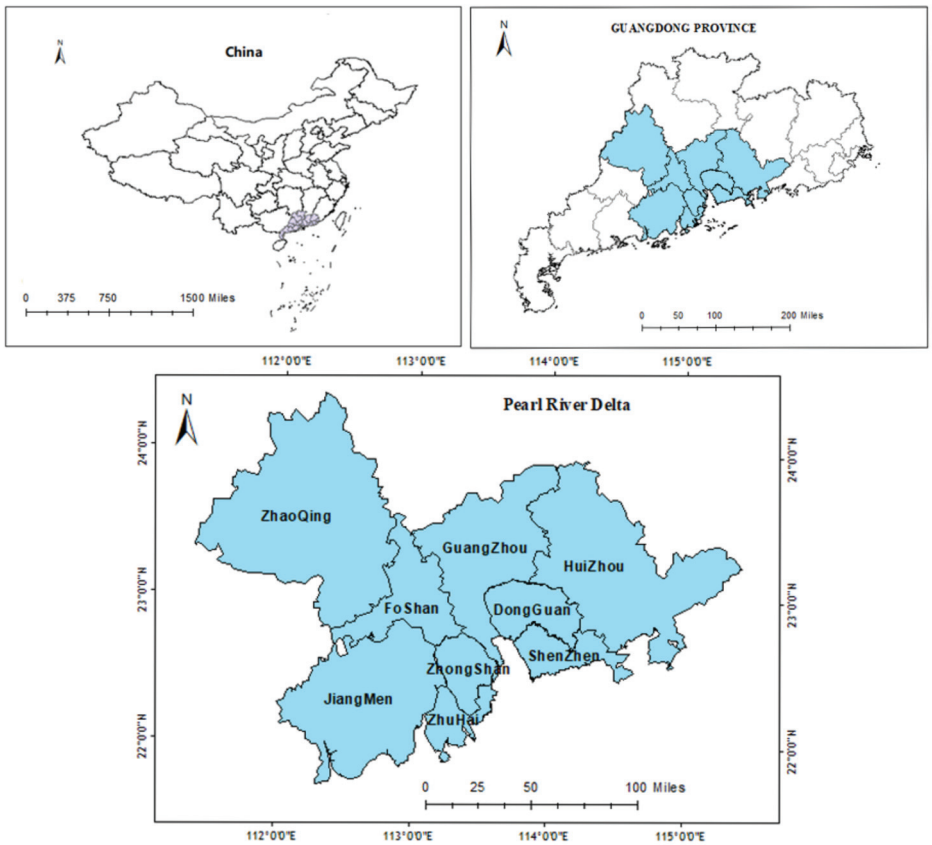



**Figure 1.** Location of the PRD in Guangdong Province in China and distribution of districts/counties. Data Source: The Resource and Environment Science and Data Center (https://www.resdc.cn/ (accessed on 13 February 2023)).

This study evaluates the HVR distribution dynamics at the district/county scale. Districts and counties in China are the political units of municipal government. There are 105 districts and counties included in the PRD[2]. The size of districts or counties in the PRD varies from 11.43 (Guancheng Street Community in Dongguan City) to 3558.75 km$^2$ (Huidong County), allowing for the collection of sufficient samples of NTL pixels for analysis within a district. A district or county generally has a balanced population structure, economic and social development level, environment capacity, land utilization status, infrastructure, and basic public service provision. In addition, it has an urban center which concentrates residences. Therefore, the district-scale study avoids a comparison of the extreme value of lights in one city and helps to gain more rational results.

### *2.2. Data Source*

#### 2.2.1. Night-Time Light Remote Sensing Images

The problems of lower spatial resolution and shorter radiometric detections in applying DMSP/OLS NTL data have led to attempts to use NPP-VIIRS NTL data ever since 2013 [25]. VIIRS performs very well in calibration and validation and can detect night-time lights spanning from 75° N to 65° S with the radiation from 3 $nW \cdot cm^{-2} \cdot sr^{-1}$ to 0.02 $W \cdot cm^{-2} \cdot sr^{-1}$ [26]. Suomi-NPP provides sensor data records, including data on clouds, sea surface temperature, and so [27]. Furthermore, the DNB (Day/Night Band) is a component of the VIIRS instrument onboard Suomi-NPP, which makes it possible to observe satellite night in the visible spectrum. As a new generation of night-time products, NPP-VIIRS enables scholars to collect daily, monthly and annual data from 2013 to 2019. Specifically, NPP-VIIRS NTL data of the PRD for the years 2013, 2016, and 2019 (see Figure 2) are collected in this study to track the changes in HVRs.

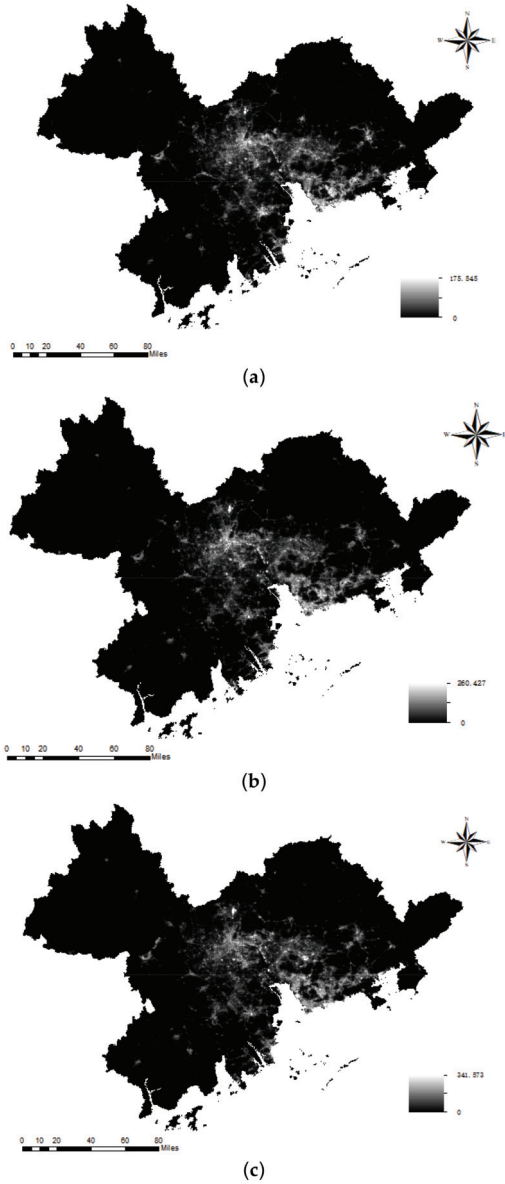



**Figure 2.** NPP-VIIRS NTL remote sensing images of the PRD. (**a**) 2013, (**b**) 2016, (**c**) 2019. Data Source: The National Oceanic and Atmospheric Administration (NOAA) (https://www.ngdc.noaa.gov/eog/viirs/download_dnb_composites.html, accessed on 3 September 2021).

In this paper, the night-time light remote sensing images we used were downloaded from the National Oceanic and Atmospheric Administration (NOAA) (https://www.ngdc.noaa.gov/eog/viirs/download_dnb_composites.html, accessed on 3 September 2021) and are shown in Figure 2.

#### 2.2.2. Urban Built-Up Area Data

The urban built-up area data are needed in this study to process NTL data. In this study, remote sensing images were obtained from Landsat 8 OLI to classify land in the PRD. The data set is provided by International Scientific & Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences. (http://www.gscloud.cn, accessed on 3 September 2021) The Landsat 8 satellite payload consists of two science instruments—the operational land imager (OLI) and the thermal infrared sensor (TIRS). OLI is a push-broom sensor with a four-mirror telescope and 12-bit quantization capacity. It collects data for visible, near-infrared, and short-wave infrared spectral bands as well as panchromatic bands.

#### 2.2.3. Housing Rent/Sale Data

By applying a Python web crawler, we obtained rent data from one of the key real-estate information platforms, namely Soufun (https://gz.fang.com/, accessed on 20 September 2019), for the city of Guangzhou (except Conghua, Zengcheng) as the case with which to verify the HVR estimation. The data obtained include the total number of housing units, the number of units on sale, and the number of units for rent in each real estate project. Statistical data of the sampled projects are shown in Table 1.

**Table 1.** Sampled data of vacant housing units (on sale or for rent) in Guangzhou.

| District | Number of Sampled Projects | Number of Total Housing Units | Number of Units on Sale or for Rent |
|---|---|---|---|
| **Nansha** | 89 | 152,214 | 7686 |
| **Tianhe** | 549 | 440,390 | 17,572 |
| **Haizhu** | 455 | 519,167 | 15,204 |
| **Panyu** | 458 | 480,830 | 22,832 |
| **Baiyun** | 285 | 347,703 | 14,280 |
| **Huadu** | 178 | 238,088 | 11,698 |
| **Liwan** | 223 | 307,323 | 8788 |
| **Yuexiu** | 334 | 408,106 | 10,918 |
| **Huangpu** | 144 | 247,643 | 8754 |

### *2.3. Data Processing*

#### 2.3.1. Workflow

The main process in this research can be divided into four main steps, as illustrated in Figure 3. Step 1 involves data pre-processing to gain each pixel's urban area ratio (UAR). This includes denoising NTL data and resampling urban built-up area data. Step 2 calculates UAR and removes non-residential lights from the light value. With the light value of each NTL pixel, Step 3 derives the HVR of each pixel by comparing the estimated light value and the largest light value. Measures are also applied to evaluate the links between changes in HVRs in different districts. Finally, this study uses the housing rent/sale information to calculate the real HVRs and to verify the HVRs estimation, a task performed in Step 4.

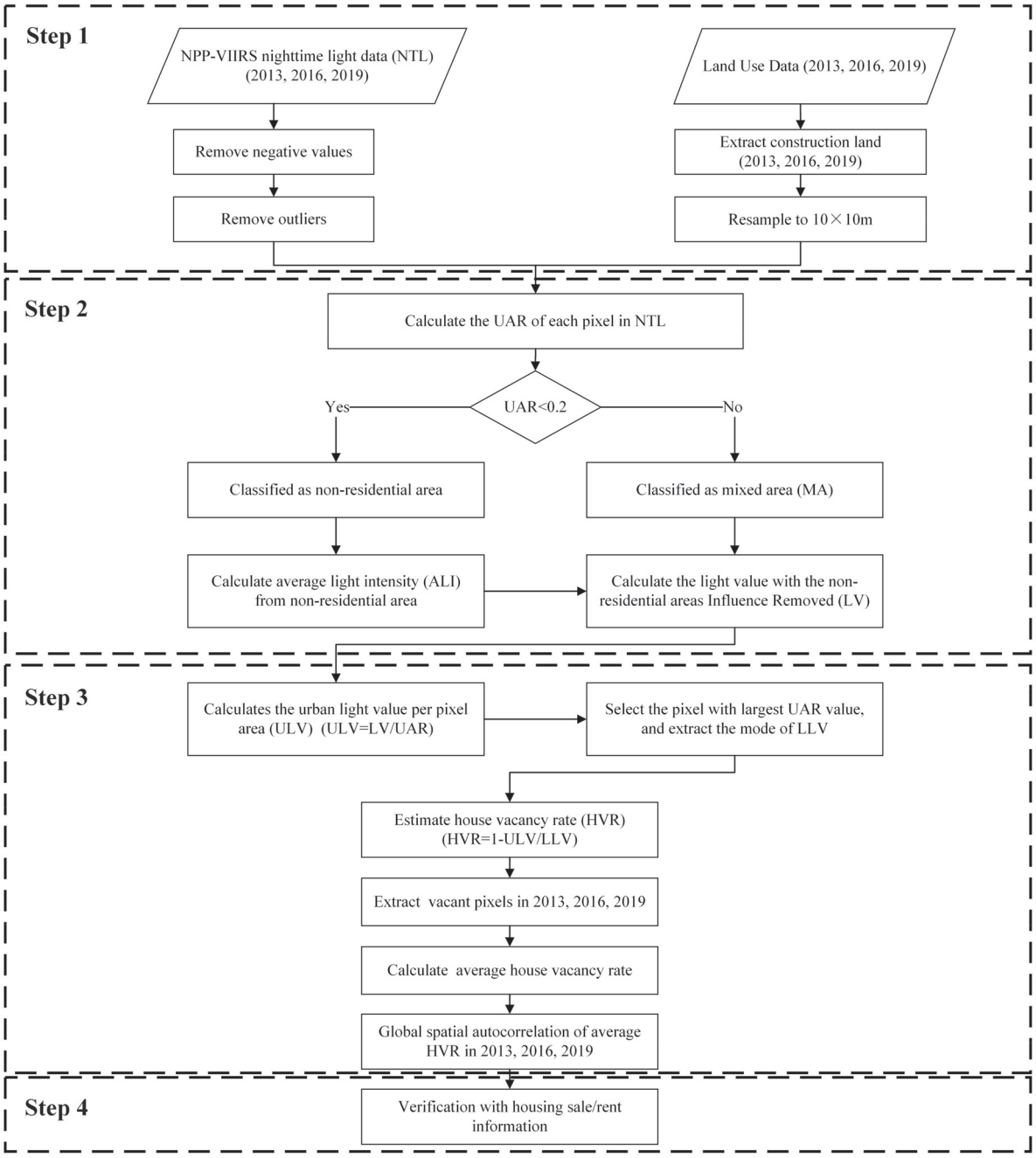



**Figure 3.** The flowchart of the proposed research.

#### 2.3.2. Pre-Processing NTL Data

The noise influenced the NPP-VIIRS remote sensing images downloaded from NOAA, resulting in the image's extreme value. Two steps were thus applied:

We removed negative values. The original night light data contained pixels with negative values. Due to the lack of metadata description, these negative values were considered to be background noise values generated during the data synthesis process. Therefore, existing studies were used to replace negative values with vacant or zero values [28]. Furthermore, according to the principle of the constant target area method, the total area covered by NTL was set to be the same for DMSP OLS and NPP-VIIRS data [16,25]. This study extracted values greater than 0 in the DMSP OLS night light data and assigned a value of 1 to generate a mask that multiplied with the NPP-VIIRS data in order to eliminate some abnormal values. To ensure the integrity of the data and later calculations, this study

replaced the negative values in the NPP-VIIRS night light data and the NTL pixel value outside the mask of DMSP OLS positive values with zero values.

We removed outliers. There is a significant positive correlation between light radiation value and economic development. In short, higher GDP means a higher NTL value. In the PRD, Guangzhou and Shenzhen have the highest levels of economic activities. As such, the light value of city centers in Guangzhou and Shenzhen was extracted as the maximum value. If the NTL value of one pixel was larger than the maximum value, the following measures were be taken: the values of the surrounding eight adjacent pixels were collected, and the maximum value of these eight pixels replaced the abnormal value. If the adjacent eight pixels were all greater than the maximum value, this study rasterized the pixels until every pixel was smaller in value than the maximum value.

The denoised picture is shown in Figure 4.

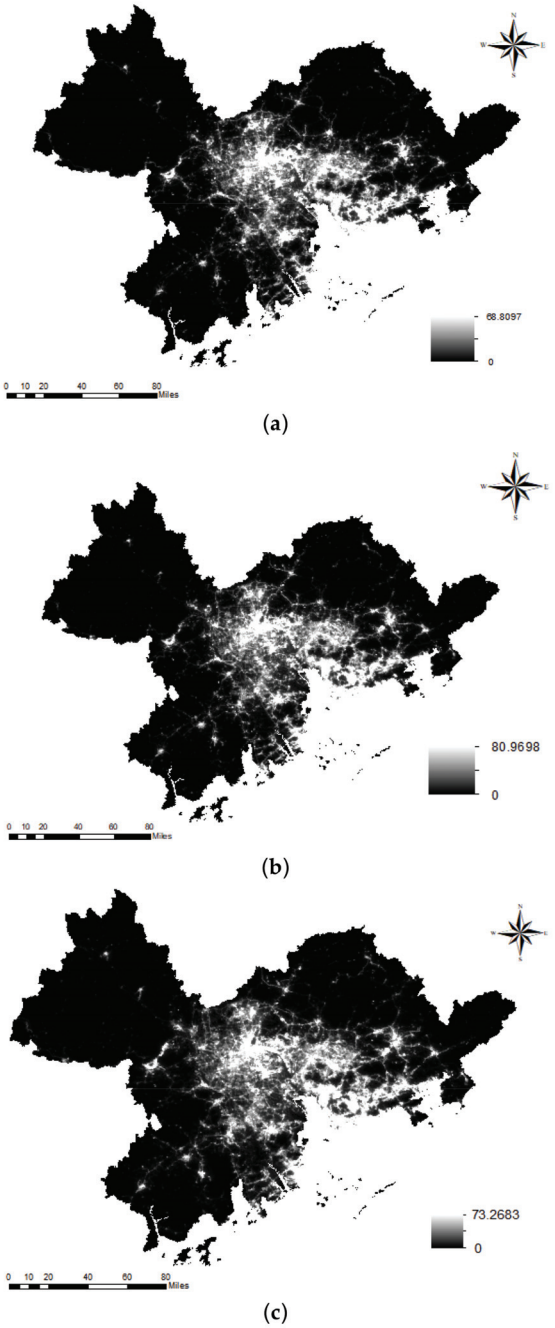



**Figure 4.** Denoised NTL remote sensing image in the PRD. (**a**) 2013, (**b**) 2016, (**c**) 2019.

2.3.3. Pre-Processing Landsat 8 OLI Data

Using the environment for visualizing images (ENVI) method, this study applies radiometric, topographic, and atmospheric corrections to avoid disturbances from clouds and atmosphere. Radiometric correction converted the digital value of each pixel in the image into surface reflectance, thereby removing photometric deviations in the image due to changes in the intensity of solar radiation. Topographic correction converted the image into a relatively highly consistent image of surface reflectance, removing topography-induced luminance bias. Atmospheric correction eliminated the influence of clouds, fog, smog, etc., in the atmosphere on the image in order to obtain more accurate surface reflectance. To achieve that, the FLAASH model was applied. It has the characteristics of simple input parameters and high output reflectance accuracy and is currently a commonly used atmospheric correction model. According to the time phase and geographic location of the Landsat 8 image data acquired in the study area, the mid-latitude summer (MLS) and urban aerosols were selected in the FLAASH model. The support vector machine (SVM) method was applied to separate construction land, water area, green field, and cultivated land according to the national standard for land classifications. SVM is a binary classification model and has been widely used in land-use information extraction [29]. As one of the most popular supervised classification methods [26], SVM performs best since it can not only solve the nonlinear and high dimensional data classification problem [30], but can also achieve better performance based on the use of fewer training samples [31]. This study used ENVI's ROI tool to extract the image information of various types of land from the image, and we chose 30–40 small triangle areas for each type of land used to compose the training set. Detailed information about sample selection is shown in Table 2. Subsequently, the SVM model was trained with the training set. The radial basis function (RBF) was applied for the parameter setting of SVM with the gamma parameter as 0.250, the penalty parameter as 100 and the probability parameter as default. Using other night light images not involved in training as verification data, the ENVI calculated the accuracy and error of the model. The result of the extraction had an overall accuracy of 0.93 and a Kappa value of 0.91.

**Table 2.** Selection of samples for training set in ENVI.

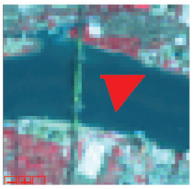
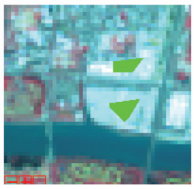
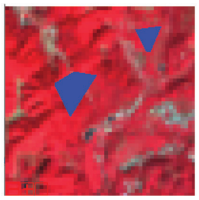
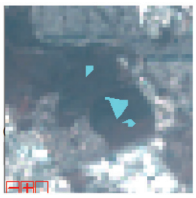
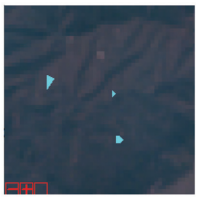
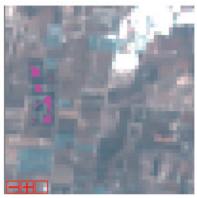
| Type | Sample | Number |
|---|---|---|
| Water |  | 34 |
| Urban |  | 40 |
| Forest |  | 32 |

**Table 2.** *Cont.*

| Type | Sample | Number |
|---|---|---|
| Grassland |  | 36 |
| Mountain |  | 34 |
| Cropland |  | 31 |

We regard construction land as a built-up area and water area, green fields, and cultivated land as constituting other categories of land use. The classified outcomes can be obtained and divided into two parts, the built-up area and the other area, based on the Bayes classification method, which classifies the remote sensing image. The urban built-up areas of the PRD for 2013, 2016, and 2019 have been extracted and shown in Figure 5.

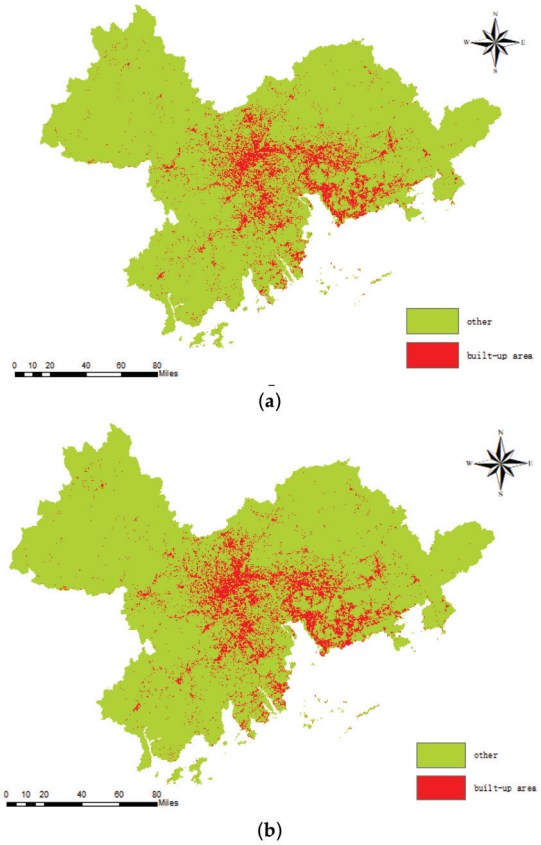
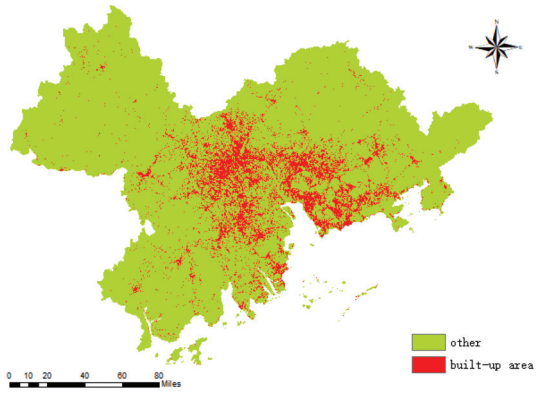



**Figure 5.** *Cont.*




(c)

**Figure 5.** Urban built-up area in the PRD in 2013, 2016, and 2019. (**a**) 2013, (**b**) 2016, (**c**) 2019. Data source: Landsat 8 OLI.

#### 2.3.4. Removing Non-Residential Lights

The light shown in the remote sensing images includes the light from the residential area and the non-residential area, such as roads and factories [18]. To obtain more accurate data, additional measures were taken to remove non-residential lights for mixed lights dominated pixels. Two steps were applied:

(1) We evaluated the urban build-up area rate (UAR). Existing studies revealed a high correlation between the urban build-up area and night lights [32]. The urban built-up area rate (UAR) could thus be used to divide data into residential and non-residential NTL pixels. Because the spatial resolution of an NTL pixel was 500 × 500 m and the spatial resolution of a land-use pixel was 30 × 30 m, the land-use images were resampled to 10 × 10 m and then superimposed with the 500 × 500 m night light data. Therefore, a night light pixel could contain up to 2500 land-use pixels. The UAR was obtained at an NTL pixel level with Formula (1).

$$\mathrm{UAR_i} = \frac{\mathrm{N_i}}{\mathrm{N_{light}}} \tag{1}$$

In the Formula (1), $UAR_i$ represents the ratio of built-up area in one NTL pixel; $N_i$ refers to the number of construction land pixels contained in the i-th pixel; and $N_{light}$ refers to the number of land-use pixels in an NTL pixel, which is 2500 in this study.

(2) We removed non-residential lights. An NTL pixel included the continuous built-up area and areas outside the built-up area. Roads and factories also had the ability to produce background light for such areas and were always included in the total NTL [18]. In order to obtain more accurate data, the impact of the background lights had to be removed. Zhou [33] proved that a UAR equaling 20% could be regarded as the watershed of resident and non-resident pixels. If the UAR was less than 20%, the NTL image mainly consisted of background lights. In this study, pixels with a UAR of more than 0.2 were labeled as residential pixels, and the light value of residential pixels was recorded as the housing light of that pixel. The pixels with UAR less than 0.2 were labeled as non-residential pixels and removed.

### *2.4. House Vacancy Rate Estimation*

#### 2.4.1. Estimating Light Intensity in the Urban Built-Up Area

Considering that the light of an NTL pixel comes from the built-up area, the light intensity of the built-up area within a pixel should be used for analysis. After obtaining the housing light of each resident pixel, the light housing value in the city at the pixel level can be easily calculated by a ratio shown in Formula (2).

$$\mathrm{ULV_i} = \frac{\mathrm{LV^i_{res}}}{\mathrm{UAR_i}} \tag{2}$$

In the Formula (2), $ULV_i$ means the light value on the built-up area at a pixel level, and $LV_{res}^i$ represents the light value without the non-residential influence.

2.4.2. Estimating HVR

Following the conclusion made by Chen et al. [18], this study regarded the largest light value in a district as the light value for full occupation. The HVR of a district was calculated according to Formula (3).

$$\mathrm{HVR_i} = 1 - \frac{\mathrm{ULV_{res}^i}}{\mathrm{LLV_m}} \tag{3}$$

In Formula (3), HVRi is the house vacancy rate at a pixel level, $ULV_{res}^i$ means the light value of the built-up area in i-th pixel. $LLV_m$ is the largest light value of urban built-up areas in the m-th district. Here, *LLV* is defined as most of the NTL of the pixels with the highest UAR. According to the "Code for classification of urban land use and planning standards of development land in China" (GB 50137-2011), residential land occupies the largest share of urban land. Therefore, it was reasonable to assume that most of the pixels with the highest UAR represented the largest light value that the residential land use could generate.

*2.5. Verification*

There are two commonly used methods for accuracy verification: one is to compare the estimated value with the actual measured value [18]; the other is to compare the estimated result with the results obtained by others in the same area using other methods [34]. Unfortunately, none of these data are available for Chinese cities. As an alternative, this study used the ratio of the number of housing units on sale or for rent to the total number of housing units in one district to characterize the housing vacancy level in the district. The sample HVR could thus be calculated with Formula (4).

$$\mathrm{HVR_i} = \frac{\mathrm{VHN_i}}{\mathrm{WSH_i}} \times 100\% \tag{4}$$

In the Formula (4), HVRi refers to the ith district's house vacancy rate, VHNi means the number of vacant housing units (housing units on sale or for rent) in ith district and WSHi is the total number of housing units in ith district. From this formula, we can obtain the sampled HVR in each district.

This study selected Guangzhou in the Pearl River Delta region in 2019 as the verification area. As shown in Table 3, the overall estimated HVRs were greater than the sampled HVRs. This may partially due to the fact that lights from commercial and business activities impact HVR in the way that they may set a higher "fully occupied light" as commercial lights always have a greater than the residential ones at night. If a pixel occupied by commercial use is set as the standard of "fully occupied pixel", HVRs of all other pixels may be overestimated due to the increase in the denominator of the Formula (4). Although choosing the majority of the pixels with the highest UAR as the largest light value that the residential land use could generate partially reduces the impact of commercial lights on HVR estimation, the overall results are still larger than those of the real ones.

However, whether estimated HVRs can be used to identify dynamic changes in HVR depends more on the correlation between the estimates and the sample HVR. A linear regression was employed to explore the relationship between the sampled HVR and the estimated HVR. As shown in Figure 6, the coefficient of determination ($R^2$) value was 0.472. This demonstrates that there existed a relatively strong relationship between the sampled HVR and the estimated HVR. The results showed that the F value is 6.258, the T value is 6.442 and the *p* value is 0.041. That is to say, the *p* value is lower than 0.05. These indexes all showed that the sampled HVR was strongly related with the estimated HVR and that this linear regression was influential and significant.

**Table 3.** The sampled HVR and the estimated HVR in Guangzhou.

| District | Estimated House Vacancy Rate | Sampled House Vacancy Rate |
|---|---|---|
| Nansha | 49.85% | 5.51% |
| Tianhe | 19.40% | 4.65% |
| Haizhu | 27.76% | 3.61% |
| Panyu | 39.45% | 5.54% |
| Baiyun | 43.16% | 5.45% |
| Huadu | 28.70% | 5.99% |
| Liwan | 30.47% | 3.47% |
| Yuexiu | 11.41% | 3.26% |
| Huangpu | 18.43% | 3.32% |

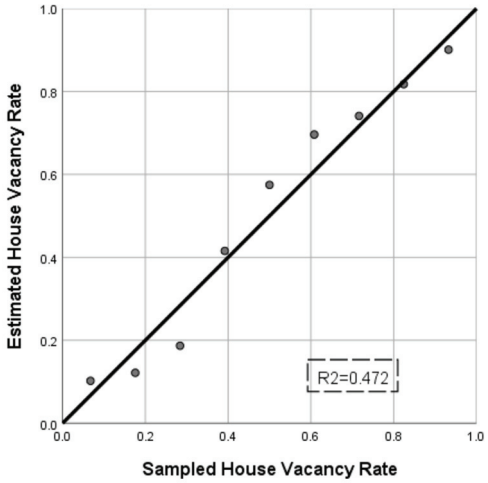



**Figure 6.** The linear regression between sampled HVR and estimated HVR.

Following Formula (5), we also employed the normalized RMSE (root mean square error) to find the difference between the statistical HVR and the estimated HVR. The result was 4.9%. That is to say, the method we used to evaluate HVR was comparatively reliable and accurate. The effectiveness was thus verified.

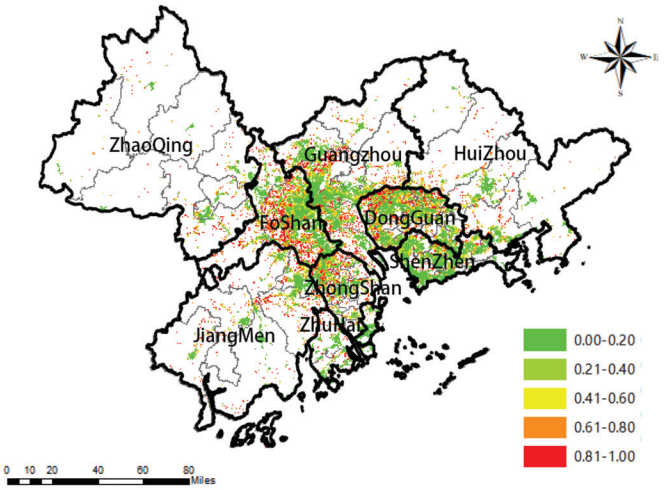
$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}} \sum_{\mathrm{t}=1}^{\mathrm{N}} (\mathrm{sampled} - \mathrm{estimated})^2} \quad (5)$$

In Formula (5), N is the number of the sampled cities; sampled means is the sampled HVR and estimated means is the estimated HVR.

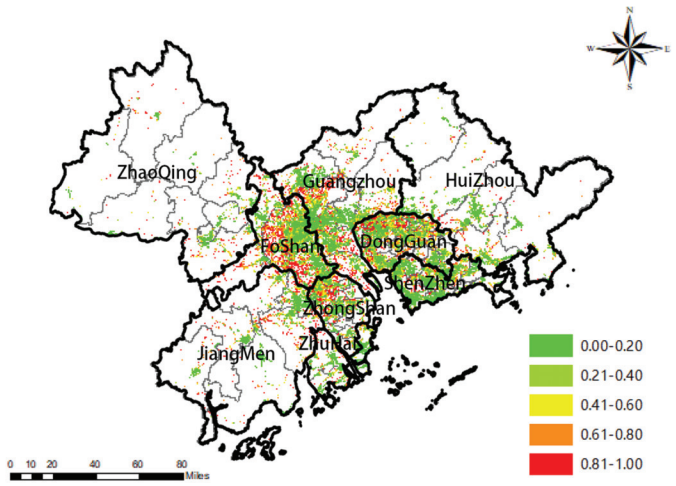
## 3. Results

### *3.1. Overall Decreasing HVRs in the PRD*

We have depicted the mapped HVR distribution in Figure 7 using color ranges from green (0–0.2) to red (0.8–1). The estimated HVR of the PRD decreased from 0.3877 in 2013 to 0.3637 and 0.355 in 2019. Because the light produced by manufacturers that remain working at night—with this being a quite common practice for manufactories in the PRD—was also included in the night light category, the large proportion of manufactural land in the PRD might cause a higher HVR to be registered for these than their actual one. It is worth observing the change in HVRs here. An increasing proportion of pixels with a healthy housing vacancy situation (HVR < 20%) can be witnessed in Figure 7, increasing from 42% in 2013 to 43.68% and 44.94% in 2019. Moreover, the increase in pixels with a healthy housing vacancy situation occurs much faster than the increase in total pixels, with a UAR larger than 20%. The proportion of pixels with a healthy housing vacancy situation increased by 9% from 2013 to 2016 and 8% from 2016 to 2019, while the proportion of construction land (pixels with UAR larger than 20%) increased by only 5% for each period.




(**a**)

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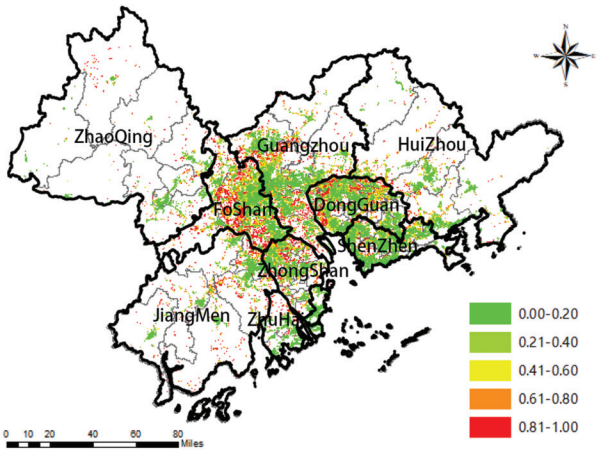
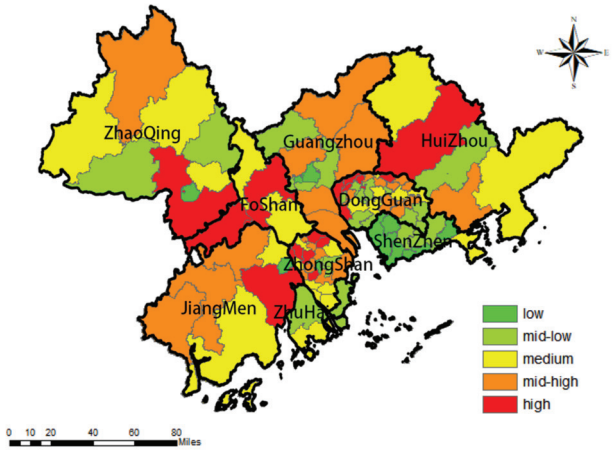



(**c**)

**Figure 7.** HVRs at pixel scale in the PRD. (**a**) 2013, (**b**) 2016, (**c**) 2019.

### *3.2. Dynamics of HVRs at the District Scale*

Looking into the PRD, HVRs have never been evenly distributed. As shown in Figure 8, we separated the districts into five groups: low, mid–low, medium, mid–high, and high. We performed this by calculating and dividing the average HVRs of all districts. The cities located west of the Pearl River Estuary had more districts with high HVRs. Especially in the cities of Jiangmen and Zhongshan, the HVRs in most districts continued rising in these 6 years studied. Together with the completion of the Humen Bridge in 1997 which linked the west and east banks of the Pearl River Estuary, the real estate market believed that citizens in rich east bank cities such as Dongguan and Shenzhen would invest and even inhabit in the west bank. This resulted in the development for irrational speculation in west bank cities. Speculation could at times also focus on one district in a city. For example, the housing vacancy situations in the city of Zhaoqing were found to be relatively healthy. The exception was the District of Huaiji, with this indicating an oversupply of real estate in this isolated county compared with its limited population. Similarly, the HVR of Boluo County in Huizhou increased dramatically from 2016 to 2019, from 0.16 to 0.43. This may be due to the speculation incentives stemming from the spillover of housing needs in Shenzhen and Dongguan.

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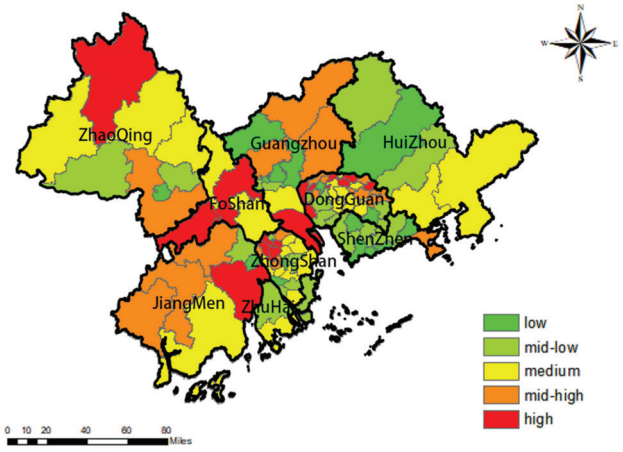


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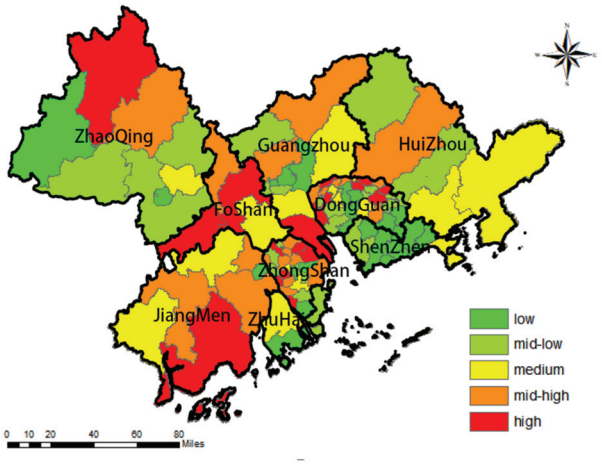
**Figure 8.** *Cont.*

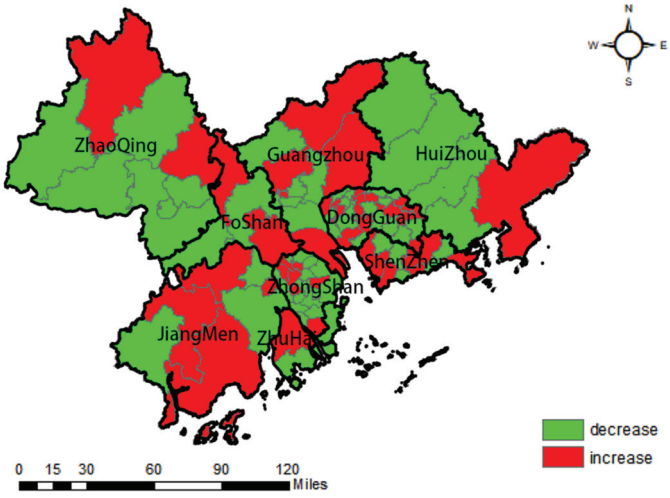



(**c**)

**Figure 8.** HVRs at district scale in the PRD. (**a**) 2013, (**b**) 2016, (**c**) 2019.

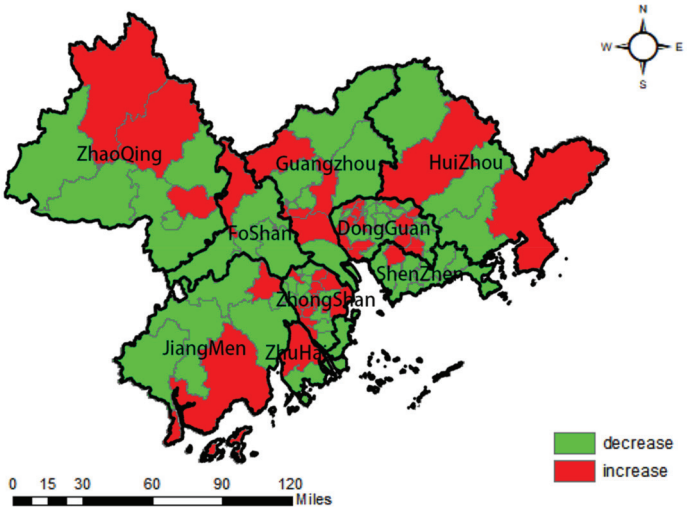
### *3.3. Spatial Differentiation of HVRs Changes*

Most cities experienced reduced HVRs in these 6 years (Table 4). In 2016, the HVRs of 64 districts were reduced compared with HVRs in 2013, and the number of districts in these circumstances increased to 71 in 2019. As shown in Figure 9, the central area of the PRD—including Shenzhen, Dongguan, and Guangzhou—experienced a reduction of HVRs to a greater extent. Such areas enjoyed better economic activities and were found to have attracted many migrants in the past three decades. With limited available vacant land for new construction, the increasing inflow of population to the central area of the PRD supported denser development and increasing population density in this area. Even for the areas that experienced the 2015 real estate bubble, HVRs reduced after 2016. Nansha District of Guangzhou seemed to be an abnormal case in the central area of the PRD and possessed a high HVR (50%). The development of Nansha Port since 2008 also stimulated real estate development in Nansha District. However, the lack of public amenities and employment chances prevented people from living in Nansha.




(**a**)

**Figure 9.** *Cont.*

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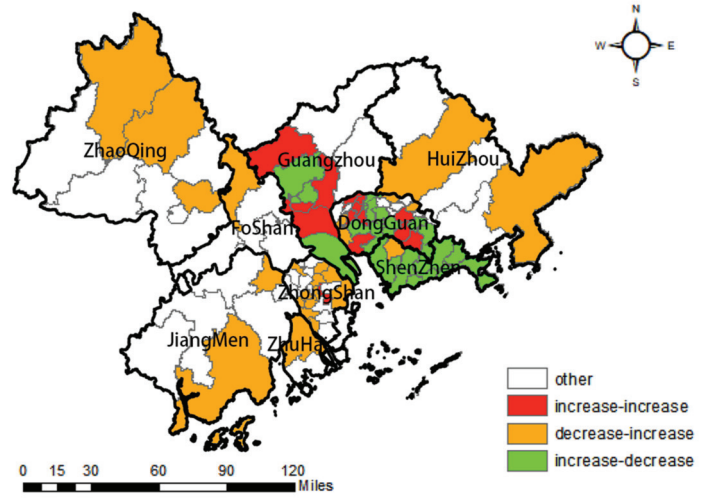



(**c**)

**Figure 9.** Spatial distribution of HVRs changes in the PRD. (**a**) 2013–2016, (**b**) 2016–2019, (**c**) 2013–2019.

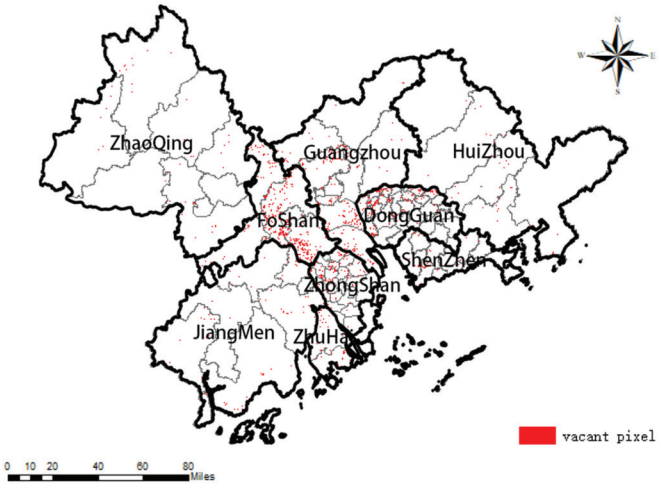
**Table 4.** HVR changes of individual cities in the PRD (2013–2019).

| City | 2013–2016 | 2016–2019 | HVR (2019) |
|---|---|---|---|
| **Guangzhou** | −3.22% | −1.23% | 0.32 |
| **Foshan** | 3.02% | −0.90% | 0.44 |
| **Zhaoqing** | −2.91% | −7.65% | 0.33 |
| **Shenzhen** | −1.21% | −15.38% | 0.21 |
| **Dongguan** | −3.08% | −7.53% | 0.37 |
| **Huizhou** | −24.18% | 12.52% | 0.33 |
| **Zhuhai** | 2.21% | −21.50% | 0.27 |
| **Zhongshan** | −8.89% | 6.64% | 0.40 |
| **Jiangmen** | −3.22% | 5.71% | 0.40 |
| **PRD** | −4.99% | −2.39% | 0.35 |

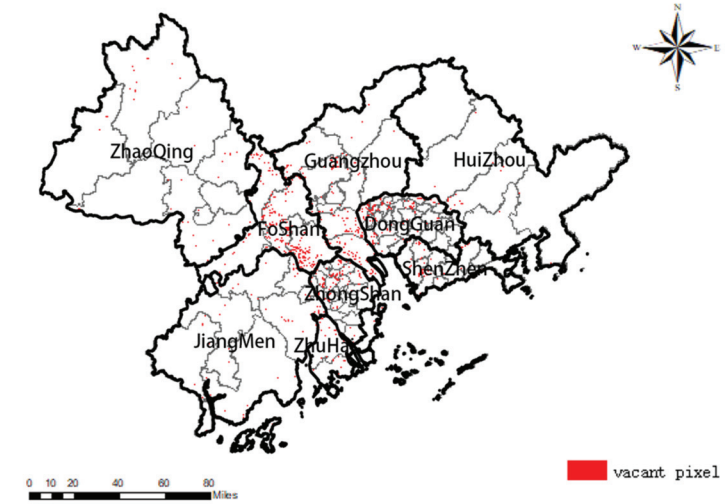
### *3.4. Potential Risk: Increasing Vacant Pixels in the PRD*

This study has paid more attention to the NTL pixels with UAR of more than 20% but which possessed a light value lower than the background light and extracted them, as shown in Table 5 and Figure 10. Such pixels could be recognized as vacant pixels where

there was development, but there are almost no inhabitants in the buildings provided in those pixels. Considering the NTL pixels' scale, vacant pixels could result from new projects under construction or increasing rates of development for investment purposes instead of residence. The number of vacant pixels increased from 2980 to 3031 in 2016 to 3076 in 2019. Of all 105 districts, 52 districts have witnessed increasing vacant pixels from 2013 to 2016, and 46 districts had increasing vacant pixels in 2019 compared with the situation in 2016. As occurred in Shenzhen and Dongguan, sometimes, vacant pixels—an oversupply of new projects—were automatically filled by the inflowing population and increasing housing needs. They both experienced reduced numbers of vacant pixels. Respectively, the number was 58 in Shenzhen and 67 in Dongguan. However, most cities had more vacant pixels in 2019 than in 2016, especially those on the outskirts of the PRD. This warns us about the risk of the use of tremendous development to increase the supply of housing units in the PRD that may increase HVRs.

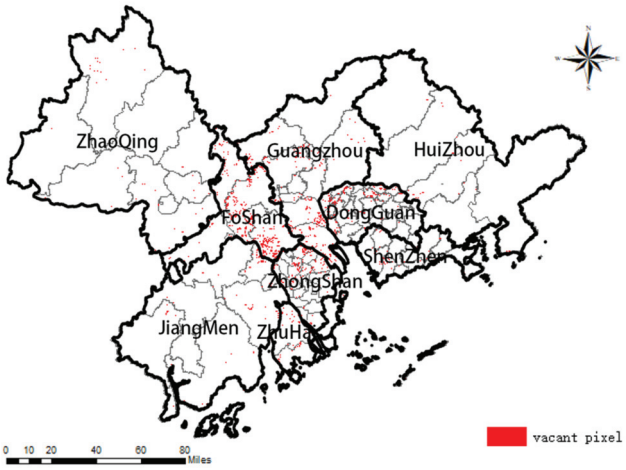



(**a**)




(**b**)

**Figure 10.** *Cont.*




(**c**)

**Figure 10.** Spatial distribution of vacant pixels in the PRD. (**a**) 2013, (**b**) 2016, (**c**) 2019.

**Table 5.** Number of vacant pixels in cities in the PRD.

| City | 2013 | 2016 | 2019 |
|---|---|---|---|
| **Guangzhou** | 596 | 639 | 684 |
| **Foshan** | 938 | 854 | 906 |
| **Zhaoqing** | 9 | 24 | 45 |
| **Shenzheng** | 144 | 190 | 132 |
| **Dongguan** | 631 | 604 | 537 |
| **Huizhou** | 48 | 46 | 53 |
| **Zhuhai** | 153 | 131 | 140 |
| **Zhongshan** | 354 | 421 | 420 |
| **Jiangmen** | 107 | 122 | 159 |
| **PRD** | 2980 | 3031 | 3076 |

## 4. Discussion and Conclusions

Cities are interconnected through spatial interactions and are merged into closely related urban network systems [4]. This strengthens the functional connection between cities and enhances the resource-gathering capacity of a continuous urban region, but there may be differentiation and mutual negative impacts within continuous urban regions. The dynamics of HVR distribution, as an important index of housing oversupply or real estate speculation, may have applications to monitoring unbalanced development within the continuous urban region and are worth in-depth study. Especially in China, the local governments have proved their powerful influence on defining urban development and have caused a remarkable scale of uneven development across and within cities.

Monitoring HVR has long been hampered by the difficulty of collecting housing vacancy information via traditional methods. By the mixed use of various big data, NTL data has shown its effectiveness in HVR estimation at the city level [18–22]. The research carried out by Chen et al. [18] has demonstrated the effectiveness of using NTL data to estimate HVR at the city level. In this study, we applied both NPP-VIIRS NTL data and Landsat 8 OLT images to estimate HVRs in the PRD at the district level, and tracked the spatial–temporal dynamics of HVR distributions to evaluate the interaction of urban development across cities for the period from 2013 to 2019. The study of district-level HVRs is theoretically significant for studying the dynamics of HVR distribution in a continuous urban region as it shows the areas of interaction between cities more precisely. With the monitoring of unbalanced regional development as the target, the most critical issue here is not the accuracy of the vacancy situation of housing units, but the judgment of the

overall vacancy rate status and dynamics throughout a continuous urban region. In this assessment, districts operate as the units.

To get rid of the noise in original images, NTL data are first denoised. The urban built-up areas are then extracted based on Landsat 8 OLT images; then, light intensity is calculated at a pixel level for residential areas. The HVR of a district was thus calculated according to the comparison between the light value of each pixel and the higher light value in a district (the majority of the NTL of the pixels with the highest UAR). Furthermore, this study uses the ratio of the number of housing units on sale or for rent to the total number of housing units in one district to characterize the housing vacancy level in the district, and compares it with the estimated HVRs. The comparison between the sampled HVRs and estimated HVRs verifies the estimated HVRs' effectiveness in identifying dynamic changes in HVRs.

Due to the large proportion of manufactural land in the PRD, high HVRs observed in the PRD do not necessarily indicate a high-risk market. This study has paid more attention to the change in and distribution of HVRs in the PRD. Overall decreasing HVRs in the PRD is proved by a faster decrease in rate of HVRs than the rate of increase in construction land. However, such changes are not evenly distributed throughout the PRD. Housing investment speculation mainly focuses on cities located west of the Pearl River Estuary, such as Jiangmen and Zhongshan, and some isolated districts in other cities, such as the District of Huaiji in Zhaoqing, the District of Nansha in Guangzhou, and the County of Boluo in Huizhou. The global Moran's I index indicates a positive and increasing correlation of the HVRs between different districts. This study also calculates the distribution of vacant pixels to indicate the increasing levels of development for speculation purposes instead of residence. Increasing levels vacant pixels in cities other than Shenzhen and Dongguan point out the risk that the tremendous development might increase the future stock of housing units in the PRD and cause larger housing vacancy problems.

In broader theoretical terms, the preceding methodological and empirical discussion in this article reflects an attempt to contribute to, and advocate for, estimating and tracking the dynamics of the HVR distribution in a continuous urban region with the use of open access data. It allows for the close and timely monitoring of the housing vacation situation in the region and may be applied as a very important tool to correct wrong development decisions and promote balanced regional development. In areas where real estate resale and rental markets are well developed and online information is abundant, HVRs can also be approximated with other methods, such as the one employed in this study to verify the results. In these methods, researchers may calculate the ratio of the number of housing units on sale or for rent to the total number of housing units. However, for a wider area in which online rental and sales information are unavailable, it is more economical and efficient to use free NTL data. This also allows for HVR comparisons over larger regions to support the analysis of uneven development and local policy adjustments.

This research proves that the HVRs at the district scale can be estimated through NPP-VIIRS night-time light data, and that the results could represent the dynamics of HVR distribution well. However, the method is not precise enough to give detailed HVRs, and there could be further improved for future studies. First, more precise data, such as Jilin-1 (0.9 m) and EROS-B (0.7 m), could offer better results in HVR estimation. Second, the use of advanced deep learning-driven super-resolution mapping techniques [35,36] could also help to improve the accuracy of the estimation. With more available data about real HVRs, the verification process could be further improved. Spatial analysis, such as the global Moran'I index or the spatial Dubin model for spatial autocorrelation analysis, could help to reveal the logic behind HVR distribution.

**Author Contributions:** Conceptualization, X.L. and W.Z.; methodology, Z.L., X.F. and W.Z.; software, Z.Y. and M.L.; validation, X.L., L.Y. and W.Z.; formal analysis, Z.L. and X.L.; data curation, Z.L. and X.L.; writing—original draft preparation, X.L.; writing—review and editing, Z.Y. and W.Z.; visualization, M.L.; supervision, W.Z.; project administration, W.Z.; funding acquisition, X.L. and W.Z. All authors have read and agreed to the published version of the manuscript.

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# Study on the Effect of Job Accessibility and Residential Location on Housing Occupancy Rate: A Case Study of Xiamen, China

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**Abstract:** The serious mismatch between industrialization and urbanization has led to the emergence of ghost cities. Industry-and-city integration aims to agglomerate industries and the population simultaneously by coordinating the planning and construction, and by mixing different functional areas including industry, office, living, and commercial functions. Based on the population spatial vector database of Jimei District in Xiamen in 2020, this paper empirically analyzes the effects of spatial patterns between industry and city, in terms of residential location and job accessibility, on the housing occupancy rate in new towns and cities. The findings demonstrate that: (1) The attraction of residential location to population varies among three different urban expansion models. The housing occupancy rate of residential areas that meet the concentric circle model is the highest, followed by the sector model, and the multiple nuclei model is the lowest; (2) The jobs–housing relationship has a stable and positive impact on the occupancy rate of commercial housing in the new town, which verifies that job accessibility is the basic demand for families' residential location choice; (3) There is a significant pattern difference in the influence of job accessibility on the occupancy rate. The occupancy rate of the sector model residential area is highly dependent on job accessibility: the higher the job accessibility, the lower the occupancy rate of the concentric residential area, while job accessibility has a weak impact on the occupancy rate of the multiple nuclei residential area. The conclusions suggest that the spatial planning of new towns should include a clear population absorbing strategy, and the residential location should follow the expansion law of the urban residential functional area, balance the relationship between industrial agglomeration and the job–housing relationship, and allocate life factors in a targeted manner according to the actual impact of job accessibility.

**Keywords:** urban expansion; housing vacancy; job accessibility; jobs–housing relationship; residential location

## 1. Introduction

China has undergone a strikingly rapid urbanization process since its economic reform starting in the late 1970s. In order to accommodate the increasing population and to ameliorate the overcrowding issues in the old city, physical urban expansion is an indispensable process. In China, in order to improve urbanization and industrialization, city expansion has been carried under different, and sometimes confusing and misleading titles, such as university, airport, and high-speed rail new towns (*xin zhen*)/new cities (*xin cheng*)/new districts (*xin qu*), because *zhen/shi/qu* also refer to administrative level and the new towns/cities/districts do not necessarily match the administrative jurisdiction area. The excessive planning and construction of new districts and towns around booming cities come at a cost of no or very low population density and a very high housing vacancy rate, resulting in the emergence of so-called 'ghost cities' [1–3]. A ghost city is not necessarily

an administrative level of a city (*shi* in Chinese), but often a new district as a sublevel administrative division of the *shi*; for example, the most infamous ghost cities are Kangbashi District in Ordos [1], and Zhengdong New District in Zhengzhou [4]. The existence of ghost cities has caused significant economic and social costs, and a waste of land resources, which violates the development objectives of intensive use of land resources and high-quality urbanization [5,6]. The reason for the ghost cities can be attributed to the serious mismatch between industrialization and urbanization [7–9], leading to the emergence of new towns and districts without industries. Housing vacancy often coexists with housing congestion, which is the major source of public dissatisfaction with housing policies, and it is also a typical manifestation of land use spatial mismatch and low utilization efficiency [10]. Scholars have put forward the concept of industry-and-city integration [11]; industry refers to activities involving goods and services production, while city refers to residential and commercial facilities, and places of leisure. Industry-and-city integration aims to match and combine industry and infrastructure, industry and settlement, and eventually attract the population and reach a seamless integration among industry, city, and people [12,13].

The core of industry-and-city integration is to agglomerate industries and the population simultaneously by coordinating the planning and construction, and a mixture of different functional areas including industry, office, living, and commercial functions. For the new towns, the number of potential jobs is estimated through the expected scale of the industry, and a certain number of houses for potential workers are built. In this way, it aims to create a job–housing balance, a spatial match between employment opportunities and living spaces [9,14]. However, efforts to promote mixed land use and built self-contained communities often do not have good results, and the trend of "job–housing separation" has become more and more obvious [15].

In other words, there is disagreement on whether job–housing proximity or job–housing separation is more conducive to population agglomeration in new towns. For the former, it is believed that residents' housing location and employment should be as close as possible to reduce commuting time, traffic congestion, and transportation costs. However, relying on decentralized job opportunities to achieve job–housing balance is at the expense of agglomeration's economic gains. Industrial agglomeration can bring economic efficiency, so the spatial pattern of job–housing separation is conducive to enterprises concentrating more effectively, enjoying the economic advantage of agglomeration, and improving labor productivity. Job–housing balance requires that every enterprise can find suitable employees in the vicinity, and every worker can find suitable jobs around the place of residence, which is difficult to achieve in the labor market. Moreover, when there are multiple workers in one family, the places of work will be very scattered, and one place of residence cannot be balanced with multiple places of employment. Finally, with the increasing diversity of urban residents' lives, families should consider not only job accessibility, but also all kinds of public services they need, such as schools, hospitals, green spaces, and commercial centers, which do not match the spatial distribution of jobs. Therefore, families may sacrifice job–housing balance to achieve the goal of maximizing their overall utility.

In reality, the family faces doubly constrained markets: the labor market and the housing market. The current understanding of the spatial relationship between industry and the city lags far behind the practical needs. Therefore, this paper attempts to clarify the application scenarios of the job–housing spatial relationship and its effect on the housing occupancy rate. This paper takes the housing occupancy rate of Jimei District as the dependent variable and examines the impact of job accessibility and housing site location. Job accessibility is calculated by the estimated labor market outcome (ELMO) model developed by Östh [16], which captures the state of competition in doubly constrained markets: the labor market and housing market. Housing site location considers and operationalizes the three models of urban expansion theories; i.e., the concentric zone model [17], sector model [18], and multiple nuclei theory [19].

This paper contributes to the current studies in the following ways. First, China lacks authoritative data on urban housing vacancies, and this paper provides a residential scale occupancy rate, instead of housing vacancy mainly based on either satellite images of nightlight brightness at the city scale, or on-the-spot investigation, or geographic location-based service data [1,2,20,21]. The accuracy of vacancy rate data obtained through survey or indirect inference in prefecture-level cities can meet the needs of national-level research. However, research on housing vacancies within cities needs to be carried out at the small-scale residential block level. Second, it connects the urban expansion model with the housing occupancy rate, and examines the difference in the job–housing spatial structure and population attraction mechanism under different urban expansion models; therefore it provides practical implications and room for urban planning and government intervention.

The paper is structured as follows. Section 2 reviews the literature. Section 3 presents the hypotheses, and is followed by methods and data in Section 4. Section 5 presents the empirical results, and Section 6 concludes.

## 2. Literature Review

### *2.1. Job–Housing Distance and Population Distribution in the City*

Population agglomeration in suburban new towns has long attracted academic attention. Gibbs [22] pointed out that after the 1960s, the concentration trend of the rural population migrating to large cities turned to suburbanization, and the population began to move from large cities to satellite cities, and from metropolises to small cities, and the places of work and residence were increasingly separated. Goldstein and Mayer [23] proposed a typical pattern of population migration within North American cities during the period of rapid industrialization. Most new European immigrants settled in the old areas of the city, and then moved to areas with better housing conditions on the edge of the city through a generation or more of adjustment and socialization, and the inner circle of the city began to be abandoned. However, not all migrants could complete the migration from the inner circle to the suburbs. Only the high-level elite among the migrants tended to settle on the edge of the suburbs, while the young and middle-aged (unmarried, married without children) tended to still choose to live in the inner circle of the city. The emergence of a large number of "urban villages" after World War II is another notable feature of the population distribution of Western cities. The population size of rural communities adjacent to big cities is increasing, and rural residents mainly rely on urban employment, which also makes the distance between jobs and residences more and more distant. In the 1980s, the trend of suburbanization in Western industrial cities turned into gentrification [24]. The once-declining central urban area experienced urban renewal, attracting high-income groups to move in again, while the original residents moved out because they could not afford the cost of living. The distance between jobs and residences of ordinary wage earners working in the old city has widened, and excessive commuting has become a problem that damages the urban environment. To curb the waste of resources and pollution caused by the spread of urban suburbanization, the new urbanism that emerged in the 1990s put forward smart growth requirements for urban land use planning, advocating increased residential density and reduced commuting to reverse the dispersion of urban population since industrialization.

However, long-term vacancy of housing not only occurs in cities with population loss: there is also a high housing vacancy rate in peripheral towns of cities with population growth [25]. This is also the problem with China's new towns, even in the eastern population growth cities [20,21]. Both the newly arrived migrant population and native residents of the old city do not tend to live in new towns, resulting in a relatively high vacancy rate of housing in the new towns. How land use planning can increase the population concentration of new towns has become the focus of China's urbanization.

### *2.2. Industry-and-City Integration and Population Aggregation*

In order to explore the population aggregation mechanism in the development of new towns in China, scholars put forward the concept of industry-and-city integration [11–13]. A high level of industry or urbanization cannot be directly translated into the attractiveness of the population. Instead, it is the integration of urbanization and industrialization, and the corresponding living and employment functions that meet people's needs, which are the driving force for the gradual increase in population. Yue and Gu [12] emphasized that within the multi-dimensional integration of industry and city in terms of the natural geographical environment, urban functions, development stages, industry types, spatial scales, and historical and cultural characteristics, the integration of employment and residential space is most crucial. On this basis, it is generally assumed that the integration of employment–residential spatial relationships can attract more people to choose to live in new towns [26,27]. However, how to realize the spatial integration of industry and city causes difficulties in both theory and application, and theoretical development lags far behind practical needs.

In the field of land use and planning, the term closest to industry-and-city integration is job–housing balance, which is used to represent the matching degree between the number of laborers and the number of jobs in a city within a certain area [28]. In land use planning, advocating the layout of employment and residences close to each other and reducing the separation of jobs and housing has gradually become the mainstream spatial layout principle of urban planning practice in China. However, when some new town developers try to implement the concept of integration of industry, city, and people to build residential areas around the industrial parks, they find that the actual occupancy rate is not high. In other words, the job–housing balance to minimize commuting cannot be directly translated into the effect of population aggregation [29]. There should be a more complex mechanism of influence between the integration of industry and city and the attractiveness of population aggregation. It is necessary to conduct an in-depth analysis from the perspective of job accessibility and the behavior of residential location choice.

### *2.3. Job–Housing Balance and Residential Location Choice*

The causal logic that the jobs–housing balance can promote population agglomeration mainly comes from the behavior of residential location selection at the micro level. Under the assumption of the classic single-center city model, all residents work in the CBD, and residents will make a trade-off between commuting costs and housing costs, so the choice of family residence becomes a problem of location choice. Since there are differences in employment opportunities, housing costs and commuting costs in each location, under the principle of utility maximization, residents tend to choose the residential location with the lowest commuting cost. Liu and Wang [8] used job accessibility to reflect the jobs and residences relationship in the region, and verified that the job accessibility of the region affects residents' commuting time, thereby affecting the choice of residential location. By extending the microcosmic behavior of residents to the regional level, the area where the occupation and residence are close has the effect of attracting the population.

However, residential–employment mixed land use alone does not achieve high employment self-containment of residents [15,29]. There are many reasons for questioning job–housing balance's effect on population aggregation. First, critics of the relationship between job–housing balance and commuting efficiency point out that the job–housing balance may not necessarily reduce commuting time, as it reduces external trips but may increase the congestion for the growing internal trips [30,31]. Ibeasb et al. [32] found that under different circumstances, it is job accessibility, not commuting time, which affects the choice of residential location. Second, the role of commuting costs in residential location decisions is not decisive. In real life, the selection of residential locations not only considers commuting costs, but also considers land prices, housing prices, and the distribution of public resources, and there are large differences in the selection goals of residential locations for different socioeconomic groups [33,34]. Through study of the Paris metropolitan area,

Korsu and Wenglenski [35] found that the job–housing balance still plays a key role in residents' job and residence location choice, but it is no longer the main factor in residential location choice. In other words, the job–housing balance is not the decisive factor in the location selection of jobs and residences, and is not a rigid principle that needs to be followed in the location selection of industries and residential areas. Third, under the market economy, job–housing separation has its inevitability and rationality. Zheng et al. [15] pointed out that the spatial pattern of "separation of jobs and housing" is conducive to a more effective concentration of enterprises, enjoying the advantages of agglomeration economies, and improving labor productivity. Relying on dispersed job opportunities to eliminate job–housing separation is at the expense of agglomeration economic benefits, which is often difficult to achieve in an urban spatial structure dominated by market forces.

To sum up, the research on urban sprawl focuses on whether the job–housing balance is conducive to population aggregation and enhances industry–city integration. The views in the literature that support or question the population aggregation effect of employment and housing are mainly from the micro level of family behavior, while the occupancy rate is a phenomenon at the level of residential areas. The distribution of population in a region cannot be directly inferred from micro-level behavior. Even if there are indeed factors that weaken the importance of job accessibility in the choice of family residential location, it does not mean that the distribution pattern of higher population density in areas close to jobs and residences will be changed at the residential area level. Second, as a spatial feature, the job–housing balance does not include the location factor and discussion of its relationship with population agglomeration. Therefore, this paper intends to focus on the occupancy rate of residential areas to explore the spatial variation law of the influence of job accessibility on occupancy rate.

## 3. Theoretical Hypotheses

Urban scientists and planners have put forward many theories to improve our understanding of the spatial urban expansion and functionality of cities. Among them, the most well-known are the concentric zone theory, the sector theory, and the multiple nuclei theory [17–19,36]. These theories take into account the coordination of residential–employment spatial relations, spatial function, and the realization of population growth. These Western classical urban expansion models are the main reference for Chinese urban planners in the land use planning of new towns and have been verified to a certain degree in Chinese literature [37–43]. The population density distribution in some Chinese cities presents an obvious concentric zone pattern, with the city center as the core and suburban new town as the extension. The population density decreases gradually from the inside out [40,41]. Sector urban expansion along main roads is a common strategy in the expansion of Chinese cities. For example, by studying the urban spatiotemporal dynamics based on remote sensing and GIS in Dongguan, Guangdong, Li et al. [42] revealed the wave-like characteristics of urban expansion along main roads. Under the influence of New Urbanism, the "group + TOD" planning model connecting new cities and old cities with modern closed transportations tools such as BRT, subway, and light rail has become increasingly popular, and the growth of urban spatial structure shows a multiple nuclei pattern [43]. However, few studies have explored the impact of urban spatial structure on housing occupancy rates, which is the starting point for the current paper.

Under different urban expansion patterns, the residential–employment spatial structure realizes different urban functions, and the reasons for attracting people to live are different. It should be noted that the job–housing relationship does not act independently on population agglomeration. It is the urban function formed by the combination of job–housing relationship and residential location that attracts people to live in an area. The housing occupancy rate varies due to the difference in the residential locations. Residential location and job accessibility both have influenced housing occupancy rates. Therefore, in the following section, we propose our hypotheses according to the combination of job accessibility and residential location under three urban expansion models; namely, the

concentric zone model, the sector model, and the multiple nuclei model. To make it clear, we elucidate each model's logic of attracting the population, and propose hypotheses on the relationship between the job accessibility and occupancy rate.

### *3.1. Concentric Zone Model and Occupancy Rate*

Burgess's theory of concentric circles divides the internal structure of the city into three rings: the central business district (CBD), the residential area, and the commuting area. The process of urban growth is that each ring expands its scope by invading the outer ring, and the urban spatial pattern after the expansion is still concentric circles [17]. Therefore, the location of the new residential area should be on the periphery of the expanded central business district and within the commuting area. At the same time, the expansion of concentric circles also emphasizes the close relationship between jobs and residences. It is advocated that the location of residential areas should be kept close to the commercial and industrial areas of workers, and the layout of high-end commercial residences in the outer commuting areas away from the center, so that the residential population is still concentrated. The population introduction mechanism of the concentric circle structure is to accommodate the residential needs of the growing population of the central business district by sharing the urban functions and facilities of the old city.

Although the concentric circle model has been criticized for having no real boundaries for the functional areas, this does not mean that the location of the concentric circles cannot be measured. In the Chinese context, cities have generally formed through the sprawl process of traditional monocentric old cities, with a central area with a high concentration of population and functions. As the population continues to increase, the population density gradually decreases from the inside to the outside. Therefore, the principle of site selection for residential areas that conform to concentric circle expansion is to arrange residential areas near high-density centers. In this way, residential population density is a reflection of the location characteristics for residential areas in the concentric zone urban structure. The higher the population density of a residential area, the closer it is to the central business district. Meanwhile, an increase in residential population density in suburban areas indicates that residential functions have been transferred to that area. Based on this, the hypothesis on the spatial relationship between industry and city and occupancy rate under the concentric circle expansion model is proposed:

**H1.** *The higher the population density around the residential block and job accessibility, the higher the occupancy rate of commercial housing*.

### *3.2. Sector Model and Occupancy Rate*

The sector model, also known as the Hoyt model, is a modification of the concentric zone model of city development. Hoyt [18] argued that cities do not develop in the form of simple rings; instead, cities extend outward along the roads and railways and the expansion of cities is in a wedge-like fashion. The location advantages formed by the convenient circulation of the traffic arteries can promote the concentration of investment, industry, and population to the traffic arteries, and will gradually form an industrial belt with the traffic lines as the main axis. With the development of the economy and the expansion of the spatial scope of the development zone, the development zone is gradually integrated with the original urban area, making the original urban area expand into a belt. The spatial layout of the sector expansion model is to lay out new industrial spaces on both sides of the trunk road, and provide supporting residential spaces nearby. The sector expansion model is also a common strategy in the expansion of industrial cities or urban industrial areas in China, and has the characteristics of tidal wave expansion along traffic roads [42]. The urban expansion process presents an oscillation between the diffusion phase and coalescence phase. The former is a dispersed development of newly expanded patches after the newly built roads, while the coalescence phase refers to infilling in the urban complex or the expansion outward from the existing urban patches [44]. It can be seen that

the population introduction mechanism of expanding the new towns in a sector mode is to provide living space for the employed population absorbed by industrial agglomeration and to attract the population to live with the convenience of employment and commuting. The main trunk roads across regions are the infrastructure for sector expansion, or axial expansion in Chinese literature [42], and are designed and constructed to intentionally highlight the purpose of improving commuting efficiency between new and old cities. The trunk roads usually adopt a closed road model similar to a highway with two-way multi-lanes and no traffic lights, and it is free of charge. The site selection characteristics of the sector expansion residential area are close to the main trunk roads across the region, and it is emphasized that the living space should be close to the employment space. Based on this, the hypothesis of the industrial–city spatial relationship and occupancy rate under the strip-shaped axial expansion model is proposed:

**H2.** *The closer the distance to the cross-regional trunk road and the higher the job accessibility, the higher the occupancy rate of commercial housing*.

### *3.3. Multiple Nuclei Model and Occupancy Rate*

The multiple nuclei model advocates solving the problems of urban sprawl and population organic evacuation by building satellite towns and districts around large cities [19]. From the perspective of the process of regional economic development, new regional growth poles are always firstly concentrated in a few areas with better conditions, and they are distributed in spots. When clusters of growth poles appear, a complete regional functional center including employment, administration, commerce, and entertainment will be formed within a certain area. Then, traffic is built to connect the scattered centers so that the crowded population in the old city can be organically evacuated to the subcenter of the city, and finally realize the population distribution pattern of polycentric aggregation. Since 2000, under the influence of new urbanism, the "group + TOD" planning model that connects the new towns with the old city by means of modern closed transportation such as BRT, subway, and light rail has become increasingly popular [45,46]. The structural growth of Chinese cities is shifting towards polycentric.

The population import mechanism of the multiple nuclei expansion model is that the overpopulation of the old city drives the population to evacuate to other urban subcenters. In order to connect the multiple centers and transfer population rapidly, subways have been built. In the multiple nuclei model, the subway stations are often located at or near the functional center in new towns, such as administrative, leisure, medical, commercial, and residential centers. Unlike the sector expansion model, the polycentric "axes" are only responsible for the transfer of populations, not all factors of production. In other words, the essence of the multiple nuclei model is to greatly improve job accessibility and realize population dispersal by using the mobility of modern means of transportation. Therefore, the residential location characteristics of the multiple nuclei model are that they are adjacent to the main stations of the modern transportation network. Based on this, the hypothesis of the industrial–city spatial relationship and occupancy rate under the polycentric expansion model is proposed:

**H3.** *The closer the commercial housing is to the subway station and the higher the job accessibility, the higher the occupancy rate of commercial housing*.

## 4. Empirical Framework and Data

### *4.1. Econometric Model*

We estimated the effects of job accessibility and residential location on housing occupancy using OLS regressions. The baseline model used takes the form:

$$Y_i = \beta_0 + \beta_1 A_i + \beta_2 M_i + \beta_3 R_i + \beta_4 D_i + \beta_5 M_i A_i + \beta_6 R_i A_i + \beta_7 D_i A_i + \sum \alpha_j X_i + \varepsilon_i$$

where $Y_i$ represents the occupancy rate of the $i$th residential block, $A_i$ represents the job accessibility, $M_i$ is the distance between the residential block and the nearest metro station, $R_i$ is the distance to the nearest trunk road, and $D_i$ represents the population density within 3 km of the residential block. $X_i$ stands for the control variables. $M_iA_i$, $R_iA_i$, $D_iA_i$ are the interactions between job accessibility and the variables of the three location models, to examine the effect of residential location (see the conceptual framework in Figure 1).

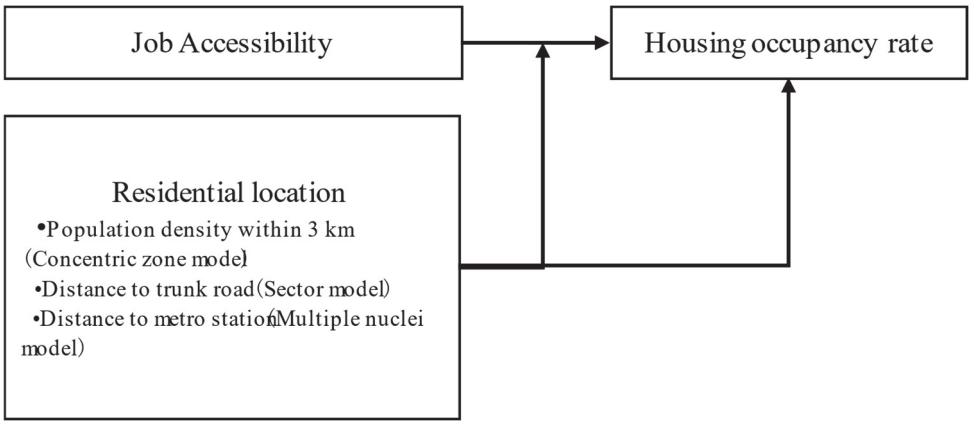


**Figure 1.** Conceptual framework.

In order to present the spatial difference of the influence of job accessibility on housing occupancy rate, this study used geographically weighted regression (GWR) to estimate the spatial heterogeneity of the job accessibility coefficient. The model is as follows:

$$Y_i = \beta_0 + \beta_{1i}(u_i, v_i)A_i + \beta_2 M_i + \beta_3 R_i + \beta_4 D_i + \sum \alpha_j X_i + \varepsilon_i$$

where $\beta_{1i}(u_i, v_i)$ is the regression coefficient of the job accessibility $A_i$ at the $i$th sample point, and its numerical magnitude changes with the change of the point position. The coefficients for other variables do not vary spatially.

*4.2. Variables*

The **dependent variable**, the occupancy rate, was calculated by dividing the number of households living in the residential block by the number of housing units. Unlike the prior studies, in which the data were often obtained by estimation, the household information used was the information registered by the public security department, and the number of housing units in each residential block was provided by the planning department. The occupancy rate ranged from 0 to 100%.

The main **independent variable** was job accessibility, which represents the spatial relationship between the distribution of the labor force-age resident population aged 18–59 and the distribution of employment opportunities in the region. Prior models of job accessibility involve the summarization of potential job opportunities within the bounds of a predetermined boundary, which creates the problem of endogeneity since the delineation of the area is not made on basis of individual preferences but rather on the basis of conditions that are common to all individuals. In this study, we used the approach developed by Östh [16] to address endogeneity. The estimated labor market outcome (ELMO) [16] is a direct response to the need for the creation of an improved measure of accessibility, mimicking the state of competition in doubly constrained markets: the labor market and housing market. Compared with the traditional two-step search method, which only uses distance as a weight, the model takes into account the situation where different individuals compete for the same job. In other words, the EMLO three-step search model first computes the weight of job competition among firms, the weight of job search competition among labor forces, and then job accessibility.

Referring to Östh [16], the calculation of ELMO was conducted via three steps.

The first step was to search for job opportunities around the residential area within the realms of an annulus, and to measure the degree of job competition among residents. Assuming that the individual labor force has requirements on the distance between jobs and residences, job opportunities within a certain realm of an annulus r were acceptable, and job opportunities outside the circle were not considered. Then, we calculated the summed potential workers ($S_i$) aged between 18 and 59 residing within the realms of an annulus of the jobs;

$$S_i = \sum s_i$$

The ELMO model assumes that job seekers have a distance preference for job opportunities, and are more interested in jobs that are close to them, and less interested in jobs that are far away. Therefore, the degree of interest of residents in residential area $i$ in the jobs provided by enterprises in the surrounding area decreases with the distance between residential block $i$ and enterprise $j$. Let $w_{ij}$ be the degree of interest of the residents of residential block $i$ in the job opportunities of enterprise j, and the number of jobs provided by enterprise $j$ in the circle $D_j$. Then, the total amount of acceptable job opportunities $AD_i$ for residential block $i$ is:

$$AD_i = \sum D_j w_{ij}$$

The $Z_i$, the job competition coefficient, is the ratio of the total labor force supply in residential block $i$ to the total available job opportunities within the realms of the annulus:

$$Z_i = \frac{S_i}{AD_i}$$

$Z_i$ reflects the employment supply and demand relations; if $Z_i > 1$, it means that the supply of labor exceeds the demand, and there is job competition among the laborers. Conversely, if $Z_i < 1$, it means that the enterprises within the realms of the annulus provide more job opportunities than the labor supply.

The second step is to search for labor supply around the enterprise, and to measure the degree of competition in recruitment among enterprises. Due to the distance between jobs and residence, enterprises can only recruit employees from residential areas with distances less than r. The job-seeking competition coefficient $Z_i$ of each residential block determines how difficult it is for enterprise j to recruit enough labor. The larger $Z_i$ is, the more difficult it is for enterprises to recruit employees from residential block $i$. The attractiveness of enterprises to labor still decays with the degree of distance $w_{ji}$. Therefore, the calculation of the number of potential job seekers $AZ_j$ that enterprise j can recruit from the surrounding area is as follows.

$$AZ_j = \sum Z_i w_{ji}$$

$DC_i$, labor demand under competition, is calculated by dividing the actual demand for jobs with the competition value $AZ_i$. High competition (value above 1) decreases the amount of $DC$ at the location, whereas low completion increases the amount of $DC$.

$$DC_i = \frac{D_i}{AZ_i}$$

Centering on the location of the residential block, the third step is to search for effective job opportunities in the surrounding area, and calculate the job accessibility of the labor force in the residential area. The higher the $DC_i$ value of the job's popularity, the lower the possibility that the job seeker will secure the job. If the recruitment competition coefficient of enterprises in the circle is very low, the possibility of employees working in this enterprise is very low. Considering the distance preference $W_{ij}$, $ADC$, the abbreviation of aggregation of demand for labor under competition is calculated as:

$$ADC_i = \sum Z_i w_{ji}$$

For a specific residential block, the effective number of jobs that the labor force is willing to go to and can go to is not equal to the jobs actually provided by the enterprises in the area. After considering the job competition among the labor force and the recruitment competition among enterprises, the effective job estimate $EE_i$ of the labor force is as follows:

$$EE_i = ADC_i * Z_i$$

Finally, the average number of available jobs for residents in residential block $i$ is the job accessibility:

$$Access_n = \frac{EE_i}{n_i}$$

**The second independent variable** is the residential site location, which is operationalized under three models of urban expansion theories; i.e., concentric zone model, sector model, and multiple nuclei theory. We used the proxies of the population density around the residential block (3 km), the distance to the trunk road (Xiamen–Shaxian Expressway and Shenyang–Haikou Expressway in this study), and the distance to the metro station (as Metro Line 1 connects multiple centers, such as the Jimei educational cluster and software park in Jimei District). For the latter two proxies, the reciprocal value was used in the model. The planning and development of new towns and districts usually use a combination of these three urban expansion strategies, and there is no clear boundary between the different modes of expansion. Therefore, the geographic location of each residential block conforms to the characteristics of the concentric zone, sectoral model, and multiple nuclei model to varying degrees.

**Control variables** include the distance from the Xiamen North Railway Station, real estate price (second-hand housing prices were captured from the Anjuke website in December 2020), delivery time of the residential block, and residential population characteristics. The reason for considering Xiamen North Railway Station was that Xiamen, as a regional central city, attracts a large number of home buyers from surrounding cities. Being close to Xiamen North Railway Station and convenient for dual-city living is an important principle for those home buyers. The behavior of home buyers from other places has resulted in changes in the occupancy rate around Xiamen North Railway Station. When analyzing the factors affecting the occupancy rate, the distance from Xiamen North Railway Station should be used as a control variable. Gaoqi Airport does not have this kind of influence and was therefore not chosen as a control variable.

**The instrumental variable** was chosen to address potential endogeneity between job accessibility and occupancy rate. We exploited the proportion of industrial land and proportion of residential land to the total construction land in the community where the residential area was located as our IV. The higher the proportion of industrial land, the more employment opportunities; the higher the proportion of residential land, the more living space; these two exogenous variables affect the level of job accessibility but have no direct impact on the occupancy rate of the residential block, which meets the requirement that exogenous variables affect independent variables but not dependent variables.

### *4.3. Overview of the Study Area and Data*

This study used the Jimei District of Xiamen as a case study. Xiamen is located in the coastal area of Fujian Province, southeast China. The city has a territory of 1699.39 km$^2$, geographically divided into two areas: Xiamen Island, which is the original and central area of the city, and Outside Island, which is a booming new area. Since 2000, Xiamen has experienced rapid urban and population expansion from the central city to the outer suburbs [47]. From 2000 to 2021, the city's population increased more than 2.5 times, from 2.05 million to 5.16 million. The studied Jimei District underwent an even more explosive population increase from 0.148 to 1.04 million, or sevenfold.

Jimei District has experienced three different development modes, which provides an example for examining the urban expansion modes' effect on the housing vacancy rate.

In the first stage before 2003, Jimei was at the **concentric expansion** ring of Xiamen's old city. Due to the spillover of the industries and population of Xiamen Island (old city), the southern part of Jimei, near the bridge connecting the inside and outside island, formed two suburban population centers. In the second stage between 2003 and 2010, the main reason for the expansion of Jimei was the opening of the Xiamen–Shaxian Expressway and Shenyang–Haikou Expressway, and the corresponding **sectoral urban expansion** and industrial agglomeration along the expressways. In the third stage from 2010 till present, Jimei was officially designated as a subcenter of Xiamen city, and the government began to build a software park, city park, municipal library, science and technology museum, administrative service center, and commercial centers, aiming to develop multiple centers. In 2010, Xiamen North High-Speed Railway Station began to operate, and in 2017, Metro Line 1 began to operate and connected municipal service facilities, commercial centers, high-tech industrial parks, and commercial residences. After more than 10 years of development, the population of Jimei reached 1.04 million in 2021, a comparable size to the old city. In the development planning of Jimei District, different urban expansion models and different strategies were used to develop industries and attract the population, making it a suitable object for the focus of this study. This paper focuses on Jimei District, rather than the entire city of Xiamen, as its research scope. It mainly examines the impact of the internal job–housing spatial relationship in the new city on occupancy rates. A comparative analysis of the three urban expansion models reveals spatial differences in the influence of job accessibility and the phenomenon of job–housing separation both inside and outside the island. The behavior involving work and living inside and outside the island will not interfere with the judgement of research conclusions.

The unit of analysis of this study is the residential block. There are two reasons why the residential block was used as the geographical unit. Prior studies often used the subdistrict level (the *jiedao* or town) or even at the city level [29,48]; the residential block is the smallest level; an analysis at such a level is more useful when it comes to conducting policy-relevant research. The second reason is that the residential block is the basic statistical unit of the census; the observation at such a geographical level would be consistent with that based on census tracts in other countries. This study collected spatial vector data on residential blocks and job opportunities, provided by the department of land and resources, public security, industrial and commercial department, and planning department. It includes 367 residential blocks, covering all types of housing; i.e., commercial housing, affordable housing, and 194 urban villages. At the same time, 392,000 household addresses were extracted from the public security's population information, and data of 477,000 employees in 48,000 large, medium, and small enterprises. After converting the above data into vector information with geographical location, all of them were included in the land use spatial map, and an ArcGIS database including land, household, employment, housing, roads, and public facilities was constructed. The data used were aggregated at the residential block level and do not breach the privacy of individuals and families, and are available upon request from the authors.

Table 1 presents the variables. The occupancy rate is shown in Figure 2. The occupancy rate close to the main urban area on the east and west sides is higher, and the occupancy rate in the central and north is lower. Figure 3 shows that the distribution of job accessibility in Jimei District gradually decreases from east to west.

**Table 1.** Definition and description of main variables.

| Variables | Descriptions | Min | Max | Mean | Std |
|---|---|---|---|---|---|
| Y | Occupancy rate: the number of households divided by the number of housing units | 0.000 | 1.000 | 0.743 | 0.281 |
| A | Job accessibility via ELMO | −2.029 | 2.153 | 0.000 | 1.000 |
| M | 1/distance to nearest metro station | −1.200 | 7.757 | 0.000 | 1.000 |

**Table 1.** *Cont.*

| Variables | Descriptions | Min | Max | Mean | Std |
|---|---|---|---|---|---|
| R | 1/distance from residential block to trunk road | −0.257 | 15.456 | 0.000 | 1.000 |
| D | Population density within 3 km | −2.648 | 2.177 | 0.000 | 1.000 |
| P | log(housing price) | 9.123 | 11.366 | 10.235 | 0.334 |
| DX | 1/distance to Xiamen North Railway Station | 0.097 | 1.751 | 0.164 | 0.137 |
| YX | Year of house delivery before 2000 | 0.000 | 1.000 | 0.453 | 0.451 |
| | Year of house delivery 2001–2010 | 0.000 | 1.000 | 0.165 | 0.372 |
| | Year of house delivery 2011–2012 | 0.000 | 1.000 | 0.111 | 0.315 |
| | Year of house delivery 2013–2014 | 0.000 | 1.000 | 0.111 | 0.315 |
| | Year of house delivery After 2015 | 0.000 | 1.000 | 0.160 | 0.367 |
| Edu | Mean of education years in residential block | 2.536 | 24.285 | 9.462 | 1.342 |
| Labor | Proportion of labor force in residential block | 0.250 | 0.983 | 0.645 | 0.084 |
| IR | Industrial land ratio | 0.000 | 0.656 | 0.151 | 0.205 |
| RR | Residential land ratio | 0.063 | 0.818 | 0.287 | 0.134 |

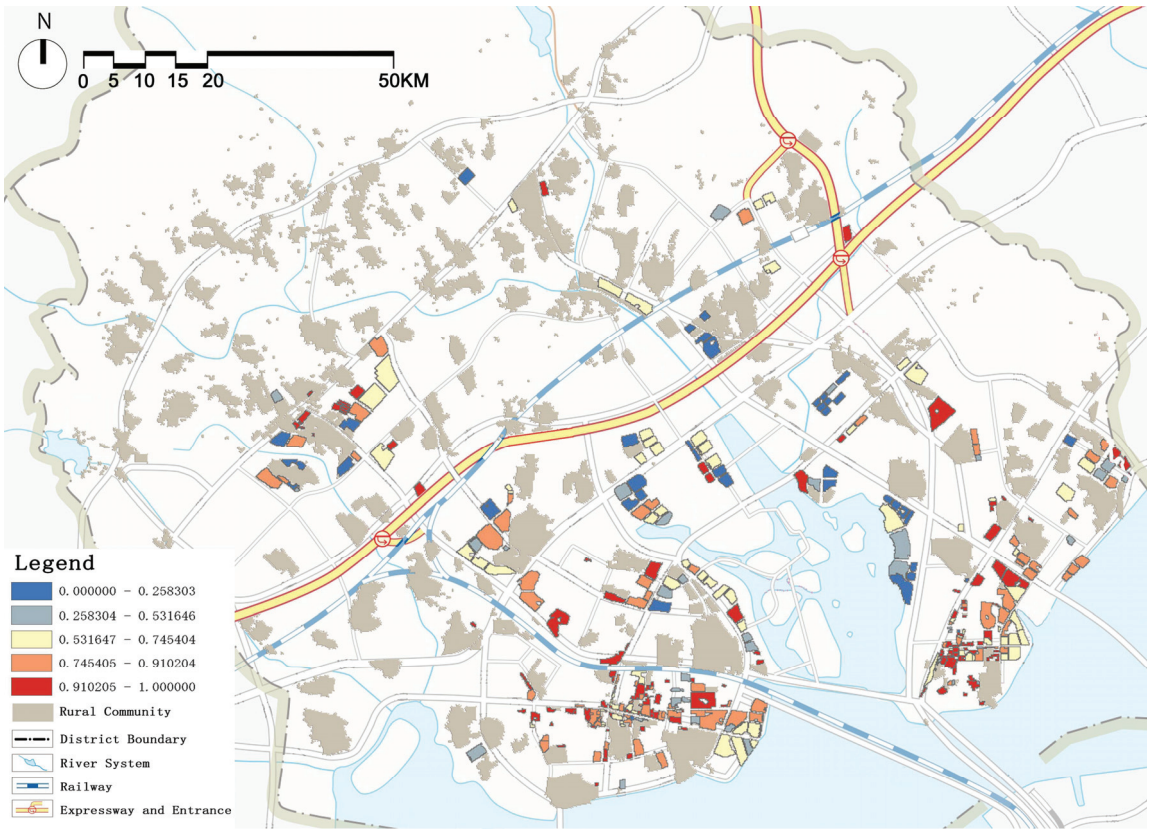


**Figure 2.** Spatial distribution of occupancy rate.

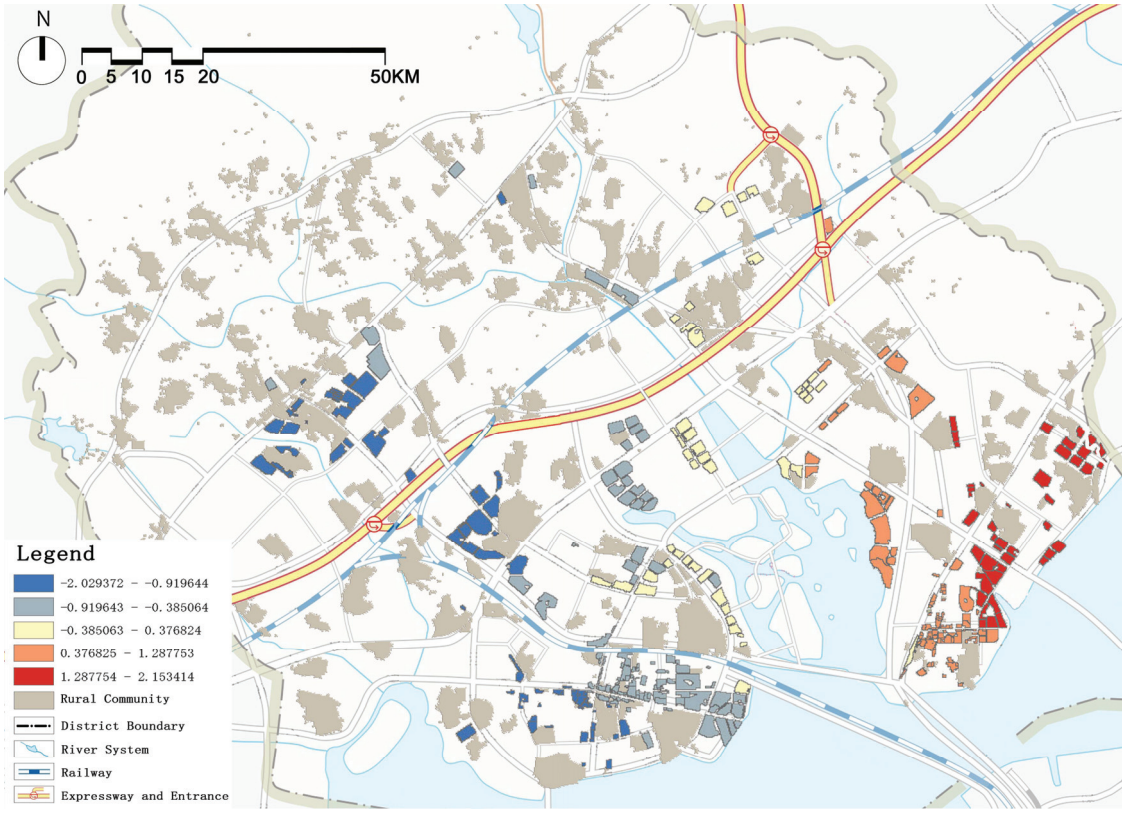


**Figure 3.** Spatial distribution of job accessibility.

## 5. Results

### *5.1. Results of the Baseline Model*

OLS regression was used to examine the interactive relationships between job accessibility and residential location on occupancy rate, as shown in Table 2. Under the condition of controlling other factors, the coefficient of the job accessibility factor was 0.069 and significant, consistent with expectations. No matter what kind of urban expansion mode, the job accessibility will have a certain impact on the occupancy rate. The results of the interaction term of job accessibility and urban expansion mode show that the effect of each residential location feature on job accessibility was not consistent with expectations. The interaction coefficient between job accessibility and the distance to the trunk road was 0.084 and significant, indicating that the closer to the trunk road and the higher the job accessibility, the higher the occupancy rate of the residential area. This means that under the sector expansion mode, the occupancy rate of residential areas is highly dependent on job accessibility, and Hypothesis 2 is verified. The interaction coefficient between the distance from the subway station and the job accessibility was not significant, which means that job accessibility had no significant impact on the occupancy rate of the polycentric residential area. Hypothesis 3 has not been verified. Unexpectedly, the interaction coefficient between the population density and job accessibility was −0.316 and significant, which is opposite to the prediction of Hypothesis 1. This means that the residential area developed by the concentric zone pattern excluded the proximity of employment and housing, and the proximity to employment opportunities was not conducive to the increase in occupancy rate. This result presents the difference between China's urban structure change and the West's. The rapid urbanization in the past 40 years in China has involved the simultaneous promotion of new city expansion and old city renewal, and the two trends of suburbanization and gentrification are intertwined. Compared with the outer suburbs, the central urban areas still have advantages in terms of public facilities, urban environment, and public services,

and the population centripetal living pattern is still obvious. The demographic appeal of high-end residential areas in the outer suburbs has not yet taken effect.

**Table 2.** OLS regression of occupancy rate.

| Variables | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | **Coefficient** | **Standard Errors** | **Coefficient** | **Standard Errors** |
| A | 0.069 *** | 0.024 | 0.021 | 0.017 |
| M | −0.048 *** | 0.015 | −0.035 ** | 0.015 |
| M × A | 0.008 | 0.048 | | |
| R | −0.022 | 0.015 | −0.009 | 0.014 |
| R × A | 0.084 * | 0.054 | | |
| D | 0.004 | 0.016 | 0.024 * | 0.015 |
| D × A | −0.099 *** | 0.018 | | |
| P | −0.146 *** | 0.051 | −0.132 ** | 0.052 |
| DX | −273.008 ** | 110.565 | −186.025 * | 113.971 |
| YX | | | | |
| 2001–2010 | −0.007 | 0.039 | −0.042 | 0.040 |
| 2011–2012 | 0.000 | 0.054 | −0.058 | 0.055 |
| 2013–2014 | 0.073 * | 0.053 | 0.096 * | 0.055 |
| After 2015 | −0.132 ** | 0.045 | −0.185 *** | 0.046 |
| Edu | 0.004 | 0.011 | 0.015 | 0.011 |
| Labor | 0.420 ** | 0.179 | 0.120 | 0.175 |
| Constant | 1.992 *** | 0.548 | 1.940 *** | 0.558 |
| $R^2$ | 0.203 | | 0.128 | |
| N | 367 | | | |

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.001$. The search radius of the job accessibility is 9 km, and the job preference is decayed with Gaussian function.

Without considering the interaction effect, Model 2 is clearer about the differences in population attractiveness of urban expansion patterns. Under the concentric circle expansion mode, the surrounding rural population density has a significant positive impact on the occupancy rate. The distance from the trunk road representing the sector expansion has no obvious effect. However, the distance from the subway station, which represents the multiple nuclei expansion, has a significant negative impact on the occupancy rate. To sum up, it is generally verified that the jobs and housing relation is still an influencing factor for occupancy rates, and the spatial variation of job accessibility and occupancy rates can be grasped from the perspective of urban expansion patterns.

### *5.2. Instrumental Evidence*

The results of the model re-estimation using the two-stage instrumental variable method are shown in Table 3. As Model 3 indicates, the proportion of industrial land and the proportion of residential land have a significant impact on job accessibility, and they meet the conditions of instrumental variables. The Hausman test showed that the chi-square value was −0.793, and the null hypothesis that all explanatory variables were exogenous could not be rejected. This implies a weak endogenous relationship between job accessibility and occupancy. The test of underidentification obtained an LM statistic value of 54.574 and a *p*-value of 0.000, less than 0.05, strongly refuting the null hypothesis of underidentification. Through the weak instrumental variable test, the statistics of Cragg-Donald Wald F and Kleibergen-Paap rk Wald-F are 40.163 and 42.328, respectively, both

of which are greater than the 10% critical value of the Stock-Yogo test, refuting the null hypothesis of weak instrumental variable; that is, there are no weak instrumental variables in the equation. For the Hansen J statistics, we obtained a chi-square statistical value of 0.873, and a $p$ value of 0.350, which was greater than 0.05, indicating that the null hypothesis of overidentification was accepted. The above test shows that the estimated results in Table 2 exclude the influence of endogeneity; the coefficient estimates of job accessibility and its related interaction items are basically consistent with the results of the baseline model, and the results of the hypothesis test are consistent with the baseline model.

**Table 3.** Results of two-stage instrumental evidence for the effect of job accessibility.

| Variables | Model 3 | | Model 4 | |
|---|---|---|---|---|
| | **Coefficient** | **Standard Errors** | **Coefficient** | **Standard Errors** |
| IR (industrial land ratio) | −1.549 *** | 0.220 | | |
| RR (residential land ratio) | −2.235 *** | 0.262 | | |
| A | | | 0.168 *** | 0.058 |
| M | −0.159 *** | 0.031 | −0.043 *** | 0.0161 |
| M × A | −1.173 *** | 0.075 | 0.151 * | 0.085 |
| R | 0.046 | 0.030 | −0.026 * | 0.015 |
| R × A | −0.493 *** | 0.107 | 0.130 ** | 0.058 |
| D | 0.011 | 0.036 | 0.011 | 0.016 |
| D × A | 0.332 *** | 0.035 | −0.138 *** | 0.025 |
| P | 0.143 | 0.107 | −0.214 *** | 0.063 |
| DX | 0.413 * | 0.220 | −0.357 *** | 0.119 |
| YX | | | | |
| 2001–2010 | −0.311 *** | 0.078 | 0.136** | 0.065 |
| 2011–2012 | −0.334 *** | 0.108 | 0.057 | 0.070 |
| 2013–2014 | 0.022 | 0.106 | 0.103 | 0.071 |
| After 2015 | −0.267 ** | 0.089 | −0.077 | 0.062 |
| Edu | 0.069 *** | 0.021 | −0.002 | 0.011 |
| Labor | −1.235 *** | 0.356 | 0.493 *** | 0.188 |
| Constant | −0.389 | 1.170 | 2.693 *** | 0.679 |
| Chi-sq(3) | −0.793 | | | |
| Kleibergen-Paap rk LM | 54.574 | | | |
| Chi-sq(2) $p$-value | 0.0000 | | | |
| Cragg-Donald Wald F | 40.163 | | | |
| Kleibergen-Paap rk Wald F | 42.328 | | | |
| Stock-Yogo 10% maximal IV size | 19.93 | | | |
| Hansen J | 0.873 | | | |
| Chi-sq(1) $p$-value | 0.350 | | | |

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.001$.

### *5.3. Robustness Test*

In the measurement of job accessibility, the distance decay, the spatial barrier between origin (residence location) and destination (workplace), is inversely related to its distance [49]. In other words, individuals located far from the job will have lesser avail-

ability than others. However, there is no definite principle for the setting of the job search radius and distance decay function [50–52]. The robustness test in this paper was to set cross-combinations of different search distances and distance decay functions, and then examine the corresponding changes in job accessibility coefficient and significance. The search radius was set at four levels: 5 km, 7 km, 9 km (Model 1 and 2 in Table 2), and 11 km, and four different decay functions were employed: Gaussian function, kernel density function, gravity function, and no distance decay.

The results are shown in Table 4. The robustness test of the search radius shows that it is a reasonable interval for the job search distance. Taking the Gaussian decay function as an example, Models 5–7 show how the coefficient of job accessibility varies with search distance. When the search radius is 5 km, the coefficient of job accessibility is not significant. As the search radius increases, the significance of job accessibility is the highest at 9 km (see Model 2), and then decreases at 11 km. In the models, the radius below 5 km means that only job opportunities within walking distance are accepted, while the radius above 11 km exceeds the boundary of the entire area (the built-up area of Jimei District is 126.9 $km^2$, and the east–west and north–south straight-line distances are about 11 km). Within a reasonable search distance between 7 and 9 km, the job accessibility coefficients are all positively significant, thus verifying the robustness of the results from the perspective of the search radius.

**Table 4.** Robustness test on the impact of job accessibility on occupancy rate.

| Decay Function (Search Radius) / Variables | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
|---|---|---|---|---|---|---|
| | **Gaussian (5 km)** | **Gaussian (7 km)** | **Gaussian (11 km)** | **No Decay (9 km)** | **Kernel Density (9 km)** | **Gravity (9 km)** |
| A | 0.006 | 0.030 * | 0.046 * | −0.032 | 0.071 *** | −0.057 *** |
| M | −0.036 ** | −0.044 *** | −0.049 *** | −0.043 *** | −0.047 *** | −0.004 |
| M × A | −0.055 *** | −0.047 | −0.040 | 0.050 * | 0.033 | −0.046 *** |
| R | −0.021 | −0.020 | −0.020 | −0.014 | −0.023 | −0.008 |
| R × A | 0.101 ** | 0.088 * | 0.090 ** | −0.303 ** | 0.083 | 0.007 |
| D | 0.012 | 0.010 | −0.004 | 0.023 | 0.005 | 0.021 |
| D × A | −0.065 *** | −0.083 *** | −00.96 *** | 0.020 | −0.098 *** | 0.017 |
| constant | 1.510 *** | 1.626 *** | 2.152 *** | 1.644 *** | 2.055 *** | 1.623 ** |
| $R^2$ | 0.191 | 0.191 | 0.196 | 0.152 | 0.203 | 0.197 |

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.001$. The regression results of the control variables are omitted for space.

The results in Models 8–10 show that the choice of the distance decay function is reasonable and the results of different functions are stable. The test results of Model 8 with no decay show that the coefficient of influence of job accessibility on occupancy rate is not significant, which is not surprising. Because if there were no difference in preference for working distance, employment and living space naturally would have no effect on housing location choice. It confirms that residents' preference for nearby employment is the realistic basis for the close layout of jobs and residences. The results of Model 9 and Model 10 on the kernel density and gravity decay functions respectively show that the convexity and concavity of the decay function shape are sensitive to the job accessibility coefficient. Under the kernel density function, the job accessibility coefficient is positive and significant, while under the gravity function setting, the job accessibility coefficient is negative and significant. However, in the two function forms of convex and concave, the concave function does not match the practical meaning of job search behavior. The concave function means that the individual's preference for short-distance job opportunities decays at an accelerated rate, while the preference for long-distance jobs decays more and more slowly. Therefore, the result of the concave function is more reliable. The output results of the Gaussian function of Model 1 and the kernel density of Model 9 are quite close, being 0.069 and 0.071, respectively. The robustness of the results is also verified from the perspective of the decay function.

### *5.4. Heterogeneity Analysis*

The baseline model above validates the spatial heterogeneity of job accessibility under different residential locations. Figure 4 further shows the levels of job accessibility coefficient measured by geographically weighted regression (GWR). The colors red, orange, light blue, and dark blue in the figure represent the changes in the job accessibility coefficient from large to small. Figure 4 vividly reflects the spatial differences in the influence of job accessibility on the occupancy rate of residential areas in the concentric zone, sector, and polycentric expansion models.

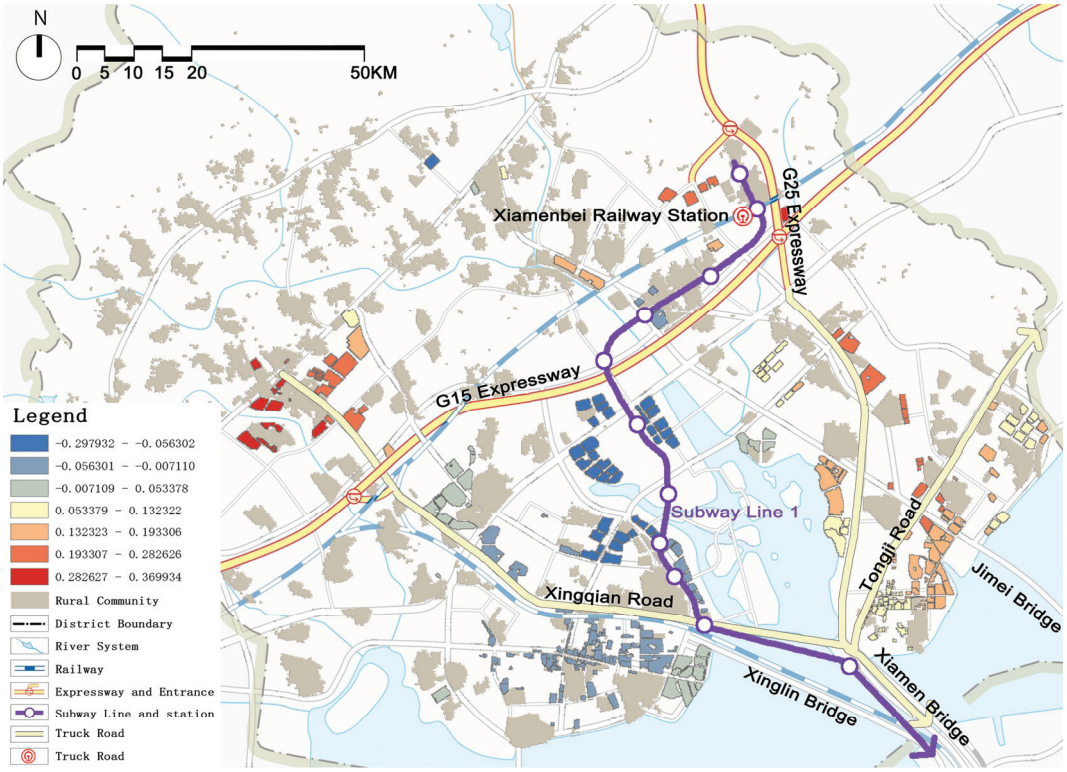


**Figure 4.** Spatial pattern of job accessibility coefficient.

The areas with the highest influence on job accessibility (red and orange areas) are along the two expressways, the north–south direction is the G25 (Xiamen–Shaxian) Expressway, the east–west direction is the G15 (Shenyang–Haikou) Expressway, and the intersection is Xiamen North Railway Station. There are many industrial parks along these two expressways. The high influence of job accessibility in these two belts confirms that the population agglomeration in the sector expansion model is highly dependent on job accessibility. Proximity to employment opportunities is a spatial condition for the occupancy of residential areas in this area.

The area with job accessibility in light blue is Xinglin Street (formerly Xinglin Town), which was the earliest suburb to realize road connection with the old city (Xinglin Bridge and Xiamen Bridge on the island). This area was the first to undertake the residential needs of the overflowing population growth in the old city, and a considerable number of residents are employed in the old city on the island. Job accessibility has an influence on the occupancy rate of the area, which confirms that under the concentric zone expansion mode, the occupancy rate of residential areas is not highly dependent on employment accessibility.

The area with job accessibility in dark blue is along the Metro Line 1, and it is an area developed by the multiple nuclei model. Job accessibility has the least influence on the occupancy rate of polycentric residential areas, indicating that the convenient population transfer reduces the commuting time to the new and old cities, and also significantly weakens the demand of new town residents for nearby employment. This finding is in

conflict with the idea of the polycentric model. From the results, it can be seen that more employment cannot improve the occupancy rate of polycentric residential areas. It may be that there is a problem with the current strategy for the development of polycentric new cities. The proximity of the residential area to the station is not welcomed by residents. It does not mean that the polycentric new city does not need employment, but that there is a problem with the spatial relationship between residence and employment. The "sleeping city" lifestyle of living in a new city with long-distance commuting every day is not popular, and residents may prefer that job opportunities gather around subway stations. It is more suitable for low-frequency travel needs such as connecting industrial divisions, administration, and entertainment between sites.

In sum, the spatial differences in the influence of job accessibility on occupancy rate are relatively obvious, which is basically consistent with the spatiotemporal characteristics of urban expansion in Jimei District, further verifying the differences in population aggregation logic in different residential locations.

## 6. Discussion and Conclusions

This paper explores the theoretical mechanisms of job accessibility under different urban expansion models to promote population concentration in new towns. The research found that: (1) Job accessibility, which represents the spatial relationship between residence and employment, has a stable and positive impact on the occupancy rate of commercial housing in new towns. The proximity of job and residence is the basic requirement of Chinese families' residential location choice, and the separation of job and residence is only a compromise of the constraints of residential choice. (2) Residential areas with different urban characteristics have varying degrees of success in attracting the population. The occupancy rate of residential areas that meet the characteristics of the concentric zone is the highest, followed by that of residential areas that meet the characteristics of the sector model site, and the residential area with polycentric site has the lowest occupancy rate. (3) The influence of job accessibility on the occupancy rate has significant differences in residential areas. The occupancy rate of residential areas in the sector model is highly dependent on job accessibility, and the higher the job accessibility of residential areas with concentric circles, the lower the occupancy rate. Job accessibility has no significant impact on the occupancy rate of the polycentric residential area.

The theoretical exploration of population agglomeration through the spatial integration of industry and city has great application value for improving the efficiency of land resource use, rationalizing the population distribution pattern, and maintaining the attractiveness of urban population. The implications and limitations of this study are further elaborated in following sections.

The research results enrich the understanding of the spatial integration of industry and city, and provide enlightenment for the integrated development of industry, city, and people. First, the planning of new towns must clarify population aggregation as the top priority. The functional positioning of new towns cannot be just as marketing symbols, such as cultural new city, ecological new city, financial new city, and subway new city. Preliminary research and forecasts should be carried out on the attractiveness of new towns, what kind of groups they can attract, and the expected size of the population gathering. Under the condition of having a relatively clear understanding of the industry level and scale of the new towns and the corresponding employment and lifestyle of the living groups, the development plan of the new towns should be carefully formulated and adjusted in a timely manner according to the population concentration. Second, the location selection of residential areas should be guided by the ecological laws of the transfer of residential functional areas. The concentric expansion of the suburbs is the easiest way to achieve population aggregation, and there is a trap of population aggregation in the leap-frog development of "sleeping cities" in the outer suburbs. Without the development of the industry first, the TOD development model overuses the convenience of the subway to increase the commuting distance between workers and residences [53]. It is only a long-

distance version of the concentric zone expansion model. The use of the multiple nuclei model should still be based on the job–housing balance in new towns, and use the subway to connect urban functions such as urban employment, administration, entertainment, and public services to form a functional network, and the residential area should not be directly close to the transit station, but close to the employment and living functional area on the periphery. Third, make reasonable use of the principle of job–housing balance according to the spatial pattern of job and housing. Residential areas also have a cluster effect. The job–housing balance does not require a blindly scattered industrial layout, which hinders the industrial cluster effect. From the perspective of ensuring the residential occupancy rate, the residential area and employment space of the concentric expansion new districts should not intersect; the polycentric new districts need the employment space to be concentrated in a small area.

Scholars have pointed out that planning should avoid blindly implementing mixed land use at the macro level [54], and this is not conducive to industry agglomeration and orderly traffic travel [55]. Other studies show that from the perspective of the micro level of individuals, the streets with relatively high mixed land use are conducive to reducing the probability of job–housing separation [29]. From the macro level of urban development, the agglomeration of population and industries at their respective agglomeration clusters are the inevitable trends and requirements of urban development, but have also caused an imbalance and mismatch for population and employment. This is particularly true in metropolises like Beijing, where the employment is gathered in the central region, and the population continues to move into and scatter in the suburbs [48]. How to reasonably arrange the use of mixed land use at small scale under the spatial structure of industrial and population agglomeration at the macro level requires in-depth research. Reasonable urban land use is not only conducive to the performance of the economy, but also for residents to find employment nearby and reduce cross-regional commuting.

There is still much room for improvement in this study. First, the research scope was limited to the Jimei District rather than the whole Xiamen city. In the future, if the job search scope is expanded to the whole Xiamen city, and the impact of the job accessibility between the new and old cities and between the new urban areas on the population structure of the city is further explored, it will have a positive impact on the overall urban development and provide more valuable insights. Second, the assumption of homogeneity of job opportunities did not involve the structural matching between different industries, occupations, and levels of positions. In the future, under the condition of data availability, if we can master the laws of the job–housing relationship at different industrial levels, we can provide more specific suggestions on the characteristics of price, area, apartment type, and floor area ratio of the residential blocks. Third, living preferences are worthy of long-term monitoring. The underlying logic of the layout of job–housing relationship affecting population aggregation is the family's preference for job–housing proximity. In the internet age, working lifestyles such as home office, cross-regional division of labor and collaboration, multi-site business operations, and frequent business trips may affect job–housing preference.

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# Evaluating the Impact of County-to-District Transformation on Urban Residential Land Supply: A Multi-Period Difference-in-Differences Model Analysis

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**Abstract:** Utilizing panel data from 264 prefecture-level cities in mainland China between 2009 and 2017, this study employs a multi-period difference-in-differences model and propensity score matching to assess the effects of county-to-district transformation (CDT) on the scale, proportion, and price of the urban residential land supply. The findings reveal the following details: (1) CDT led to a short-term increase in the overall proportion and price of this land, whereas its influence on the scale of the supply exhibited a time lag; (2) the policy's impact on residential land supply varied across different types of cities, with a more pronounced effect on the scale, proportion, and price in large cities; and (3) the current implementation of CDT primarily modified the urban land's supply–demand relationship through the expansion of built-up space, conversion of spatial function, and agglomeration of population and the labor force, consequently affecting the supply of the aforementioned land. Finally, this paper puts forward relevant policy suggestions on how to adjust land supply and effectively regulate the land market during the process of promoting the withdrawal of counties in the future.

**Keywords:** land market; county-to-district transformation; urban residential land supply; multi-period difference-in-differences

## 1. Introduction

In recent years, the rapid development of the Chinese economy and society has led numerous cities in China to actively promote county-to-district transformation (CDT) [1]. This process involves incorporating surrounding counties or county-level cities under the jurisdiction of a central urban district of a newly designated district government [2]. County-to-district transformation in China signifies, to some extent, the expansion of cities into suburban and rural areas. However, it diverges from the phenomenon of urban sprawl observed in many countries, including the United States and certain European countries, which is the result of uncontrolled growth that is typically driven by housing demands and development [1,2]. Conversely, CDT represents a form of urban expansion guided by local governments through administrative means. Furthermore, it differs distinctively from metropolitan integration, which is a process whereby the cities involved maintain separate administrative jurisdictions; CDT entails the inclusion of administrative units under the jurisdiction of a single city. In China, the primary objectives of this practice are to expand urban space, enhance urban competitiveness, and foster the coordinated development of urban areas [3]. Nevertheless, as CDT implementation progresses, the developmental orientation of cities often undergoes adjustments, especially during their expansion into large cities or megacities. Urban governments increasingly focus on spatial function transformation, industrial structure optimization, and attracting external population inflows and labor forces agglomeration, which inevitably result in significant impacts on urban land use and allocation. Given that land is

a fundamental element of urban development, the transformation of spatial functions, the upgrading and optimizing of industries, and the resulting changes in population and labor force all impose new requirements on the urban land supply. Consequently, it is crucial to systematically explore the effects and underlying mechanisms of CDT on urban land supply.

Based on the existing literature, research on the relationship between regional integration and land use has primarily focused on two areas. First, within the context of regional integration, researchers have employed statistical methods and remote sensing analysis to depict the dynamics of land use changes in specific urban agglomerations. Additionally, econometric techniques have been utilized to explore the underlying factors driving these changes [4–7]. Second, studies have shed light on the impacts of the regional integration process on land management. Numerous investigations have highlighted the benefits of intercity government cooperation and the spatial integration of labor and housing markets within metropolitan areas when promoting effective land use management [8–11]. Nevertheless, a considerable body of evidence demonstrates that regional integration inevitably leads to socioeconomic conflicts and poses severe challenges to land management. For example, Gao et al. [12] examined the spatial spillover effects of regional economic integration on urban land use efficiency in the Wuhan metropolitan area since 2001. They observed that regional economic integration facilitates resource optimization and improves urban land use efficiency. Furthermore, Ma et al. [13] identified three types of land use conflicts in the Beijing-Tianjin-Hebei urban–rural transition zone and investigated the implicit role of regional integration policies in such conflicts using a theoretical framework. The results revealed that the policy objectives of conflict regulation were not effectively achieved.

Regarding the practice of CDT, existing research on the phenomenon's effects is relatively abundant and primarily focuses on analyzing its multi-dimensional consequences on macro-level social and economic development. Some studies have examined the effects of CDT on economic growth [14]. For example, based on their analysis of CDT samples from 1990 to 2007 in China, Li and Xu [15] found that it had a short-term promotional effect on urban economic growth that was chiefly driven by large-scale infrastructure investment. Other investigations have also scrutinized the effects of the phenomenon on urbanization. For instance, research has indicated that CDT can facilitate urban spatial development [16], promote population aggregation and local labor force urbanization [17], drive industrial structure upgrading [18], improve public service allocation [19], and achieve coordinated regional development [20]. However, in some cases, this type of transformation may also result in artificial urbanization and imbalanced urban development [21]. In recent years, scholars have investigated the impact of CDT on land, which fundamentally supports economic and social development. These studies have focused on land use efficiency [22,23] and changes in urban land use's structure and spatial layout [24–26]. Additionally, a few researchers have explored the relationship between CDT and changes in urban housing and land prices. Wang and Zhang [27] found that CDT drives up housing prices in megacities, whereas it slows down the growth rate of housing prices in their prefecture-level counterparts. Meanwhile, Ji and Jin [28] discovered that local officials sold industrial land in the merged areas at low prices in order to pursue promotions in Shangyu City, Zhejiang Province. To date, relatively few studies have established a connection between CDT and land supply, and they have failed to systematically investigate its influence on the changes to the urban land supply. Our research utilizes statistical data of prefecture-level cities to examine the impact and mechanisms of CDT in China regarding alterations to the aforementioned variable. The study is organized in the following manner. First, policy background and theoretical analyses are discussed, including the policies and practices relating to CDT in China since the reform and opening up. Subsequently, the study explores the mechanisms of CDT with regard to changes to urban residential land supply. Second, a multi-period difference-in-differences (DID) model is constructed for empirical evaluation, and the variables and data are explained. Finally, the study analyzes the empirical results of the model, draws brief conclusions, and offers policy recommendations.

This study's contributions and research significance are twofold. On the one hand, from the perspective of residential land supply, exploring and revealing the effects of CDT on changes to the urban land market contributes to a comprehensive understanding of the phenomenon's effect on urban development, particularly in relation to the utilization and allocation of land elements. Moreover, our work bolsters theoretical understandings of the driving factors behind changes in urban land supply, particularly with regard to residential land. On the other hand, the DID model provides a precise assessment of CDT's impact on the scale, proportion, and price of the urban residential land supply, thereby enhancing the empirical evidence for its effectiveness. Indeed, it offers valuable insights to policymakers in relevant regions for adjusting land supply and improving regulatory policies, which will have significant practical implications.

## 2. Policy Background and Theoretical Analysis

### *2.1. Policy Background*

Since the initiation of the reform and opening up, China has implemented extensive administrative division adjustments to mitigate the adverse effects of administrative boundaries on economic development, which result from discrepancies between administrative and economic regions [29]. This administrative restructuring primarily encompasses the transformation of prefectures into prefecture-level cities, the amalgamation of prefectures and prefecture-level cities, the conversion of counties to county-level cities, the transition of counties to districts, and the reconfiguration of district boundaries. As one of the most prevalent types of administrative division adjustments, CDT entails the integration of various resources, such as land, population, industry, and infrastructure [1]. By examining relevant information on administrative division adjustments from China's administrative divisions website (http://www.xzqh.org, accessed on 15 December 2020), this study identified four distinct stages of CDT practice since the reform and opening up (Figure 1), with each of them exhibiting unique characteristics in response to urban development [3].

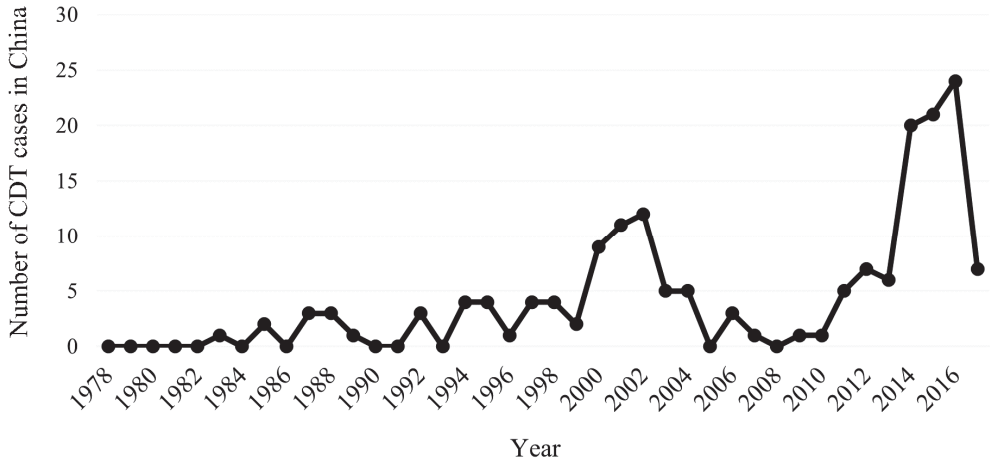



**Figure 1.** Number of CDT cases in China from 1978 to 2017.

(1) Initial exploration of CDT (1983–1997): During the early stages of China's reform and opening up period, the primary focus of administrative restructuring was on transforming prefectures into prefecture-level cities and counties into county-level cities [30]. It was not until 1983 that cities began experimenting with the implementation of CDT. For over a decade, the practice of this phenomenon in China was sporadic until 1997, with fewer than 30 cases existing. Many were primarily within the eastern region (12 cases) and within cities of higher administrative levels and larger scales, such as sub-provincial cities and municipalities directly under the central government's control.

(2) First peak in CDT (1998–2004): Due to the conflict between the conversion of counties to county-level cities and urbanization demands, CDT approval was suspended in 1997. Concurrently, local governments sought to increase fiscal revenue through urban land expansion following the tax-sharing reform in 1994. As a result, CDT adoption increased significantly, with 48 cases reported between 1998 and 2004. Although examples remained concentrated in economically developed eastern coastal areas (33 cases), they also occurred in several different types of cities and were no longer exclusive to directly controlled municipalities or provincial capitals. The number of cases in general prefecture-level cities rose to 24.

(3) Postponement period of CDT (2005–2009): Due to the central government's tightened approval process, CDT reform entered a cooling-off period. During this time, CDT cases declined substantially, with only five cities (Baishan in Jilin Province, Harbin in Heilongjiang Province, Chongqing Municipality, Urumqi in Xinjiang Uygur Autonomous Region, and Nantong in Jiangsu Province) implementing the practice.

(4) Second peak in CDT (2010–2017): In 2009, the Ministry of Finance actively promoted the implementation of provincially administered county reform, prompting local governments to eagerly pursue CDT to prevent the detachment and uncontrolled management of counties within their jurisdictions. There were 91 cases of CDT distributed across the eastern (43 cases), central (12 cases), western (31 cases), and northeastern (5 cases) regions. Compared to the first peak, the number of CDT examples during this stage increased significantly overall, and inter-regional differences gradually diminished. From an administrative perspective, the number of cases in general-level cities rapidly increased, reaching 60 cases and accounting for 65.3% of the total during this stage. This trend suggests that general-level cities have actively sought opportunities to expand urban development space and enhance economic development scale, leading to the continued emergence of CDT practices.

### *2.2. Theoretical Analysis*

Government policies and decisions primarily influence the scale and proportion of urban residential land supply in response to changes in housing demand, which is referred to as demand-driven supply changes. Conversely, the driving factors of residential land prices are relatively complex and are closely related to fluctuations in housing and residential land supply and demand. Residential land supply policies partially influence these factors. For instance, the supply price of high-quality residential land will be considerably higher than that of ordinary residential land. With these factors in mind, CDT can impact the supply of urban residential land through the following three pathways (Figure 2).

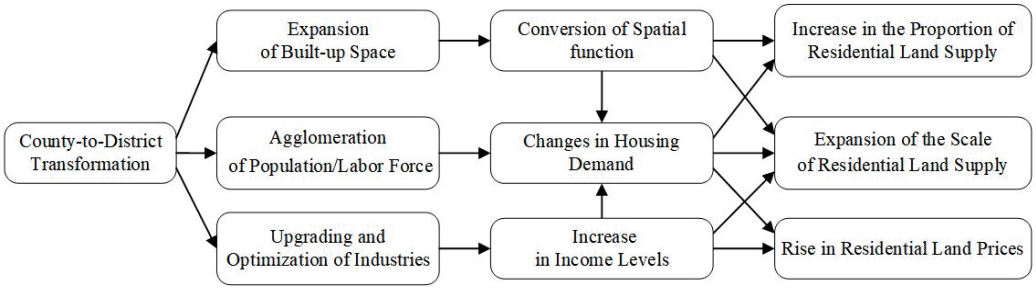



**Figure 2.** Theoretical framework.

First, following CDT, the expansion of built-up space and the transformation of urban functional positioning will substantially increase the demand for housing, leading to changes in the supply of residential land (functional transformation effect).

Second, the urban industrial upgrading and optimization driven by CDT will improve the city's economic development and residents' incomes, ultimately leading to alterations in housing demand and residential land supply (income-boosting effect).

Third, after CDT, particularly as a result of the expansion of built-up space and the upgrading and optimization of industries, the city will attract more population inflows and labor force agglomeration [17], leading to an increase in housing demand and corresponding changes in the supply of residential land (scale-expansion effect).

To clarify, the above effects of CDT on changes in urban residential land supply can be further explained as follows:

(1) Functional transformation effect: On the one hand, as CDT is implemented, and counties are progressively integrated into the comprehensive urban development plan as part of the central urban area, they hold the potential to develop as new commercial and residential hubs for the entire city. This may lead to an expansion of the residential land supply within the original county area. On the other hand, due to the expansion of built-up areas, many cities adopt or transition toward a large-city model, which transforms spatial functions, particularly the growth and extension of residential and service areas based on the initial plan. Consequently, the city government will inevitably intensify residential construction and public facilities investment [19], leading to a substantial increase in the proportion of residential land supply for the entire city.

(2) Income-boosting effect: Generally, before CDT, and influenced by factors such as location and size, counties primarily focused on developing urban support industries and agriculture. As they gradually become part of the central urban area and infrastructure improves, they will not only prioritize acquiring related industries by relocating from the central city, but they will also serve as an incubator for emerging industries; thus, these areas foster the enhancement and optimization of the city's entire industry [31]. This will contribute to the city's overall economic development and significantly increase the residents' income. It is plausible that the rise in urban residents' income will result in heightened demand for housing, particularly high-quality housing. Consequently, this will encourage the government to expand the residential land supply scale, leading to a price increase in residential land due to the heightened demand for high-quality accommodation.

(3) Scale-expansion effect: This effect is primarily associated with the agglomeration of the population and the labor force, and the impact of CDT on the urban populace and workers can be observed in the following three situations. First, the expansion of urban areas and investment in supporting infrastructure attracts more people to migrate and gather, especially those from outside the area [32]. Second, CDT is a catalyst for urban-based industry upgrading and optimization, particularly the rapid development of commercial and service industries, which significantly promotes the introduction and concentration of the labor force. Third, the development of the urban economy and the improvement in residents' income after CDT also helps curb the outflow of the population and workers [33]. Each of these situations may increase the demand for housing in the entire city to varying degrees, leading to an expansion in the supply scale and proportion of residential land.

Based on the preceding analysis, this study proposes the following research hypothesis: There will be a significant change in the supply of urban residential land after CDT implementation. Specifically, with the execution of CDT and the integration of relevant counties into the urban area, the supply scale of residential land in the entire city will notably expand, and the proportion of residential land supply will correspondingly increase. Moreover, due to the escalating demand of urban residents for high-quality housing and the lagging decision making of urban governments in the land supply response, the level of residential land prices will also exhibit an upward trend.

## 3. Model and Data

### *3.1. Multi-Period DID*

We treated policy implementation as a quasi-natural experiment to investigate the precise influence of the practice of CDT policy on urban residential land supply. A multi-period

DID model was employed to effectively address endogeneity issues in the analysis. More specifically, we adopted the methodology proposed by Beck et al. [34] and Gentzkow [35] to construct a baseline model, which is as follows:

$$Y_{\mathrm{it}} = \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_t + \alpha_3 Treat_i \times Post_t + \varepsilon_{it} \quad (1)$$

In Equation (1), $Y_{\mathrm{it}}$ represents the dependent variable, including the supply, proportion, and price of residential land. $Treat_i$ is a dummy variable that indicates whether city i belongs to the treatment group. If it has implemented a CDT policy, $Treat_i = 1$; otherwise, it is 0. $Post_t$ denotes the time variable, and in the years after city i implements the policy, $Post_t = 1$; otherwise, it equals 0. Meanwhile, the interaction term $Treat_i \times Post_t$ represents the policy implementation effect. $\alpha_0$ is the constant term, $\alpha_1$ and $\alpha_2$ are the regression coefficients of the dummy variable and the time variable, $\alpha_3$ is the net effect of the practice of CDT on the supply of urban residential land, and $\varepsilon_{it}$ is the error term. Given that the timing of policy implementation varies across cities, the above model applies only to cases in which the implementation timing is consistent. Therefore, this study incorporated the interaction term between grouping variables and time variables into the model and adopted the following multi-period differential model:

$$Y_{\mathrm{it}} = \beta_0 + \beta_1 Reform_{it} + \gamma \sum_n Controls_{it} + \mu_i + f_t + \varepsilon_{it} \quad (2)$$

If the city i implemented the CDT policy in year t, then from this year onward, $Reform_{it} = 1$, or it is 0 otherwise. $\sum_n Controls_{it}$ represents a series of control variables that affect the dependent variable, and $\gamma$ is the regression coefficient of that variable. $\mu_i$ denotes individual fixed effects, $f_t$ denotes time-fixed effects, and $\beta_0$ represents the constant term. $\beta_1$ is the estimated net effect of the CDT policy that requires particular attention.

### *3.2. Data, Variables, and Descriptive Statistics*

(1) Dependent variables: As the Ministry of Land and Resources (currently the Ministry of Natural Resources) generally selects indicators, such as supply scale, structure, and price for compiling and summarizing information on urban land supply, this study employed three indicators of its own: residential land supply area (Supply, unit: $hm^2$), the proportion of residential land supply (Prop, the ratio of residential land supply to total land supply, unit: %), and residential land price (Price, unit: RMB yuan/$m^2$) to reflect the situation and changes in urban residential land supply. The first two data sets were obtained from China Land and Resources Statistical Yearbook, which collected panel data for 285 prefecture-level cities in China. The residential land price data were sourced from the China Land Value Information Service Platform (www.landvalue.com.cn, accessed on 23 December 2020), which includes monitored information on land prices in 105 cities, such as municipalities directly under the central government's jurisdiction, provincial capital cities, and cities specifically designated in the state plan. Given the level of data availability, this paper primarily investigated the impact of CDT policy on the overall residential land supply of prefecture-level cities.

(2) Independent variable: To ensure data typicality and availability and to exclude interference caused by the first wave of policy implementation, this study selected the timespan from 2009 to 2017 as the research period [4]. The key explanatory variable is the CDT policy (Reform, which is designated according to the relevant discussions in Section 3.1). It is important to note that the policy-related research object of this study refers to the practice of local governments actively applying for and obtaining central government approval for the CDT to expand the urban spatial scale. However, it does not include CDT practices indirectly caused by other administrative adjustments, such as converting prefectures to prefecture-level cities and counties to county-level cities [36]. This study pre-processed the samples as follows: First, four special municipalities with independent administrative status, namely, Bei-

jing, Shanghai, Chongqing, and Tianjin, were excluded. Second, samples that had experienced this transformation at least once between 2005 and 2008 or two or more times during the sample period were excluded to avoid the mutual interference of policy practices in different timespans and to concentrate on the dynamic effects of CDT policy. Third, samples with significant data missing, including some prefecture-level cities in the Xinjiang Uygur Autonomous Region, Qinghai Province, and Tibet Autonomous Region, were excluded. After the screening, a total of 264 prefecture-level city samples were obtained, of which 79 prefecture-level cities with observable residential land prices were selected for analysis with regard to the impact of CDT on residential land prices.

(3) Control variables: First, economic development indicators were selected. Economic growth can directly stimulate the demand for residential land [37]. Consequently, gross regional product (Gdp, unit: RMB ten thousand yuan) and fiscal expenditure (Gov, unit: RMB ten thousand yuan) were utilized to reflect the degree of urban economic development. Second, since the development of the real estate industry is a crucial factor in influencing the supply of residential land [38], the proportion of real estate investment to fixed asset investment (Inv, unit: %) was employed to characterize the activity of real estate investment. Third, as the adjustment and upgrading of the industrial structure will inevitably lead to the reorganization of construction land across different sectors [39], the ratio of secondary and tertiary industries (Is, unit: %) was used to reflect changes in the urban industrial structure. Finally, areas with high population densities have a relatively greater demand for residential land [40], so population density (Pd, unit: persons/km$^2$) was used to measure the urban population. The data for the aforementioned control variables were sourced from the China City Statistical Yearbook, the China Stock Market and Accounting Research Database (https://www.gtarsc.com/, accessed on 23 December 2020), and various provincial and municipal statistical bulletins.

This study applied a natural logarithmic transformation to continuous variables with significant numerical differences (excluding those measured in ratios or percentages). Additionally, linear interpolation was employed to impute missing values, and 1%-level trimming was performed on all continuous variables to mitigate errors resulting from outliers [41]. Descriptive statistics for the variables used in the model are presented in Table 1.

**Table 1.** Descriptive statistics.

| Variable | | Implication | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|---|
| Dependent variable | ln*Supply* | Residential land supply total, take logarithm value | 2376 | 5.320 | 0.935 | 2.754 | 7.373 |
| | *Prop* | Proportion of residential land supply | 2376 | 0.205 | 0.107 | 0.022 | 0.513 |
| | ln*Price* | Residential land price, take logarithm value | 711 | 7.627 | 0.831 | 5.361 | 10.734 |
| Independent variable (full sample) | *Reform* | Whether to implement the policy practice | 2376 | 0.103 | 0.304 | 0 | 1 |
| Independent variable (samples of key monitored cities for land prices) | *Reform* | Whether to implement the policy practice | 711 | 0.142 | 0.349 | 0 | 1 |

**Table 1.** *Cont.*

| Variable | | Implication | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|---|
| Control variable (full sample) | ln*Gdp* | Gross regional product, take logarithm | 2376 | 16.316 | 0.850 | 14.445 | 18.405 |
| | *Inv* | Real estate as a percentage of fixed investment | 2376 | 0.147 | 0.089 | 0.022 | 0.441 |
| | ln*Gov* | Fiscal expenditure, take logarithm | 2376 | 14.545 | 0.666 | 12.972 | 16.285 |
| | *Is* | Industrial structure | 2376 | 0.869 | 0.078 | 0.545 | 0.997 |
| | ln*Pd* | Population density, take logarithm | 2376 | 5.709 | 0.905 | 1.603 | 7.882 |
| Control variable (samples of key monitored cities for land prices) | ln*Gdp* | Gross regional product, take logarithm | 711 | 16.923 | 0.840 | 14.445 | 18.405 |
| | *Inv* | Real estate as a percentage of fixed investment | 711 | 0.186 | 0.099 | 0.032 | 0.671 |
| | ln*Gov* | Fiscal expenditure, take logarithm | 711 | 14.916 | 0.707 | 12.874 | 16.900 |
| | *Is* | Industrial structure | 711 | 0.899 | 0.077 | 0.584 | 0.997 |
| | ln*Pd* | Population density, take logarithm | 711 | 6.133 | 0.777 | 3.657 | 7.825 |

Note: The term "full sample" refers to the 264 prefectural-level city samples obtained after screening and selection, and the term "samples of key monitored cities for land prices" denotes the 79 prefectural-level city samples for which land price data were available.

## 4. Results and Discussion

### *4.1. Results of the Baseline Model*

To accurately assess the net impact of CDT policy, we employed a multi-period DID model to complete our baseline regression analysis. The results are presented in Table 2. Models 1–3 display the regression results without control variables, and Models 4–6 show the results with the control variables included. Both individual and time-fixed effects were controlled across all models.

**Table 2.** The impact of CDT on urban residential land supply.

| Dependent Variable | ln*Supply* | ln*Prop* | ln*Price* | ln*Supply* | ln*Prop* | ln*Price* |
|---|---|---|---|---|---|---|
| **Independent Variable** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** |
| *Reform* | 0.141 *** | 0.013 * | 0.081 ** | 0.142 *** | 0.015 * | 0.064 * |
| | (0.044) | (0.008) | (0.037) | (0.043) | (0.008) | (0.036) |
| ln*Gdp* | | | | 0.491 ** | −0.001 | 0.093 |
| | | | | (0.204) | (0.015) | (0.106) |
| *Inv* | | | | 0.882 *** | 0.100 * | 1.021 *** |
| | | | | (0.284) | (0.056) | (0.197) |
| ln*Gov* | | | | 0.823 *** | 0.033 ** | 0.185 ** |
| | | | | (0.157) | (0.015) | (0.075) |
| *Is* | | | | 2.997 *** | 0.147 | 0.856 |
| | | | | (0.995) | (0.139) | (0.664) |
| ln*Pd* | | | | 0.193 | −0.032 | 0.644 *** |
| | | | | (0.289) | (0.052) | (0.203) |
| Control variable | NO | NO | NO | YES | YES | YES |
| Individual fixed effect | YES | YES | YES | YES | YES | YES |

**Table 2.** *Cont.*

| Dependent Variable | ln*Supply* | ln*Prop* | ln*Price* | ln*Supply* | ln*Prop* | ln*Price* |
|---|---|---|---|---|---|---|
| **Independent Variable** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** |
| Time fixed effect | YES | YES | YES | YES | YES | YES |
| Constant term | 5.306 *** | 0.203 *** | 7.613 *** | −18.510 *** | −0.221 | −1.611 |
| | (0.011) | (0.000) | (0.009) | (2.915) | (0.398) | (1.664) |
| Observations | 2376 | 2376 | 711 | 2376 | 2376 | 711 |
| $R^2$ | 0.757 | 0.416 | 0.954 | 0.783 | 0.419 | 0.960 |

Note: 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 2. The clustering of robust standard errors of regression coefficients is shown in parentheses.

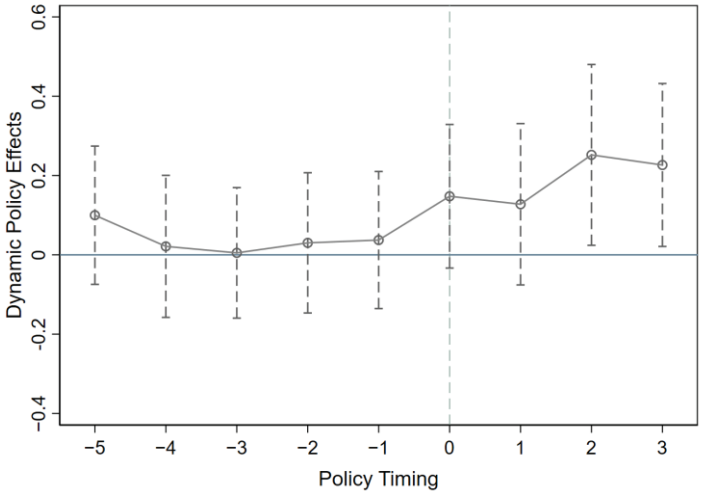
In Models 1–3, the coefficients of reform were consistently positive for the three dependent variables (Supply, Prop, and Price), and each passed significance tests at the 1%, 10%, and 10% levels, respectively. In Models 4–6, the Reform on Supply, Prop, and Price coefficients remained positive, with values of 0.142, 0.015, and 0.064, respectively, and each passed the corresponding significance tests. These findings indicate that CDT policy has significantly increased residential land supply in relevant cities, mitigated the low proportion of residential land availability, and contributed to the rise in residential land prices.

### *4.2. Parallel Trend Test*

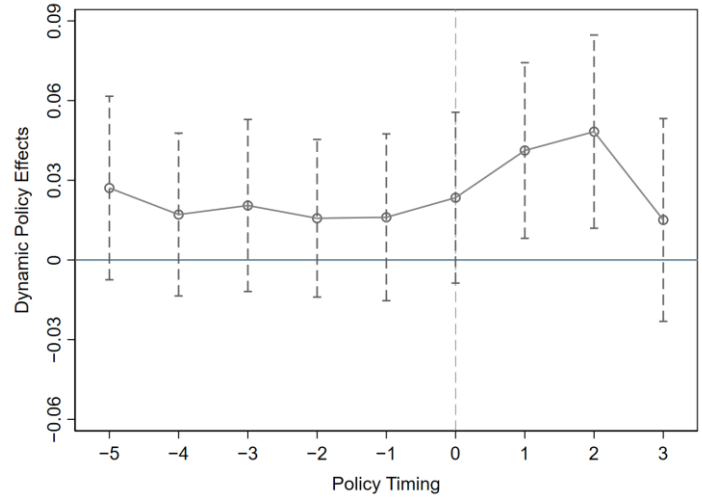
The DID model, which is based on natural experiments, necessitates the fundamental assumption of homogeneity. Specifically, the pre-treatment trends of the dependent variables in the treatment and control groups must be similar to ensure unbiased estimation [42]. To satisfy this condition, this investigation employs the event study methodology suggested by Li et al. [43], Wang et al. [44], and Yu et al. [45] to empirically analyze the dynamic effects of CDT practices. Consequently, the following model has been constructed:

$$Y_{it} = \beta_0 + \sum_{k=-6}^{k=4} \beta_k \times D_{i,t_0+k} + \gamma \sum_n Controls_{it} + \mu_i + f_t + \varepsilon_{it} \quad (3)$$

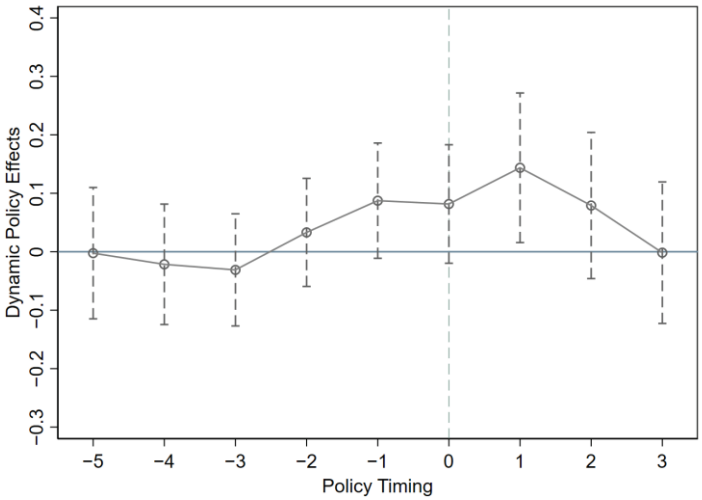
$D_{i,t_0+k}$ represents a series of dummy variables, assuming a value of 1 in year k following CDT policy implementation (where $k < 0$ denotes the period preceding policy implementation, and $t_0$ signifies the implementation year) and 0 otherwise. A regression analysis is conducted using $k = -6$ as the reference group. The estimated coefficients, which demonstrate a 95% confidence level, are illustrated in Figure 3. As the figure shows, the coefficients $\beta_{-5}$–$\beta_{-1}$ exhibit fluctuations around 0, with 0 encompassed within their 95% confidence interval, regardless of residential land supply, the proportion of residential land supply, or residential land prices. This finding suggests that no significant difference existed with regard to residential land supply between the treatment and control groups prior to the policy implementation of CDT, fulfilling the parallel trend test's requirements.




(**a**) Residential land supply scale




(**b**) Residential land supply proportion




(**c**) Residential land supply price

**Figure 3.** Parallel trend of urban residential land supply.

### *4.3. Robustness Test*

#### 4.3.1. Difference-in-Differences after Propensity Score Matching (PSM-DID)

Given that the CDT policy is not a random event, but necessitates rigorous approval processes at multiple levels, including on-site inspections by the Ministry of Civil Affairs and the State Council prior to implementation, we employed propensity score matching (PSM) to create a comparable control group [46,47]. This approach ensures the exogeneity of the policy and mitigates selection bias in the sample grouping. Following the "Subordinate District Standards" (a draft document for soliciting opinions) established by the Ministry of Civil Affairs in China in 2014, we selected sample feature variables across four dimensions: economic aggregate, fiscal revenue, population scale, and industrial structure [48]. Subsequently, using the logit model, we calculated propensity scores and applied the nearest neighbor matching method. The samples of the experimental and control groups were matched at a 1:4 ratio, and the matched sample was subsequently used for the DID test. It is important to note here that the year of CDT policy implementation varies across regions. In accordance with the method proposed by Nie et al. [32], we matched data based on information from 2009, as this is the only time point in the sample period when all regions were unaffected by the policy. Table 3 presents the PSM-DID regression results. Meanwhile, Models 4–6 demonstrate that the positive effects of CDT on Supply, Prop, and Price were 0.152, 0.016, and 0.066, respectively, which passed significance tests at levels of 1%, 10%, and 10%. These findings suggest that PSM effectively addresses the endogeneity issue of the policy, and that the baseline regression results are robust.

**Table 3.** Results of PSM-DID regression.

| **Dependent Variable** | **ln*Supply*** | **ln*Prop*** | **ln*Price*** | **ln*Supply*** | **ln*Prop*** | **ln*Price*** |
|---|---|---|---|---|---|---|
| **Independent Variable** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** |
| *Reform* | 0.151 *** | 0.014 * | 0.074 ** | 0.152 *** | 0.016 * | 0.066 * |
| | (0.045) | (0.008) | (0.037) | (0.044) | (0.008) | (0.038) |
| Control variable | NO | NO | NO | YES | YES | YES |
| Individual fixed effect | YES | YES | YES | YES | YES | YES |
| Time fixed effect | YES | YES | YES | YES | YES | YES |
| Observations | 2291 | 2291 | 686 | 2291 | 2291 | 685 |
| $R^2$ | 0.758 | 0.424 | 0.956 | 0.785 | 0.427 | 0.960 |

Note: 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 2. The clustering of robust standard errors of regression coefficients is shown in parentheses.

#### 4.3.2. Placebo Test

To eliminate potential estimation bias due to unobservable variables, we conducted a placebo test to assess the robustness of the DID results, which follows the methodologies of Chetty et al. [49] and Zhou et al. [50]. Specifically, individual examples were randomly selected from the samples as the treatment group, and a random time was chosen as the policy implementation threshold. The number of "pseudo-treatment' groups should align with the original treatment group. Subsequently, "pseudo-policy dummy variables" were generated for the purposes of baseline regression. This procedure was repeated 500 times to obtain the kernel density of the estimated coefficient and the corresponding *p*-value distribution of the pseudo-policy dummy variables (Figure 4). As shown in the figure below, the estimated coefficients of the pseudo-policy dummy variables display a normal distribution with a mean of zero, and most scatter points fall above the horizontal line of $p = 0.1$ (insignificant at the 10% level). Moreover, the vertical lines representing the true estimation coefficients are situated in the low-tail position of the kernel density distribution of the random sampling coefficient, significantly differing from the core estimation coefficients obtained through random testing. This suggests that the model specification does not suffer from serious variable omission issues, and the baseline regression results pass the placebo test.

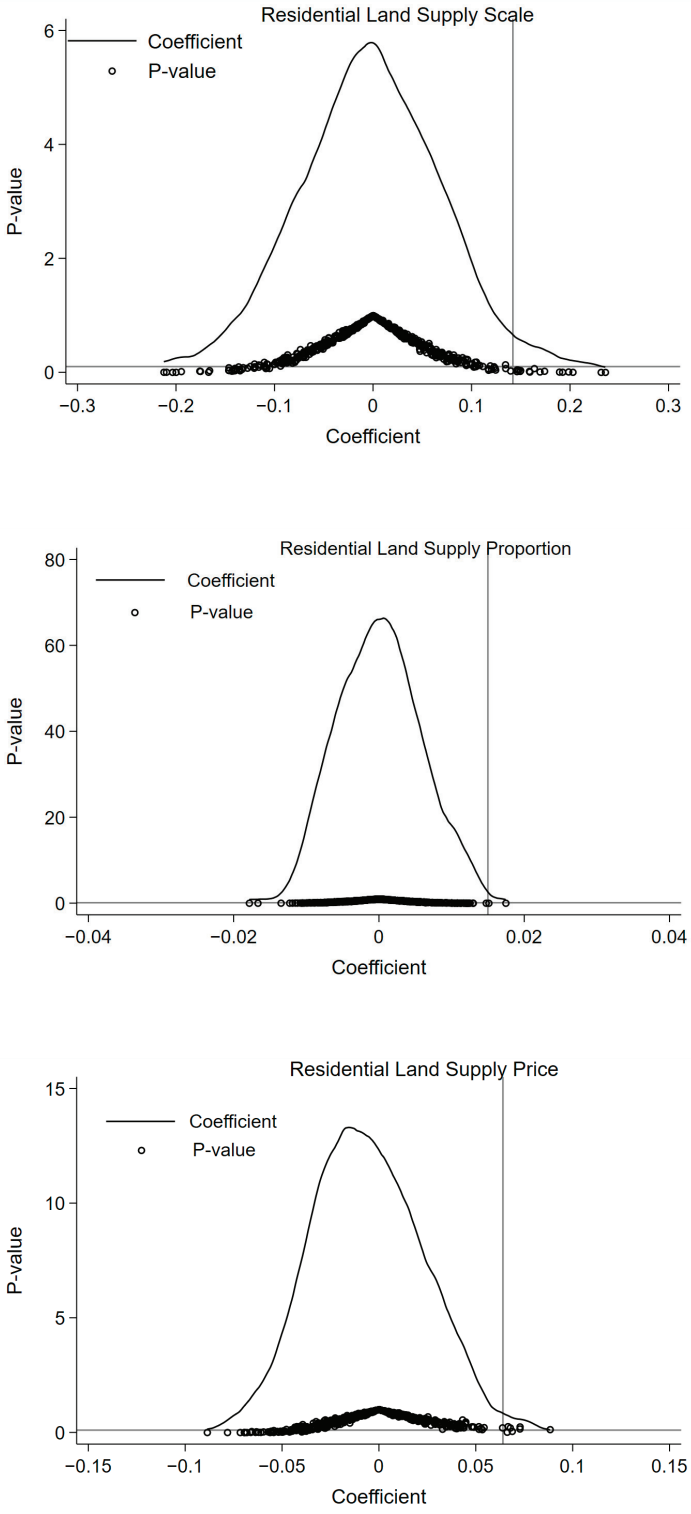



**Figure 4.** Results of the placebo test.

#### 4.3.3. Policy Spillover Effect Test

Policy interventions must not cause spillover or equilibrium effects to satisfy the stable unit treatment value assumption within the context of a DID model, and behavioral changes in the treatment group should not impact those in the control group [51]. However, it is crucial to investigate how CDT policy influences the residential land supply in surrounding

prefecture-level cities. To address this issue, we referred to the approach of Jiang et al. [52] and constructed the following model:

$$Y_{\mathrm{it}} = \lambda_0 + \lambda_1 NR_{it} + \gamma \sum_n Controls_{it} + \mu_i + f_t + \varepsilon_{it} \quad (4)$$

$NR_{it}$ = 1 if city i implemented the CDT policy in its adjacent prefecture-level cities in and after year t; otherwise, it takes a value of 0. $\lambda_1$ represents the spillover effect of the policy. It should be noted that this model primarily investigates the impact of the policy on adjacent prefecture-level cities that have not implemented CDT while excluding cities that have undergone such interventions. As the majority of the sample's residential land prices are unmonitored, this study mainly reported the impact of CDT policy on the scale and proportion of residential land supply in the surrounding prefecture-level cities, as illustrated in Table 4. The results indicate that CDT practices do not significantly affect the supply of residential land in the surrounding prefecture-level cities, and the baseline regression satisfies the assumption that the individual treatment effects are stable.

**Table 4.** Test of the policy spillover effect.

| **Dependent Variable** | **ln*Supply*** | **ln*Prop*** | **ln*Supply*** | **ln*Prop*** |
|---|---|---|---|---|
| **Independent Variable** | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
| *NR* | −0.039 | −0.011 | −0.054 | −0.013 |
| | (0.053) | (0.008) | (0.047) | (0.008) |
| Control variable | NO | NO | YES | YES |
| Individual fixed effect | YES | YES | YES | YES |
| Time fixed effect | YES | YES | YES | YES |
| Observations | 1784 | 1784 | 1784 | 1784 |
| $R^2$ | 0.703 | 0.402 | 0.742 | 0.703 |

Note: The clustering of robust standard errors of regression coefficients is shown in parentheses.

### *4.4. Results of Heterogeneous Regression*

Significant disparities in land supply exist among various regions of China due to differences in economic development and land supply preferences. From experience, coastal cities with developed economies and large populations prefer to supply residential and commercial land, whereas some manufacturing-dominated cities tend to supply more industrial land [53,54]. Within cities, the government tends to prioritize the supply of industrial and infrastructure-related land for investment promotion, resulting in there being a relatively low proportion of residential land available, especially in economically developed cities [55]. Consequently, a heterogeneity analysis of the CDT policy effects is essential. Based on the "Notice of the State Council on Adjusting the Standards for Urban Scale Division," which was released in 2014, cities were classified into four categories in accordance with the makeup of the 2017 urban population: small cities (<0.5 million), medium cities (0.5–1 million), type-II large cities (1–3 million), and type-I large cities (3–5 million) [5]. The total sample comprised 104 small cities, 93 medium cities, 57 type-II large cities, and seven type-I large cities, with 15, 27, 19, and 5 cities in these respective strata undergoing CDT policy intervention. Among the sample of cities with monitored land prices, the ratios of cities and those experiencing CDT policy intervention were 3:0, 31:5, 36:15, and 6:5 for the four respective city types. Due to the small sample size of cities categorized as type I, in order to maintain the validity of the regression results, this paper mainly uses a multi-period, difference-in-differences model to empirically test the impact of CDT on the supply of residential land in small- and medium-sized cities and type-II large cities. Table 5 displays the heterogeneity regression results relating to the effect of CDT policy on residential land supply for different city types.

**Table 5.** Heterogeneity regression results.

| | ln*Supply* | | | ln*Prop* | | | ln*Price* | |
|---|---|---|---|---|---|---|---|---|
| **City Type** | **Small City** | **Medium City** | **Type-II Large City** | **Small City** | **Medium City** | **Type-II Large City** | **Medium City** | **Type-II Large City** |
| *Reform* | 0.130<br>(0.093) | 0.160 **<br>(0.071) | 0.262 ***<br>(0.067) | −0.003<br>(0.019) | 0.017<br>(0.014) | 0.031 **<br>(0.013) | 0.006<br>(0.104) | 0.092 **<br>(0.044) |
| Control variable | YES | YES | YES | YES | YES | YES | YES | YES |
| Individual fixed effect | YES | YES | YES | YES | YES | YES | YES | YES |
| Time fixed effect | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 936 | 837 | 513 | 936 | 837 | 513 | 279 | 324 |
| $R^2$ | 0.692 | 0.720 | 0.772 | 0.415 | 0.390 | 0.460 | 0.930 | 0.964 |

Note: 1. *** $p < 0.01$, ** $p < 0.05$; 2. The clustering of robust standard errors of regression coefficients is shown in parentheses.

As shown in Table 5, CDT implementation fostered an increase in residential land supply in small -and medium-sized cities, as well as among type-II large cities. Regarding the proportion of residential land supply, the phenomenon exhibited a significant positive effect on type-II large cities, whereas it had no significant impact on small and medium-sized cities. A possible explanation is that the overall competitiveness of small- and medium-sized cities is relatively weak, resulting in the slower transformation of regional functional positioning and limited attractiveness to the foreign labor force during the CDT process. Consequently, there may not be an urgent need to increase the residential land supply. In contrast, CDT can facilitate development-based and population-related (labor force) influxes to large cities; given the limited land supply, large-city governments may be willing to adjust the proportion of residential land available to meet the growing demand for residential space. In terms of residential land prices, CDT policy had a notably positive impact on the increase in land prices in large type-II cities but did not significantly influence either small- or medium-sized cities. This could be due to the fact that large type-II cities, typically categorized as second-tier cities, generally have a more tight land supply and demand relationship than medium-sized cities. On the one hand, the land supply of type-II large cities is more strictly restricted, but on the other hand, type-II large cities, due to the high level of economic development and more optimal public service systems in these places, can trigger an increase in real residential demand and the speculative demand of the population, resulting in rising residential land prices.

To explore the impact of CDT on urban residential land supply more intuitively, this paper selects typical cases of the practice from cities of different scales as natural experiments and uses the synthetic control method proposed by Abadie and Gardeazabal [56]. In contrast with the difference-in-differences method, the synthetic control method uses the city of the control group to fit the counterfactual state of a treatment group, so that the common trend fit of the control group and the treatment group is higher, and the bias is less pronounced. We selected Meizhou City in Guangdong Province and Baoding City in Hebei Province as respective examples, and the results are highlighted in Figures 5 and 6, respectively. It is clear in Figure 5 that after CDT practices were undertaken in Meizhou City in 2013, the true value of the residential land supply scale in the area began to grow significantly higher than its synthetic value, and the two curves underline the divergent change trajectories; the real value was always greater than the synthetic value, and the proportion of urban residential land supply was not obvious, indicating that CDT in Meizhou City markedly increased the scale of urban residential land supply, but it had no obvious impact on the proportion of it. Meanwhile, Figure 6 shows that since CDT was implemented in Baoding City, Hebei Province, in 2015, the scale, proportion, and price of

the urban residential land supply have been significantly improved. This is consistent with the results of our heterogeneity test, which is described above.

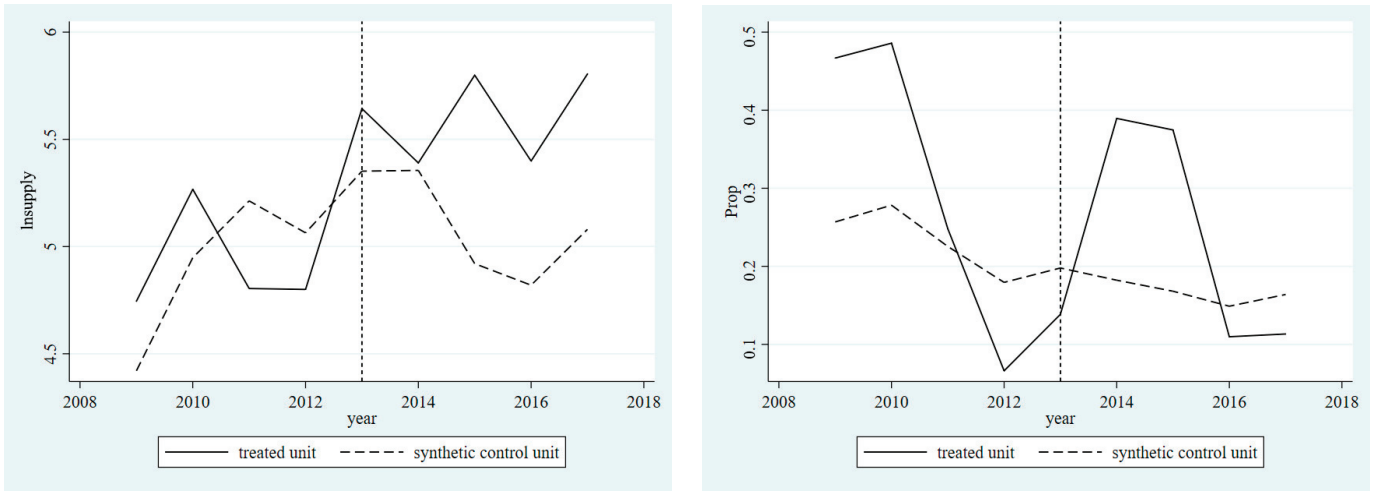



**Figure 5.** Comparison of the scale and proportion of actual and synthetic residential land supply in Meizhou City, Guangdong Province.

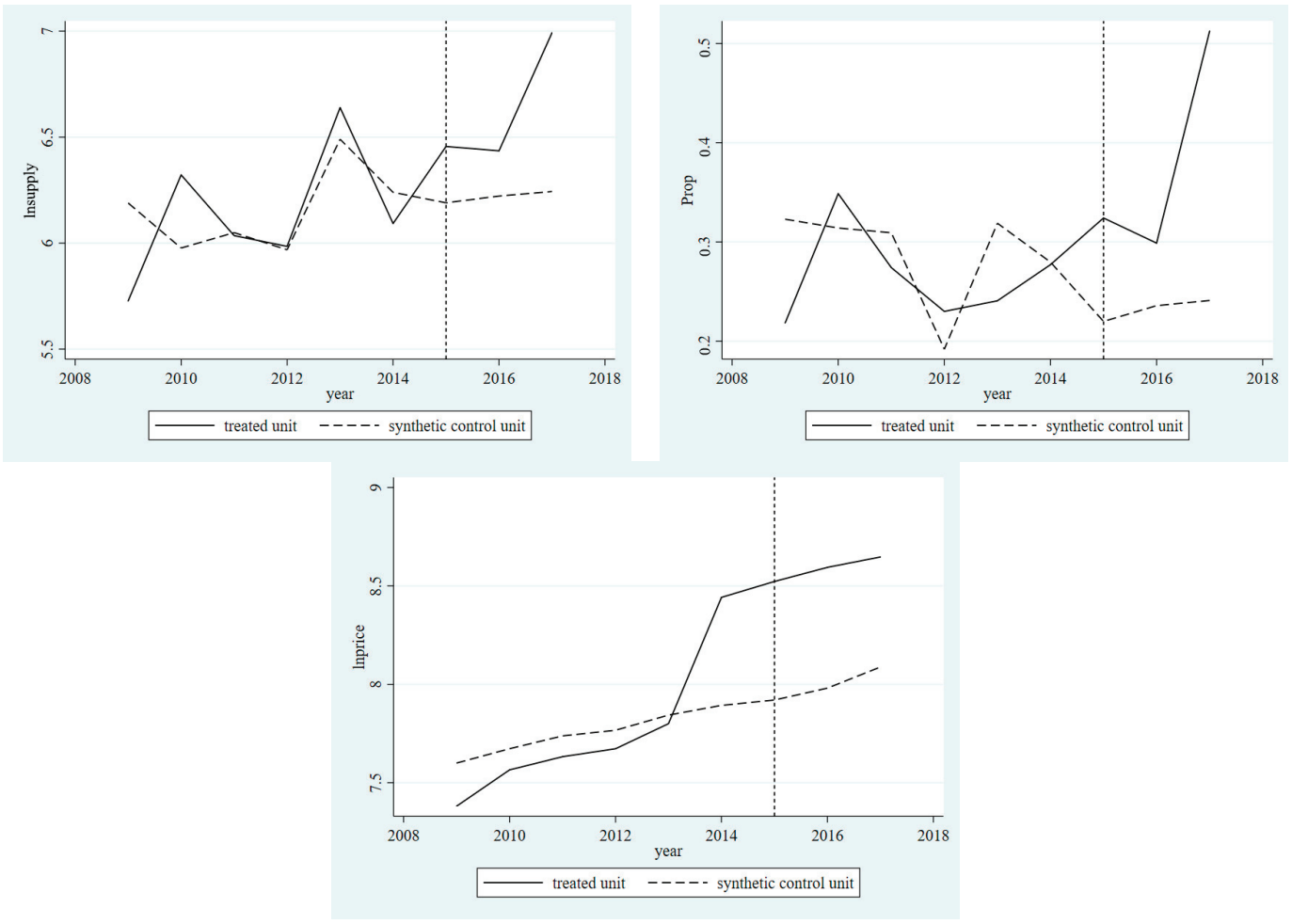



**Figure 6.** Comparison of the scale, proportion, and price of actual and synthetic residential land supply in Baoding City, Hebei Province.

### *4.5. Mechanism Analysis*

In the preceding theoretical analysis, this study proposed that CDT policy could affect the supply of urban residential land via three pathways: the functional transformation effect, the income-boosting effect, and the scale-expansion effect. To empirically test the validity of this mechanism, this study utilized the urban built-up area (Bua, unit: $km^2$), the average wage of employees (Ptw, unit: RMB ten thousand yuan), the ratio of population density between the previous and current year (Pdr) [38], and the number of employees at the end of the year (Ne, unit: ten thousand people) [6] as proxies for urban construction service space, income level, population mobility, and labor force agglomeration, respectively. In line with the approaches of Fan et al. [57] and Wang et al. [58], the aforementioned proxy variables were used as dependent variables, and Equation (2) was employed to estimate the effects. The results are presented in Table 6. The estimated coefficients of the independent variable for Model 1, Model 3, and Model 4 were all positive, and the estimated coefficient for Model 2 was not significant. This finding suggests that following CDT policy implementation, decision-making authority is typically transferred to the city government (often at the prefecture level), prompting the local government to implement unified planning and management measures to enhance functional transformation and service space expansion. Consequently, the merged county and the city become more closely connected, which increases the development and construction intensity of the city and ultimately results in the expansion of urban built-up areas. Simultaneously, as the level of construction space expands, service facilities improve, employment opportunities rise, and the population and labor force of the entire city also experience significant growth. However, the impact of CDT on the income level of urban residents is not significant, possibly due to the short-term challenges in promoting industrial upgrading and optimizing policy practices to improve residents' incomes. Although CDT does not significantly enhance the income levels of urban residents, it indirectly drives changes in residential land prices by impacting its demand and supply via other pathways. In summary, these results validate the theoretical analysis presented in the previous section.

**Table 6.** Mechanism validation of the impact of CDT on residential land supply.

| **Dependent Variable** | **ln*Bua*** | ***Pdr*** | **ln*Ne*** | **ln*Ptw*** |
|---|---|---|---|---|
| **Independent Variable** | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
| *Reform* | 0.147 *** | 0.327 ** | 0.034 ** | 0.035 |
| | (0.019) | (0.166) | (0.015) | (0.028) |
| Control variable | YES | YES | YES | YES |
| Individual fixed effect | YES | YES | YES | YES |
| Time fixed effect | YES | YES | YES | YES |
| Constant term | 1.859 *** | 91.790 *** | −1.500 * | 10.140 *** |
| | (0.525) | (4.733) | (0.887) | (0.317) |
| Observations | 2376 | 2376 | 2112 | 2292 |
| $R^2$ | 0.941 | 0.177 | 0.957 | 0.301 |

Note: 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 2. The clustering of robust standard errors of regression coefficients is shown in parentheses.

## 5. Conclusions and Recommendations

CDT policy serves as a dynamic mechanism for redistributing development power and resources, which is critical for optimizing regional urban systems and promoting urban development [59]. This study employed panel data from Chinese prefecture-level cities between 2009 and 2017 and utilized multi-period and PSM-DID methods to assess the impact of CDT policy on overall residential land supply. The results indicate that the phenomenon primarily influences the urban land supply–demand relationship by fostering spatial expansion, facilitating the functional transformation of construction space, and promoting population and labor force aggregation, thereby affecting the supply of urban residential land. Specifically, the expansion of built-up areas caused by CDT has increased

the scale and proportion of residential land on the supply side. At the same time, the labor agglomeration and increased income levels it has facilitated have led to an increase in the demand for residential land. Furthermore, the adjustment of supply and demand has changed residential land prices; of course, the increase in demand here includes not only the increase in real demand due to factors such as population expansion, but also the increase in speculative demand caused by urban expansion. Nevertheless, the increase in supply is relatively insufficient, resulting in an increase in the price of residential land. It is worth noting that the dynamic test results (Figure 3) show that the impact of the CDT on the scale, proportion, and price of urban residential land supply is heterogeneous across time. More precisely, the promotional effect on the proportion of residential land supply and the residential land price has short-term characteristics, which are reflected in the first year and the first-to-second year after removing counties into districts, whereas the impact on the scale of residential land supply only begins to increase in the second year after the CDT, and the related effects seem to lag. This may be because after CDT occurs, the original county and the prefecture-level municipal governments need a defined transition period to transfer land management practices, approval, and other authoritative roles, leading to a delay in land transfer and planning. After that, the scale of residential land supply gradually increased, the real residential demand and speculative demand caused by the CDT were satisfied, and the positive effect of the withdrawal of counties on land prices decreased. Moreover, heterogeneity analysis demonstrates that CDT practice has a promotional effect on the scale of residential land supply in small- and medium-sized cities and large cities. Additionally, CDT has a stronger positive impact on the proportion and price of residential land supply in large cities compared to their small- and medium-sized counterparts.

Considering that this study mainly investigated the impact of past CDT practices on urban land supply, and given the ongoing prevalence of such practices in China's urban areas, the research findings bear significant policy implications for relevant city governments with regard to optimizing land supply and effectively regulating the land market during the CDT process. First, governments must foresee the impact of the phenomenon on economic and social development, particularly in terms of population- and labor-force-related changes, and they should subsequently adjust the supply of residential land from the supply perspective to address fluctuations in residential land prices caused by CDT. Second, to mitigate the impact of the transformation on the proportion of residential land supply, city governments must also adjust the urban land supply structure in a timely manner, especially in accordance with the population and industrial changes experienced by the entire city, so as to effectively prevent the imbalance of the urban land supply structure. Third, different types of cities should concentrate on various land-based market regulation measures during the CDT process. For example, some large cities may need to attend to the regulation of the scale, proportion, and price of residential land supply. Finally, a sound income distribution mechanism needs to be established, the compensation standard for land acquisition during this process must be raised reasonably, the legitimate rights and interests of landless peasants need to be protected, the construction of affordable housing and controlled land/housing prices should be completed via various methods (such as "fixed construction, competitive land price", "limited land price, and competitive construction" in the land transfer link), and the social welfare brought about by the construction of affordable housing while pursuing land transfer income should be promoted.

We acknowledge that this study has certain limitations and shortcomings. First, due to the diverse and complex effects introduced by CDT, although we have endeavored to examine the various potential impacts and mechanisms of the phenomenon on urban residential land supply, there may still be omissions, which necessitate further exploration in the future. Second, as the available residential land price data are limited to 105 cities, the analysis coverage regarding the impact of CDT on urban land prices is relatively restricted. Third, owing to the absence of long-term time-series data, this study has not been able to investigate the far-reaching effects of this form of transformation on the residential land

supply. Consequently, more in-depth research will be required in the future as relevant data become accessible.

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**Data Availability Statement:** The data that support the findings of this study are available from the author upon reasonable request.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Notes

1 Strictly speaking, the term "county" include county-level cities in this context and the phrasing should be "county (or county-level city)-to-district transformation." For the sake of brevity, however, this paper shall adopt the shorthand "county-to-district transformation."

2 The urban hierarchy in China can be generally classified into three levels. The first level consists of municipalities directly under the jurisdiction of central government, including Beijing, Tianjin, Shanghai, and Chongqing, which concurrently govern multiple districts and counties (or county-level cities). The second level comprises prefecture-level cities, which also govern several districts or counties (or county-level cities), including some sub-provincial cities and regular prefecture-level cities. The third level consists of county-level cities, which are governed by prefecture-level cities and are administratively unified with the districts under their jurisdiction.

3 In the following text, the number of CDT cases in different regions, periods, and degrees of cities is obtained through the statistical analysis of relevant data on China's administrative divisions website.

4 First, in terms of the stages of CDT practice, this study primarily focused on the second peak of CDT (2010–2017). Compared to the first peak (1998–2004), this period has more policy practice samples, and the distribution of sample cities' locations and scales is more balanced, making the samples more representative and comprehensive. Second, to reduce estimation bias caused by policy expectations (the impact of the first peak of CDT on the current period), the threshold of this policy should be in or after 2005. Finally, due to data availability (the monitoring range of national land prices was only upgraded to 105 cities since the fourth quarter of 2008, and the relevant statistical yearbooks have not published the total supply and proportion of residential land supply in each city after 2017), this paper ultimately selected 2009 as the pre-treatment point and 2017 as the post-treatment point.

5 To maintain the validity of the regression results, we did not include the types of cities with a small number of samples in the empirical analysis-mega-cities and super large cities.

6 The data of the aforementioned dependent variables were sourced from the *China City Statistical Yearbook*. Additionally, a logarithmic transformation was applied to the continuous variables (excluding those measured in proportion) during the model estimation.

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# Needs Hierarchy for Public Service Facilities and Guidance-Control Programming in Small Chinese Towns Influenced by Complex Urbanization of Residents: The Evidence from Zhejiang

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**Abstract:** Due to the rapid urbanization of China, residential areas and residents in small towns exhibit dual and complex urbanization patterns and characteristics. The "one-size-fits-all" approach to programming public service facilities has led to inefficient use of idle facilities and the frequent use of facilities that are not integrated into the public service system. Therefore, an investigation of programming logic based on residents' needs within the complex urbanization patterns and characteristics of small towns is urgently required. This study distinguishes between rural and nonrural facilities, using the Kano model to evaluate residents' hypothetical satisfaction with the provision of facilities or lack thereof. Based on the "rural and nonrural" facility need coupling model, four stages of urbanization were identified. Using the Better–Worse coefficient and the chi-square test, this study analyzes residents' cognitive needs and population attributes across various stages of urbanization. Moreover, the study examines the "residential area–resident facility" matching relationship. Ultimately, a "required + optional item" public service facility guidance-control system based on the matching of human–land urbanization is proposed to improve the current programming system for public service facilities. This system provides a theoretical basis for improving the public service level in small towns and ensuring optimally relevant regulations.

**Keywords:** small towns; public service facilities; programming; suitability; human–land urbanization patterns and characteristics

## 1. Introduction

The development patterns of cities and rural spaces are becoming ubiquitously similar across the globe. In the three-level "city–town–village" structure, small towns are widely regarded as vital nodes connecting cities and villages [1]. They not only offer essential employment, basic services, and public transportation to residents and nearby rural settlements but also serve as the economic hinterlands of cities, attracting relocated businesses and developing supporting industries [2]. Due to the advanced processes of industrialization and urbanization, small towns in developed countries are usually urbanized areas that do not include farmland or typical rural production activities [3]. They tend to be residential units at a smaller scale than cities and are defined by standardized indicators, such as population size and density [4], which are similar to those used to define cities. China continues to undergo urbanization. Some small towns have already shown standardized and homogeneous features similar to those of cities, while others serve

as spatial support for nearby urbanization [5,6]. The impetus of rural industrialization and the influx of enterprises have led to the expansion of township construction land [7], which corresponds to a reduction in rural residential areas and available space [8]. The evolution of urban–rural relationships has thus resulted in the emergence of "semi-urban, semi-rural" characteristics in small towns. The geographer McGee referred to the pattern formed by the flow and reconfiguration of these factors between urban and rural areas as "Desakota" (derived from the Indonesian words "desa", meaning village, and "kota", meaning town) [9], while other scholars have referred to this pattern as the urban–rural continuum [10]. In a township's construction land, there are various types of residential areas. These include urban communities and areas with urban features, such as apartment resettlement areas [11]. In addition, there are residential areas with rural features, such as rural settlements [12] and homestead resettlement areas [13]. As urbanization occurs, farmers undergo a transition from a rural lifestyle to an urbanized one, involving the stages of "local nonrural, passive urbanization, and gradual urbanization" [14]. Consequently, residents of small towns enter different stages of urbanization; there is a mismatch in the degree of urbanization between residential areas and residents. For instance, some residents living in rural settlements near towns will experience a high degree of urbanization due to long-term environmental infiltration. As a result, the speed of urbanization among residents outpaces improvements in their living spaces [15]. However, some residents exhibit characteristics that are inconsistent with the environment due to their low adaptability after environmental transformation [16]. For example, some residents have converted their living spaces into rural-style living quarters and have even repurposed them for production activities, which is incongruous with the intended use of these areas [17].

This complex human–land urbanization pattern has intensified the challenges associated with constructing a living environment in small towns, which is reflected in the programming of public service facilities. As a space carrier supporting the production and living needs of residents, the programming of public service facilities is crucial in improving the quality of the corresponding living environment. Although some small towns in China have shown urban-like characteristics, a considerable number of small towns have "semi-urban, semi-rural" characteristics. Currently, the programming of public service facilities in small towns is based on urban-like standards, such as the national "Standard for Planning of Towns" (GB50188-2007) and relevant local regulations. This approach to facility programming, which focuses on achieving the "full coverage of indicators", fails to consider the classification and guidance of residential areas based on urbanization patterns, resulting in the inefficient usage of idle and frequently used facilities that are not included in the public service system [18]. This has a negative impact on the livability of the environment and the surrounding rural areas [19], leading to population outflow and the issue of rural hollowing out.

In the process of constructing a living environment in villages and towns, several countries advocate a "place-based approach" [20] and a development model that considers grassroots forces [21] rather than blindly pursuing universal standards. For example, the Commission of European Communities suggested in its "Green Paper on Territorial Cohesion" that strategies for development should be based on the inherent characteristics of the territory and leverage the unique assets of the area, such as its physical, human, and social capital as well as its natural resources [22]. Considering the diversity of rural areas, the European Commission proposed the LEADER series of programs (Links Between Actions of Rural Development) to address local needs through region-specific development strategies [23]. China is a vast country with a variety of small towns; the traditional top-down political and governance systems [24] cannot fully implement the standardized "one place, one policy" approach in facility programming. Therefore, introducing the concept of "control and guidance" is necessary. To avoid the misallocation of resources and since residents are the direct users of these facilities, exploring the principle of programming based on residents' needs is crucial. This is applicable to different residential area patterns such that the programming of facilities matches the dual human–land urbanization pattern

under top-down control. By implementing optimal facility programming, this study aims to enhance the quality of human settlements and promote the sustainable development of small towns, thus achieving parity in public services between urban and rural areas.

## 2. Methods

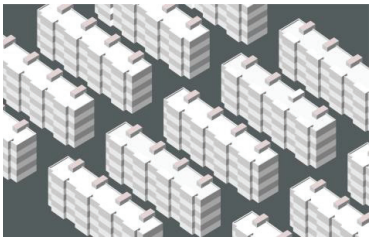
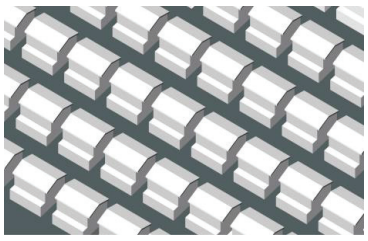
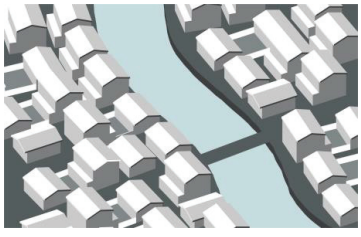
### *2.1. Cognitive Paths of Resident Types in Diverse Urbanization Patterns*

Due to the neglection of urbanization patterns of residential areas and the practice of solely exploring residents' needs in different urbanization stages from the perspective of human urbanization patterns, decision makers must identify the complex urbanization characteristics of different population groups and select facility types based on the diverse needs of residents within the practice of programming in small towns. The operational feasibility of the outcomes and guidance of relevant decision-making departments may be relatively low. Therefore, this study first focuses on residential areas, exploring the types and characteristics of residents' urbanization according to the urbanization patterns of residential areas, in order to develop a facility-programming system tailored to different residential areas.

#### 2.1.1. Cognitive Perception of the Types of Urbanization Patterns in Residential Areas

From the perspective of spatial layout, urban community areas, apartment resettlement areas, and homestead resettlement areas all present planned features, while rural settlements demonstrate a self-organized form. In terms of residential form, there is not a significant difference between urban community areas and apartment resettlement areas; both comprise multistoried or high-rise structures. In contrast, homestead resettlement areas retain low-rise courtyard forms similar to those found in rural settlements (Table 1). Based on spatial analysis, research has confirmed that rural settlements and homestead and apartment resettlement areas are gradually becoming more urbanized. Homestead and apartment resettlement areas exhibit "rural-like" and "urban-like" urbanization characteristics, respectively [25]. Based on the trends of urbanization features present in the four types of residential areas, this study categorizes residential areas into two types: "urban-biased residential areas" (i.e., urban and urban-like areas), such as urban community and apartment resettlement areas, and "rural-biased residential areas" (i.e., rural and rural-like areas), such as rural settlements and homestead resettlement areas.

**Table 1.** Illustrative diagrams of spatial layouts and residential forms of different residential areas.

| **Urban-Biased Residential Areas** | | **Rural-Biased Residential Areas** | |
|---|---|---|---|
| Urban community area | Apartment resettlement area | Homestead resettlement area | Rural settlement |
|  | |  |  |

#### 2.1.2. Analysis of Urbanization Characteristics Based on Residents' Facility Needs

There are multiple academic approaches to distinguishing an individual's urbanization stage. Some studies have observed a correlation between population attributes and individuals' urbanization stages, indicating that attributes such as household registration status, gender, years of education, and age have varying degrees of impact on an individual's level of urbanization [26]. However, an individual's urbanization stage is not only determined by their surface-level population attributes but also by their "inner" identifica-

tion and adaptation to urban life and production [27]. Therefore, this study uses the degree of residents' needs for different types of facilities as the main criterion for distinguishing individuals' urbanization stages.

During nearby urbanization, residents experience transformations in their living environments and modes of living and producing, such as relocating from rural areas to multistoried buildings and resettling in a homestead [28]. In this context, residents often choose to contract their land, shifting away from agriculture as a primary source of income. Some residents, due to their strong adaptability to their environments, adjust to the production modes and lifestyles available in urban areas; they have a higher need for certain living service facilities [29]. In addition, some residents are still undergoing adaptation to their identity-related and environmental changes. They continue to hold traditional ideological beliefs and rely on living service facilities, such as ancestral halls and cultural auditoriums to hold gatherings [30]. Furthermore, they rely on the community for economic income [31] and depend on productive services, such as materials and machine shops, for their agricultural economic activities. Thus, the varying degrees of the requirement for different types of facilities among residents reflect the differences in their stages of urbanization. By summarizing the characteristics of these phenomena, this study classifies facility types into rural and nonrural facilities. Rural facilities are unique to rural areas and continue to be relied upon by less-urbanized residents, while nonrural facilities are available in urban and rural areas. Subsequently, this study analyzes residents' different urbanization stages based on their varying levels of requirement for the two types of facilities, classifies the residents accordingly, and establishes a "residential area–resident facility" matching relationship.

Construction of "Rural and Nonrural Facility" Library: To clarify the scope of this research, in this study, a public service facility and a library were constructed for rural and urban communities. The library was created by reviewing national and local regulations, policy guidelines, and relevant literature and by conducting field observations of frequently used facilities that had not yet been incorporated into the public service facility system. Then, we compared the library with the "Standard for Urban Residential Area Planning and Design" (GB50180-2018) and selected facility types that are only available as rural facilities, while those available in both urban and rural areas were selected as nonrural facilities (Table 2).

**Table 2.** "Rural and nonrural facility" library.

| Types | | Facilities |
|---|---|---|
| Nonrural facilities | Education | Kindergarten, primary school, junior school, senior high school, training institution, adult vocational and technical school |
| | Medical | Clinic, hospital, specialized clinic, emergency medical site (nucleic-acid-testing site), Hugh sanatorium |
| | Cultural and Sports | Outdoor sports ground, indoor sports venue, cultural activity center, exhibition hall |
| | Social Welfare | Home aged care service center, nursing home, service station for the disabled, social welfare institute, villager canteen |
| | Administration | Neighborhood (village) service center |
| | Commerce | Grocery, agricultural market, food store, sales and maintenance department of non-motor vehicles, hardware store, pharmacy, department store, book and video store, cultural goods store, express/postal service station, self-service cabinet, bank, telecom business hall, insurance institution, restaurant/teahouse, beauty and hair salon, photographic studio, public bathroom |
| | Infrastructure | Bus station, motor vehicle parking lot, public toilet, garbage collection point |
| | Productive Service (Tourism, etc.) | Tourist reception center, hotel/homestay, tourist souvenir shop |

**Table 2.** *Cont.*

| Types | | Facilities |
|---|---|---|
| Rural facilities | Productive Service (Agriculture, etc.) | Agricultural machine shop, agricultural materials shop, grain-drying site, agricultural product storage station, product sales site, agricultural product acquisition station, farm tool storage station, agricultural technical education station, agricultural cooperative |
| | Cultural and Sports | Cultural auditorium, ancestral hall, temple, film-screening venue, broadcasting station |

Construction of the Model Framework for Residents' Urbanization Characteristics: After classifying the residents based on their levels of recognition of the types of facility, a "rural and nonrural" facility need coupling model framework was constructed to reflect the differentiation of residents' urbanization stages (Figure 1).

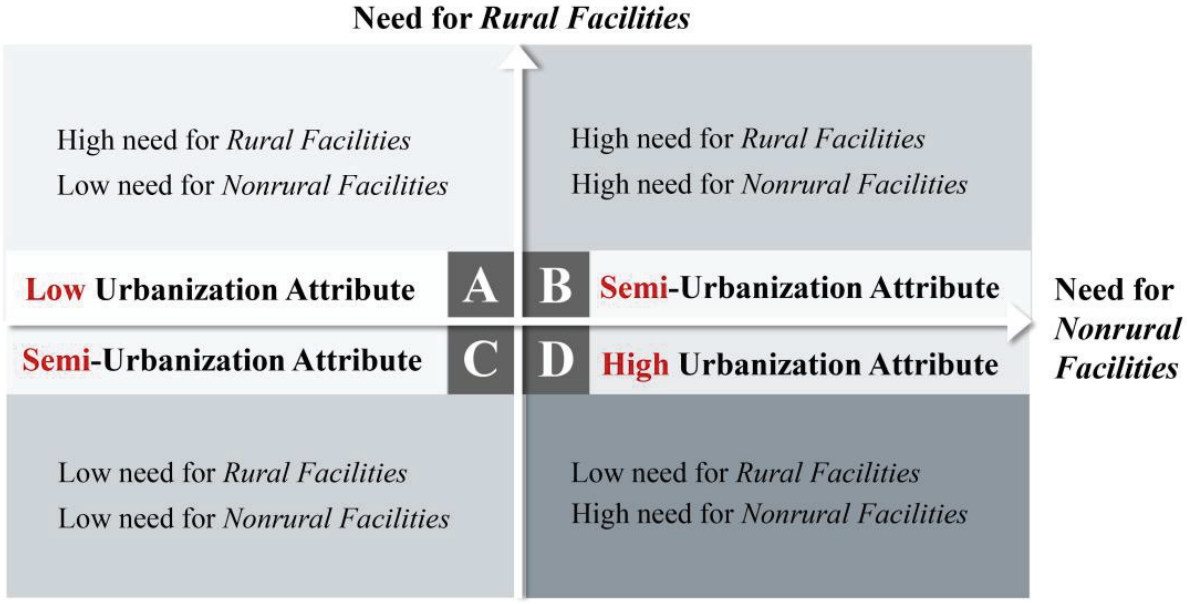



**Figure 1.** Framework of the "rural and nonrural" facility needs coupling model.

Related studies have shown that the cognitive characteristics of residents' production and living needs in small-town apartment resettlement areas reflect their levels of urbanization [32]. Residentswith a high standard of living and with low production requirements belong to the urban group. Hence, the degree of need for community production is a factor that reflects residents' level of urbanization. However, the indication system for their living needs includes rural and nonrural facilities, as defined in this study. Therefore, this system fails to account for the important fact that rural living service facilities tend to be used by residents with low levels of urbanization. Thus, this study further refines the model framework for residents' urbanization characteristics, categorizing rural facilities into dimensions of production and living needs, and suggesting that residents who present high levels of requirement for rural facilities in terms of either production or living needs should be classified as those with a "high need for rural facilities."

Matching Analysis of the Residents' Urbanization Characteristics: Using the chi-squared test, we conducted a significance test on the percentages of individual characteristics among different urbanization stage groups. The significant differences between the four categories of urbanization characteristics and population attributes were analyzed. The urbanization characteristics of residents living in various urbanization patterns of residential areas were described, providing support for menu-oriented facility programming.

*2.2. The Facility Programming Path Based on Residents' Needs*

2.2.1. Establishment of a Guidance and Control Hierarchy Based on Needs Theory

"Need" is the internal force that drives individuals to seek and utilize specific objects [33]. It represents the pre-motivational factor driving human behavior [34] and is the key driver of facility usage. Considering the restrictions imposed by policies and funding in villages and towns [35], the establishment of facilities cannot be achieved overnight. Therefore, prioritization based on the urgency of a need is necessary [36–38]. In terms of the hierarchy of needs, American psychologist Abraham Maslow proposed a theory encompassing physiological, safety, social, esteem, and self-actualization needs [39]. Maslow believed that lower-level needs must be adequately met before higher-level needs can be satisfied [40] and that this process is irreversible [41]. Clayton P. Alderfer, an American psychologist, developed the Existence–Relatedness–Growth (ERG) Theory, building upon Maslow's Hierarchy of Needs [42]. Both theories suggest that once lower-level needs are met, there is a desire for higher-level needs. However, the ERG Theory expands upon this idea by proposing that different levels of needs can coexist [43,44] and multiple needs can simultaneously act as motivators. Moreover, the ERG Theory incorporates the idea of "frustration-regression", which suggests that when higher-level needs are not met, individuals may regress to lower-level needs [45,46]. In the allocation of public service facilities, not all high-level needs can be met. Therefore, low-level needs should be controlled through "rigid" measures, while high-level needs should be guided through "flexible" measures. A "required + optional item" programming model should be adopted to respond to the structural characteristics of residents' public service facility needs (Figure 2). Hence, facility implementation should prioritize satisfying the mandatory requirements (low-level needs) before the optional requirements (high-level needs). To identify the overall need hierarchy of residents with different urbanization levels in each analyzed residential area, an individual need structure is identified. Then, based on certain principles, this study integrates the needs of the residents and, subsequently, obtains a programming guidance-control system for different residential areas.

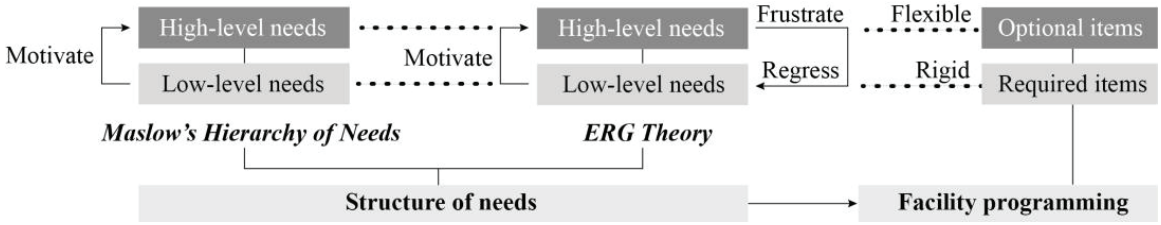



**Figure 2.** "Required + Optional Item" Programming Model Based on Needs Theory.

2.2.2. Identification of Needs Structure Characteristics Based on the Kano Model

As this study explores the issue of whether a facility should be allocated in different "human–land urbanization patterns", it focuses on examining people's attitudes toward the provision of a given facility. Therefore, satisfaction was selected as the measurement indicator. The measurement methods for satisfaction can be divided into two categories: experiential and hypothetical evaluation. The former measures overall satisfaction using standardized scales, such as SERVQUAL [47], or through methods with their own indicator systems, such as the analytical hierarchy process (AHP) [48]. Additionally, there are methods that assess individual attribute satisfaction, such as importance performance analysis, which segments attributes into four quadrants [49]. To develop the programming guidance-control system, facilities that are not yet available but may constitute part of residents' potential needs should be considered in addition to those included in the public service system. Accordingly, this study aims to employ a "hypothetical" method to measure satisfaction in order to identify the characteristics of the needs structure. The Kano model is precisely such a method, which was proposed by Professor Kano Noriaki of the Tokyo Institute of Technology in 1984 [50]. This model has been widely applied in the fields of

service development and improvement [51,52]. It suggests that not every service provision or lack thereof will increase or decrease, respectively, users' satisfaction with the service in question [53].

There are typically two types of satisfaction assessment questions asked of users: positive and negative. Positive refers to the satisfaction of the respondent when the service attribute is present or functioning properly (Functional). Negative refers to the satisfaction of the respondent when the service attribute is lacking or experiencing malfunction (Dysfunctional) [54]. The responses to positive and negative questions are correlated, reflecting five attributes: must-be (M), one-dimensional (O), attractive (A), indifferent (I), and reverse quality (R) (Figure 3). The Kano evaluation table (Table 3) maps the responses to positive and negative questions to cognitive attributes. For example, if a respondent chooses "Dissatisfied" for dysfunctional and "It should be that way", "I am indifferent", or "I can live with it" for functional, the corresponding cognitive attribute in the Kano evaluation table is the Must-be quality attribute (M). Compared to the traditional linear Likert scale method, the Kano model can identify residents' satisfaction with the provision or non-provision of a certain facility, thus avoiding respondents' cognitive bias toward providing positive responses [55]. In particular, the Kano model effectively conveys the desired "urgency" of facility construction, providing valuable support for the classification of facilities based on residents' actual needs, especially in situations where resources are limited.

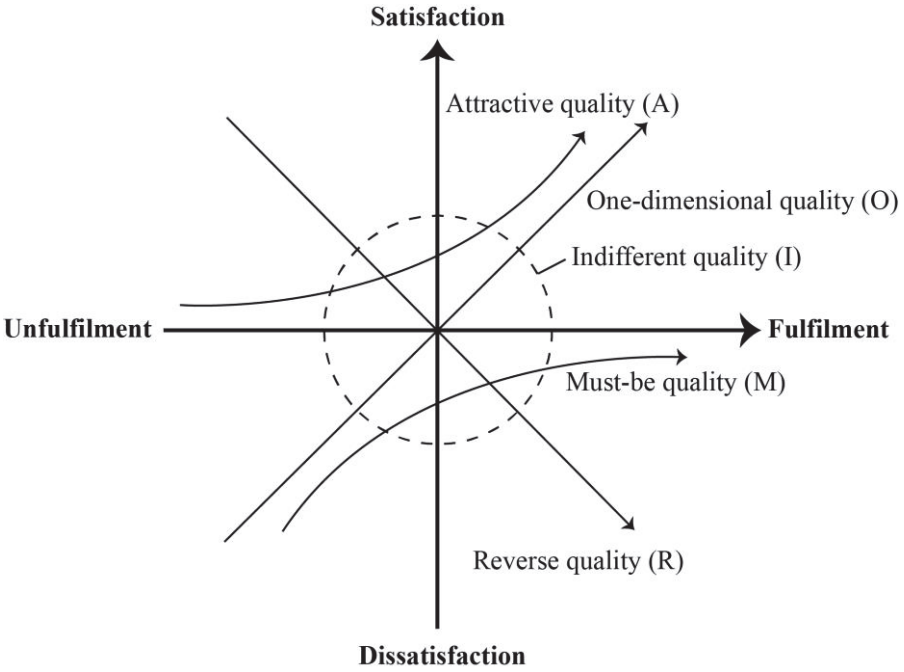



**Figure 3.** Kano's model of quality attributes [56].

**Table 3.** Kano evaluation table.

| Criteria/Attributes | | Dysfunctional | | | | |
|---|---|---|---|---|---|---|
| | | **Satisfied** | **It Should Be That Way** | **I Am Indifferent** | **I Can Live with It** | **Dissatisfied** |
| **Functional** | Satisfied | Q | A | A | A | O |
| | It should be that way | R | I | I | I | M |
| | I am indifferent | R | I | I | I | M |
| | I can live with it | R | I | I | I | M |
| | Dissatisfied | R | R | R | R | Q |

Each level is defined as follows:

- Must-be quality (M): Facilities that are essential to the lives of residents. Providing these facilities in the community may not increase residents' satisfaction; however, without such facilities, residents will be extremely inconvenienced.
- One-dimensional quality (O): Facilities that residents expect to have. The provision of these facilities will satisfy the residents, while the absence of such facilities will make the residents feel dissatisfied; however, they can tolerate such an absence.
- Attractive quality (A): Facilities that are unexpected and will pleasantly surprise residents. Such facilities are beyond residents' expectations and do not affect their normal lives if they are unavailable; however, if provided, they can greatly improve satisfaction and quality of life.
- Indifferent quality (I): Facilities that are not a concern for residents. Whether such facilities are provided or not has a minimal effect on the residents' quality of life.
- Reverse quality (R): Facilities that residents do not want.

The research flow chart is shown in Figure 4.

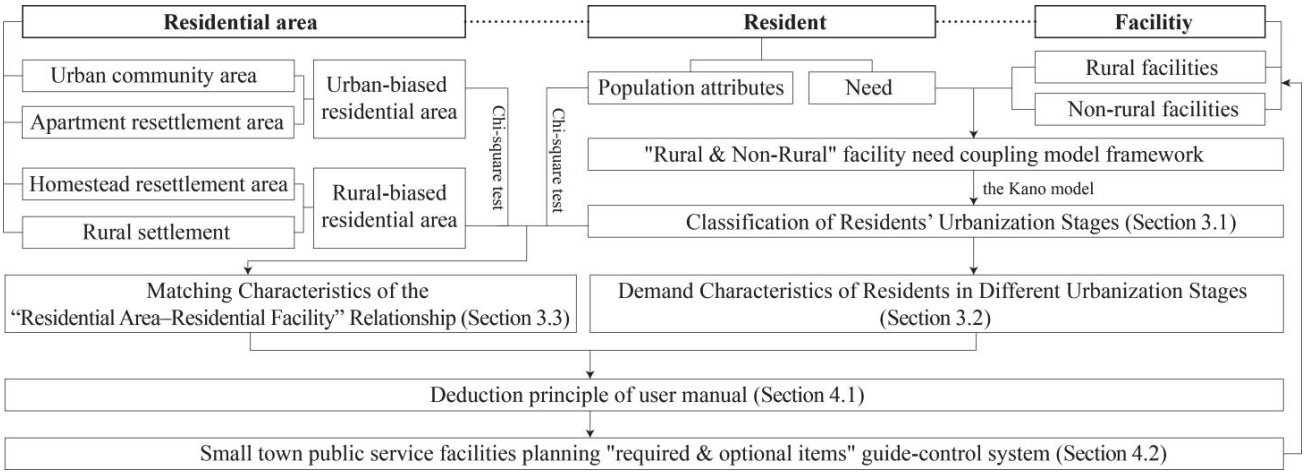



**Figure 4.** Research flow chart.

### *2.3. Investigation Method*

#### 2.3.1. Sample Selection

This study aimed to select a sample of small towns that exhibit the dual complexity of human–land urbanization. Due to the development trend of the industrial economy over the past decade, S town in Jiaxing City, Zhejiang Province, has been continuously developing industrial parks in its northern and eastern regions, resulting in a gradual expansion of township construction land into urban areas (Figure 5). Currently, the township construction land includes various types of residential areas, such as rural settlements, homestead resettlement areas, urban community areas, and apartment resettlement areas (Figure 6). Differences in urbanization characteristics are evident among residents in the different residential areas. The majority of the residents living in rural-biased residential areas have not yet converted their household registration and continue to rely on agriculture as their primary source of income. Meanwhile, most residents living in urban-biased residential areas have fully transitioned away from agriculture, and displaced farmers have found employment in local industrial parks. Overall, the residential areas and residents within S Town exhibit complex urbanization characteristics, making the town an appropriate sample for the study.

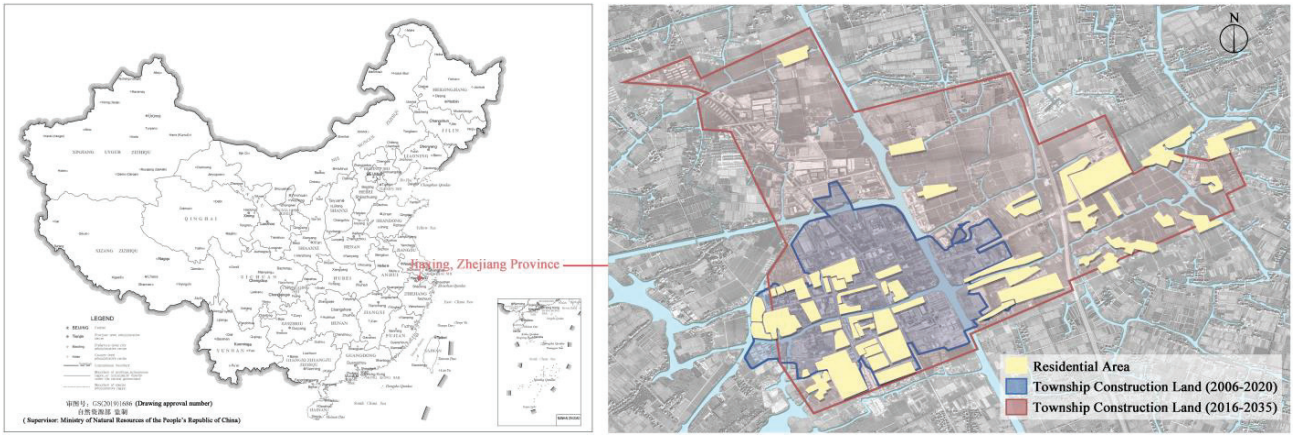



**Figure 5.** Changes in the scope of township construction land.

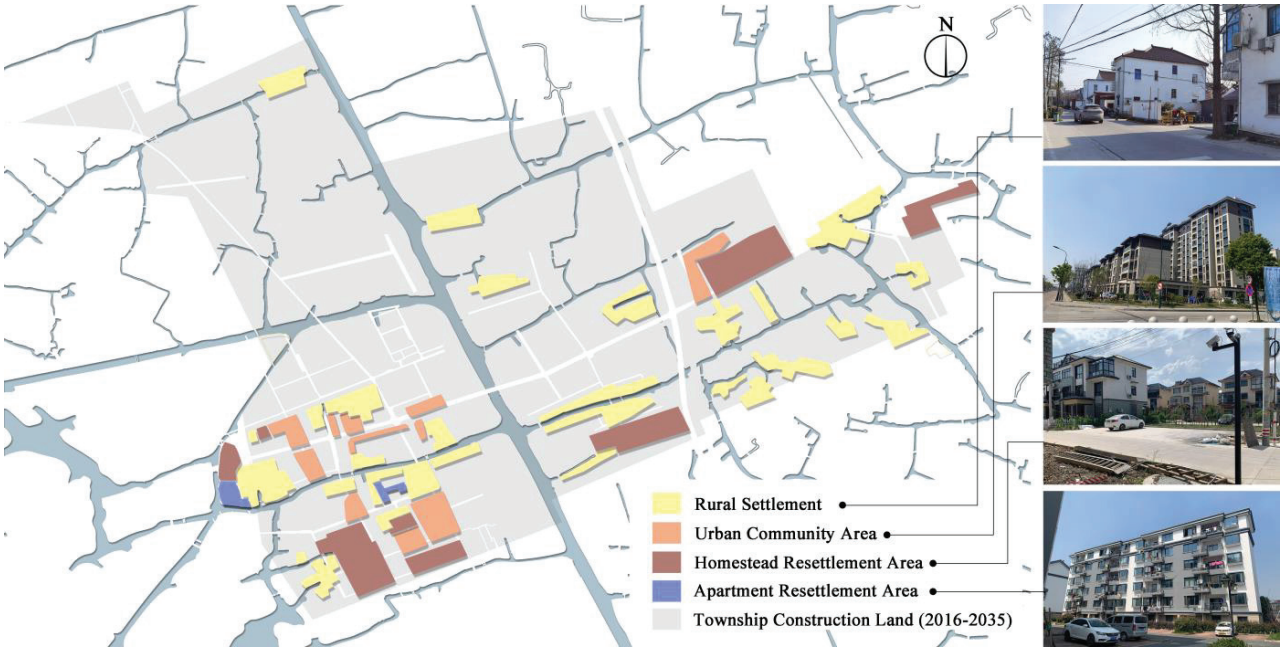



**Figure 6.** Plane distribution of various residential area types.

### 2.3.2. Questionnaire Design and Investigation Process

The survey questionnaire comprises two sections: gathering basic demographic information about residents and conducting a satisfaction survey using the Kano model. The basic demographic information serves as a tool for evaluating population attributes across various stages of urbanization. It encompasses details such as residential area, gender, age, registered permanent address, educational level, religious beliefs, household responsibilities, employment status, annual household income, marital status, and living arrangements with family members, among others. The satisfaction survey specifically targets each facility and incorporates a combination of positive and negative questions. An illustrative example of the questionnaire is provided in Table 4.

Before conducting the investigation, it is important to provide training to the investigators and simulate investigate scenarios, thereby mitigating potential information collection errors resulting from subjective interpretation biases. As this study aims to identify the genuine needs of residents within the context of human–land urbanization patterns, it was also essential to clarify during the training that the interviewees should have been registered residents who had been residing in the town in question for a long period.

Temporary residents or those who commute to the town for work do not fall within the scope of this investigation. The investigation adopts a semi-structured interview approach to avoid potential biases in questionnaire comprehension due to factors such as educational level. With the coordination and assistance of government officials, the investigators visited residents' homes, explained the questionnaire to them, and collected data on an individual basis. This approach helped to ensure the validity of the questionnaire data to a certain extent.

**Table 4.** Example of satisfaction questionnaire based on the Kano model.

| Type | Facility and Service | If There Is Such a Facility Nearby | | | | | If There Is No Such Facility Nearby | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Satisfied | It Should Be That Way | I Am Indifferent | I Can Live with It | Dissatisfied | Satisfied | It Should Be That Way | I Am Indifferent | I Can Live with It | Dissatisfied |
| Medical | Clinic | | | | | | | | | | |
| | Hospital | | | | | | | | | | |
| …… | …… | | | | | | | | | | |

To ensure adequate representation of the overall population, both regular days and special days (weekdays: 7–8 July 2022; weekends: 9–10 July 2022) were selected, and investigators were assigned to conduct surveys in each residential area. The study balanced the data collection quantity between rural- and urban-biased residential areas. A total of 260 questionnaires were distributed. After excluding questionnaires with missing information or incomplete responses, 252 valid questionnaires were collected, comprising 112 and 140 responses from urban- and rural-biased residential areas, respectively.

## 3. Results

### *3.1. Classification of Residents' Urbanization Stages*

This study used the Kano evaluation table to determine the cognitive attributes with respect to facilities among individual residents. To measure the participants' levels of recognition of rural and nonrural facilities, attribute values were assigned (must-be = 1, one-dimensional = 2, attractive = 3, indifferent = 4, and reverse = 5). The average value for the different types of facility attributes was calculated for each individual, and a violin plot was created (Figure 7) to make a preliminary judgment on the data distribution. There were distinct peaks and valleys in the three categories, indicating that the residents' perception of these facilities had a certain degree of clustering, further confirming the hypothesis of population classification and demonstrating the feasibility of clustering. As a violin plot can visually determine the number of clustering groups, the K-means clustering method was used to cluster the cognitive attributes of the three types of facilities into high and low levels (Figure 8). As a result, four groups were identified, with Groups A, B, C, and D consisting of 35, 90, 98, and 29 individuals, respectively.

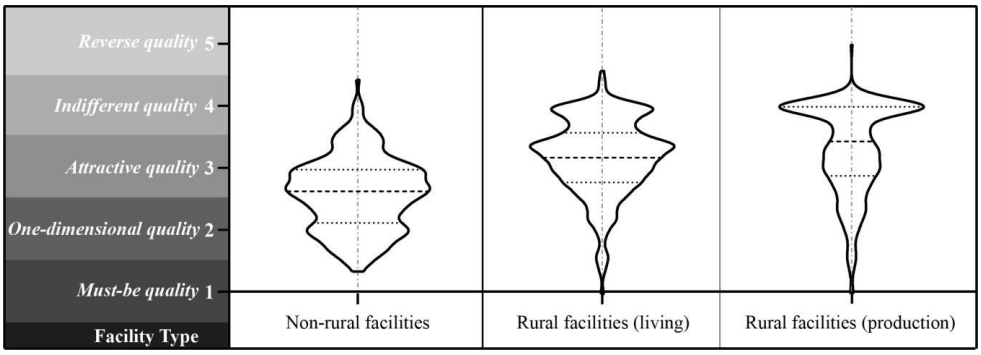



**Figure 7.** Violin plots of the mean values of the individual residents' cognitive attributes.

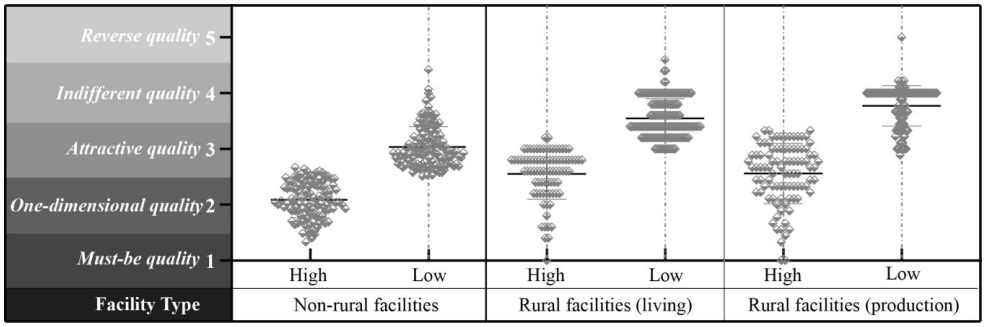



**Figure 8.** Distribution of the mean values of the individual residents' cognitive attributes after clustering.

*3.2. Demand Characteristics of Residents in Different Urbanization Stages*

After determining the individual residents' cognitive attributes regarding facilities, a further assessment of the needs of the groups was necessary. In the traditional Kano model, when there are multiple cognitive attributes that are close to or have a percentage similar to the highest-rated attribute, defining the attribute category based on the maximum value may result in some people's needs being ignored [57]. This study applied better–worse coefficient analysis to identify the similarity of individuals' cognitive attributes. Better and worse values represent the degrees of improvement in the satisfaction of residents after a facility is provided and those of the increase in dissatisfaction after it is not provided, respectively [58]. The calculation method for better and worse values is as follows:

$$\text{Better (SI)} = (A + O)/(A + O + M + I) \text{ and} \quad (1)$$

$$\text{Worse (DSI)} = -1 \times (O + M)/(A + O + M + I), \quad (2)$$

The better and worse values were used to plot a four-quadrant diagram based on their absolute values. As better and worse values are continuous, the intersection point of the axes was established as the average value. The four quadrants represent the following categories: one-dimensional (I), attractive (II), indifferent (III), and must-be (IV) qualities. Consequently, the four groups' facility attributes were classified (Table 5, Figures 9–12).

Upon examining the number of cognitive attributes for each of the four groups (Figure 13), it was observed that group C displayed the weakest sense of urgency for facilities, with only four must-be quality facilities (6.78%) and 24 indifferent quality facilities (40.68%). Group A followed Group C in rank, with nine must-be quality facilities (15.25%). In contrast, Group B displayed the strongest sense of urgency for facilities, with a larger number of must-be and one-dimensional quality facilities; it was observed that 30 facilities (50.85%) could cause dissatisfaction if they were not planned. Furthermore, the study ranked the urgency levels of cognitive attributes for each facility across the four groups. For instance, with regard to a clinic (A = 1, B = 1, C = 2, and D = 2), Groups A and B were classified as Rank 1, while Groups C and D were classified as Rank 3. The number of attributes with Ranks 1–4 for each group's perception of 59 facilities were measured (Figure 14). Group B perceived 52 facilities (88%) to correspond to Rank 1, which is sufficient for covering most of the needs of Groups A, C, and D. Upon further comparison with Groups A, C, and D, eight facilities showed a high level of urgency in ACD but were not covered by Group B (Figure 15). In terms of facility types, Groups A and B continued to have high demand for agriculture-related industry services. Residents in these groups considered agricultural materials and machine shops to be essential and placed great value in clan relationships formed by rural geography and familial ties. They also believed that cultural auditoriums were necessary. Group A had a strong demand for agriculture-related industry services and considered product sale sites and agricultural product acquisition stations to be indispensable. Meanwhile, Groups C and D were indifferent to whether rural facilities were available.

**Table 5.** Better–worse coefficient calculation and cognitive attribute results.

| Types | | Facilities | Group A | | Group B | | Group C | | Group D | | Cognitive Attribute * | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Better | \|Worse\| | Better | \|Worse\| | Better | \|Worse\| | Better | \|Worse\| | A | B | C | D |
| Nonrural facilities | Medical | Clinic | 0.4286 | 0.6571 | 0.2444 | 0.7444 | 0.4694 | 0.4184 | 0.3448 | 0.5517 | 1 | 1 | 2 | 2 |
| | | Hospital | 0.6857 | 0.4000 | 0.3111 | 0.8111 | 0.5464 | 0.2990 | 0.1724 | 0.8276 | 2 | 2 | 2 | 1 |
| | | Specialized clinic | 0.4412 | 0.1765 | 0.3889 | 0.3889 | 0.5052 | 0.1546 | 0.3793 | 0.2414 | 4 | 3 | 3 | 3 |
| | | Emergency medical site (Nucleic-acid-testing site) | 0.4571 | 0.7143 | 0.1556 | 0.8778 | 0.5625 | 0.4583 | 0.3103 | 0.8276 | 2 | 1 | 2 | 2 |
| | | Hugh sanatorium | 0.3939 | 0.1212 | 0.5444 | 0.2333 | 0.3918 | 0.0619 | 0.4138 | 0.1034 | 4 | 3 | 3 | 3 |
| | Cultural and sports | Outdoor sports ground | 0.6765 | 0.2941 | 0.3556 | 0.5778 | 0.5104 | 0.1354 | 0.4483 | 0.4483 | 3 | 2 | 3 | 2 |
| | | Indoor sports venue | 0.7429 | 0.0286 | 0.5667 | 0.3222 | 0.4896 | 0.0521 | 0.5517 | 0.1034 | 3 | 3 | 3 | 3 |
| | | Cultural activity center | 0.6471 | 0.2647 | 0.4222 | 0.5111 | 0.5361 | 0.1546 | 0.4138 | 0.3448 | 3 | 3 | 3 | 3 |
| | | Exhibition hall | 0.6286 | 0.0286 | 0.5111 | 0.1111 | 0.4639 | 0.0309 | 0.4483 | 0.1379 | 3 | 3 | 3 | 3 |
| | Education | Kindergarten | 0.5429 | 0.4571 | 0.1000 | 0.9444 | 0.3196 | 0.4536 | 0.1034 | 0.9310 | 2 | 1 | 1 | 1 |
| | | Primary school | 0.4571 | 0.5143 | 0.1111 | 0.9000 | 0.2887 | 0.4021 | 0.1034 | 0.9655 | 2 | 1 | 1 | 1 |
| | | Junior school | 0.5143 | 0.4571 | 0.1889 | 0.8222 | 0.3711 | 0.3299 | 0.1034 | 0.9310 | 2 | 1 | 2 | 1 |
| | | Senior high school | 0.5294 | 0.2353 | 0.3111 | 0.5000 | 0.3958 | 0.2292 | 0.3103 | 0.3793 | 3 | 3 | 2 | 3 |
| | | Training institution | 0.3824 | 0.0588 | 0.5222 | 0.2667 | 0.3229 | 0.1250 | 0.2414 | 0.2069 | 4 | 3 | 4 | 3 |
| | | Adult vocational and technical school | 0.2857 | 0.0286 | 0.4111 | 0.2333 | 0.2577 | 0.0515 | 0.2414 | 0.1379 | 4 | 3 | 4 | 3 |
| | Social welfare | Home aged care service center | 0.6176 | 0.5294 | 0.2222 | 0.6444 | 0.4536 | 0.2268 | 0.3793 | 0.3103 | 2 | 1 | 2 | 3 |
| | | Nursing home | 0.4857 | 0.2571 | 0.3000 | 0.4889 | 0.3608 | 0.1546 | 0.3793 | 0.2759 | 3 | 3 | 3 | 3 |
| | | Service station for the disabled | 0.4412 | 0.2059 | 0.2556 | 0.4667 | 0.2784 | 0.1237 | 0.3103 | 0.2759 | 4 | 4 | 4 | 3 |
| | | Social welfare institute | 0.5143 | 0.1143 | 0.3000 | 0.4444 | 0.3333 | 0.1042 | 0.3448 | 0.1379 | 3 | 3 | 4 | 3 |
| | | Villager canteen | 0.5588 | 0.0882 | 0.4889 | 0.2556 | 0.4433 | 0.0722 | 0.3793 | 0.0690 | 3 | 3 | 3 | 3 |
| | Administration | Neighborhood (village) service center | 0.3429 | 0.8857 | 0.1222 | 0.9444 | 0.3673 | 0.5000 | 0.2069 | 0.6552 | 1 | 1 | 2 | 1 |
| | Commerce | Agricultural market | 0.6286 | 0.7429 | 0.1667 | 0.9889 | 0.5876 | 0.5670 | 0.1724 | 0.9655 | 2 | 1 | 2 | 1 |
| | | Grocery | 0.6857 | 0.6000 | 0.1889 | 0.9444 | 0.5102 | 0.5306 | 0.2069 | 0.9310 | 2 | 1 | 2 | 1 |
| | | Food store | 0.6857 | 0.3143 | 0.3111 | 0.7667 | 0.5567 | 0.2887 | 0.2069 | 0.7586 | 2 | 2 | 2 | 1 |
| | | Pharmacy | 0.4571 | 0.6286 | 0.1111 | 0.9222 | 0.4694 | 0.4490 | 0.1379 | 0.8966 | 2 | 1 | 2 | 1 |
| | | Bank | 0.4000 | 0.4000 | 0.1444 | 0.9667 | 0.4375 | 0.3750 | 0.1379 | 0.8966 | 1 | 1 | 2 | 1 |
| | | Telecom business hall | 0.2571 | 0.1714 | 0.1444 | 0.8111 | 0.3542 | 0.2708 | 0.1034 | 0.6897 | 4 | 1 | 1 | 1 |
| | | Beauty and hair salon | 0.6000 | 0.4571 | 0.1444 | 0.9111 | 0.4479 | 0.4375 | 0.1724 | 0.7931 | 2 | 1 | 2 | 1 |
| | | Department store | 0.5429 | 0.1429 | 0.3333 | 0.6556 | 0.6392 | 0.2165 | 0.3103 | 0.6207 | 3 | 2 | 2 | 2 |
| | | Cultural goods store | 0.3429 | 0.0857 | 0.2444 | 0.5889 | 0.3542 | 0.1354 | 0.0714 | 0.6071 | 4 | 1 | 4 | 1 |
| | | Insurance institution | 0.2000 | 0.0000 | 0.1910 | 0.4270 | 0.1771 | 0.0833 | 0.0357 | 0.2500 | 4 | 4 | 4 | 4 |
| | | Photographic studio | 0.3714 | 0.0857 | 0.2333 | 0.4222 | 0.1939 | 0.0714 | 0.0714 | 0.2500 | 4 | 4 | 4 | 4 |
| | | Public bathroom | 0.2000 | 0.0000 | 0.2809 | 0.3146 | 0.1237 | 0.0619 | 0.1034 | 0.2414 | 4 | 3 | 4 | 4 |

**Table 5.** *Cont.*

| Types | | Facilities | Group A | | Group B | | Group C | | Group D | | Cognitive Attribute * | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Better | \|Worse\| | Better | \|Worse\| | Better | \|Worse\| | Better | \|Worse\| | A | B | C | D |
| Rural facilities | | Sales and maintenance department of non-motor vehicles | 0.4571 | 0.4571 | 0.1222 | 0.8444 | 0.2577 | 0.2165 | 0.1724 | 0.6207 | 2 | 1 | 1 | 1 |
| | | Hardware store | 0.3143 | 0.2000 | 0.1667 | 0.8444 | 0.2268 | 0.1546 | 0.0690 | 0.7931 | 4 | 1 | 4 | 1 |
| | | Express/postal service station | 0.4571 | 0.4286 | 0.1556 | 0.8889 | 0.4737 | 0.4632 | 0.2759 | 0.8621 | 2 | 1 | 2 | 2 |
| | | Self-service cabinet | 0.4571 | 0.2571 | 0.4333 | 0.3778 | 0.4227 | 0.2268 | 0.2069 | 0.5517 | 3 | 3 | 2 | 1 |
| | | Restaurant/teahouse | 0.5714 | 0.0857 | 0.3111 | 0.7444 | 0.4388 | 0.2959 | 0.3448 | 0.7241 | 3 | 2 | 2 | 2 |
| | Infrastructure | Bus station | 0.4286 | 0.7714 | 0.1222 | 0.9444 | 0.4021 | 0.5670 | 0.1034 | 0.9655 | 1 | 1 | 2 | 1 |
| | | Motor vehicle parking lot | 0.4571 | 0.5429 | 0.2000 | 0.8444 | 0.4694 | 0.5918 | 0.1724 | 0.8621 | 2 | 1 | 2 | 1 |
| | | Public toilet | 0.3824 | 0.7059 | 0.1000 | 0.9778 | 0.3830 | 0.5213 | 0.1034 | 1.0000 | 1 | 1 | 2 | 1 |
| | | Garbage collection point | 0.3030 | 0.8485 | 0.1111 | 1.0000 | 0.4157 | 0.6966 | 0.1034 | 1.0000 | 1 | 1 | 2 | 1 |
| | Productive Service (Tourism, etc.) | Tourist reception center | 0.3714 | 0.0286 | 0.4205 | 0.1591 | 0.2577 | 0.0103 | 0.3448 | 0.0345 | 4 | 3 | 4 | 3 |
| | | Tourist souvenir shop | 0.3235 | 0.0000 | 0.4659 | 0.0795 | 0.2474 | 0.0103 | 0.3103 | 0.0000 | 4 | 3 | 4 | 3 |
| | | Hotel/Homestay | 0.2941 | 0.1765 | 0.1573 | 0.5730 | 0.1939 | 0.0714 | 0.0690 | 0.4138 | 4 | 1 | 4 | 4 |
| | Productive service (Agriculture, etc.) | Agricultural machine shop | 0.3143 | 0.3143 | 0.0778 | 0.6667 | 0.1895 | 0.0526 | 0.1481 | 0.0370 | 1 | 1 | 4 | 4 |
| | | Agricultural materials shop | 0.2571 | 0.6571 | 0.0667 | 0.7889 | 0.2128 | 0.1064 | 0.1481 | 0.2222 | 1 | 1 | 4 | 4 |
| | | Grain-drying site | 0.2000 | 0.1143 | 0.1124 | 0.2022 | 0.1563 | 0.0104 | 0.1034 | 0.0345 | 4 | 4 | 4 | 4 |
| | | Agricultural product storage station | 0.2353 | 0.1176 | 0.1910 | 0.1798 | 0.1340 | 0.0103 | 0.0690 | 0.0000 | 4 | 4 | 4 | 4 |
| | | Product sales site | 0.4571 | 0.4000 | 0.2444 | 0.4444 | 0.2577 | 0.0000 | 0.1379 | 0.0690 | 2 | 4 | 4 | 4 |
| | | Agricultural product acquisition station | 0.3429 | 0.4286 | 0.2778 | 0.3889 | 0.2371 | 0.0000 | 0.1034 | 0.0000 | 1 | 3 | 4 | 4 |
| | | Farm tool storage station | 0.1250 | 0.0625 | 0.1744 | 0.1163 | 0.1809 | 0.0000 | 0.0690 | 0.0000 | 4 | 4 | 4 | 4 |
| | | Agricultural technical education station | 0.5714 | 0.1143 | 0.4333 | 0.2889 | 0.2105 | 0.0000 | 0.1034 | 0.0345 | 3 | 3 | 4 | 4 |
| | | Agricultural cooperative | 0.4571 | 0.2857 | 0.3371 | 0.2809 | 0.1354 | 0.0313 | 0.1034 | 0.0345 | 3 | 3 | 4 | 4 |
| | Cultural and sports | Cultural auditorium | 0.5429 | 0.7143 | 0.3333 | 0.7333 | 0.4536 | 0.2062 | 0.2069 | 0.3103 | 2 | 2 | 3 | 4 |
| | | Ancestral hall | 0.3714 | 0.1714 | 0.3483 | 0.2584 | 0.1563 | 0.0000 | 0.0357 | 0.0357 | 4 | 3 | 4 | 4 |
| | | Temple | 0.4000 | 0.2000 | 0.3596 | 0.2360 | 0.2083 | 0.0208 | 0.0714 | 0.0357 | 4 | 3 | 4 | 4 |
| | | Film-screening venue | 0.7714 | 0.2571 | 0.6111 | 0.2556 | 0.4896 | 0.0729 | 0.5517 | 0.1034 | 3 | 3 | 3 | 3 |
| | | Broadcasting station | 0.3714 | 0.0571 | 0.2809 | 0.1798 | 0.2688 | 0.0108 | 0.2500 | 0.0000 | 4 | 3 | 4 | 3 |

* Cognitive Attribute: Must-be quality = 1, One-dimensional quality = 2, Attractive quality = 3, and Indifferent quality = 4.

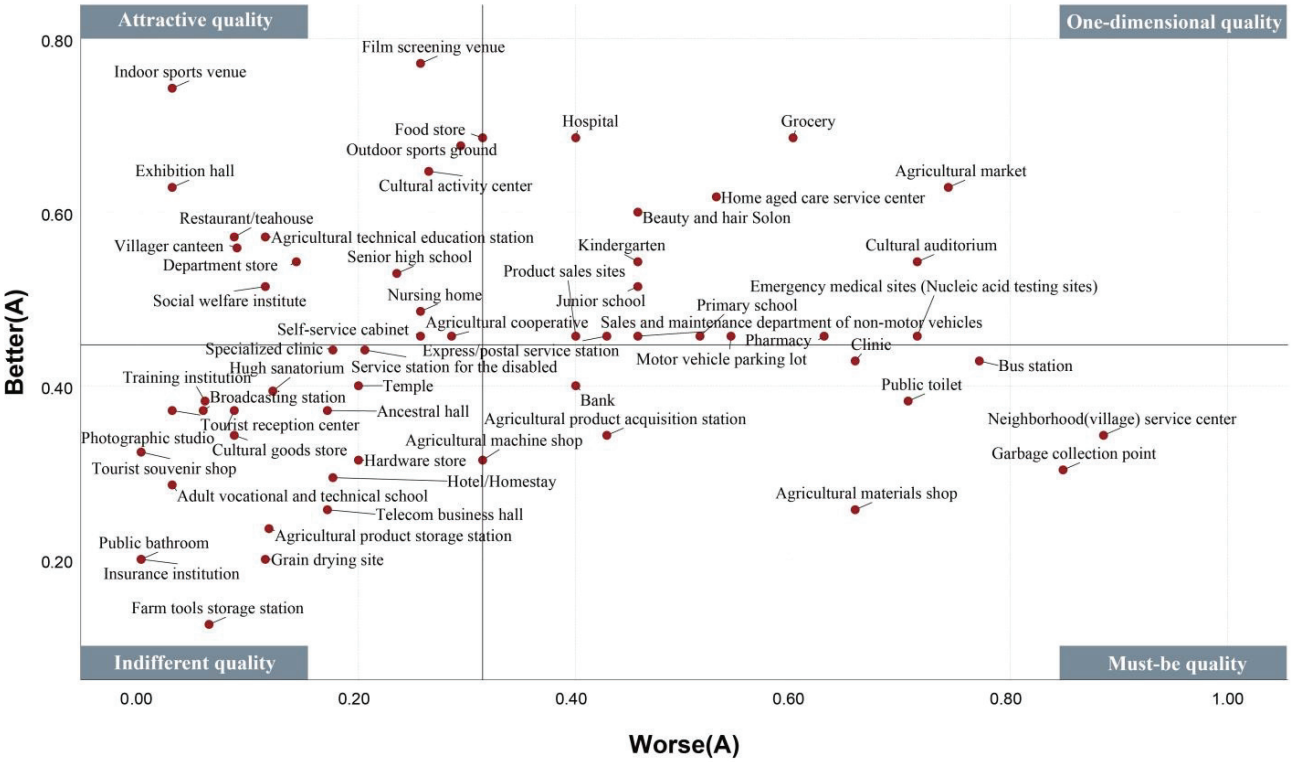



**Figure 9.** Classification of better–worse four-quadrant facility attributes (Group A).

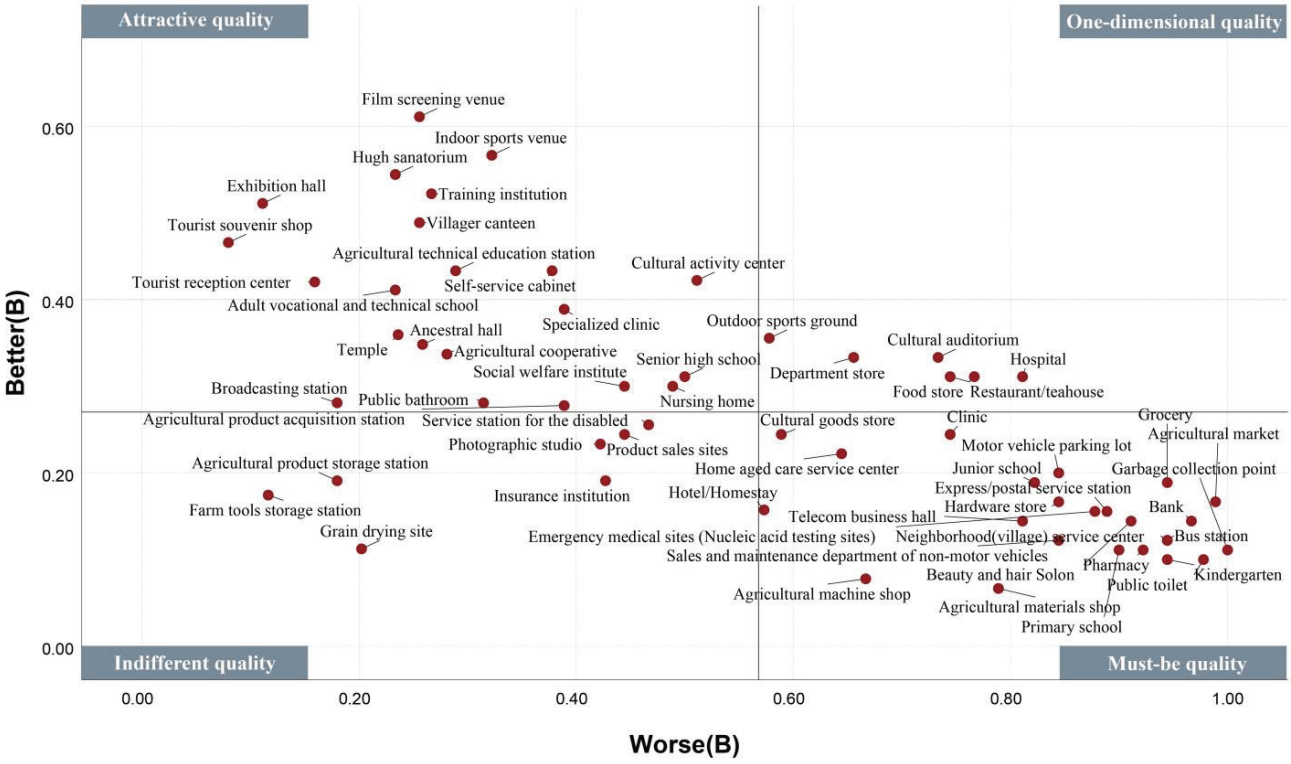



**Figure 10.** Classification of better–worse four-quadrant facility attributes (Group B).

**Figure 11.** Classification of better–worse four-quadrant facility attributes (Group C).

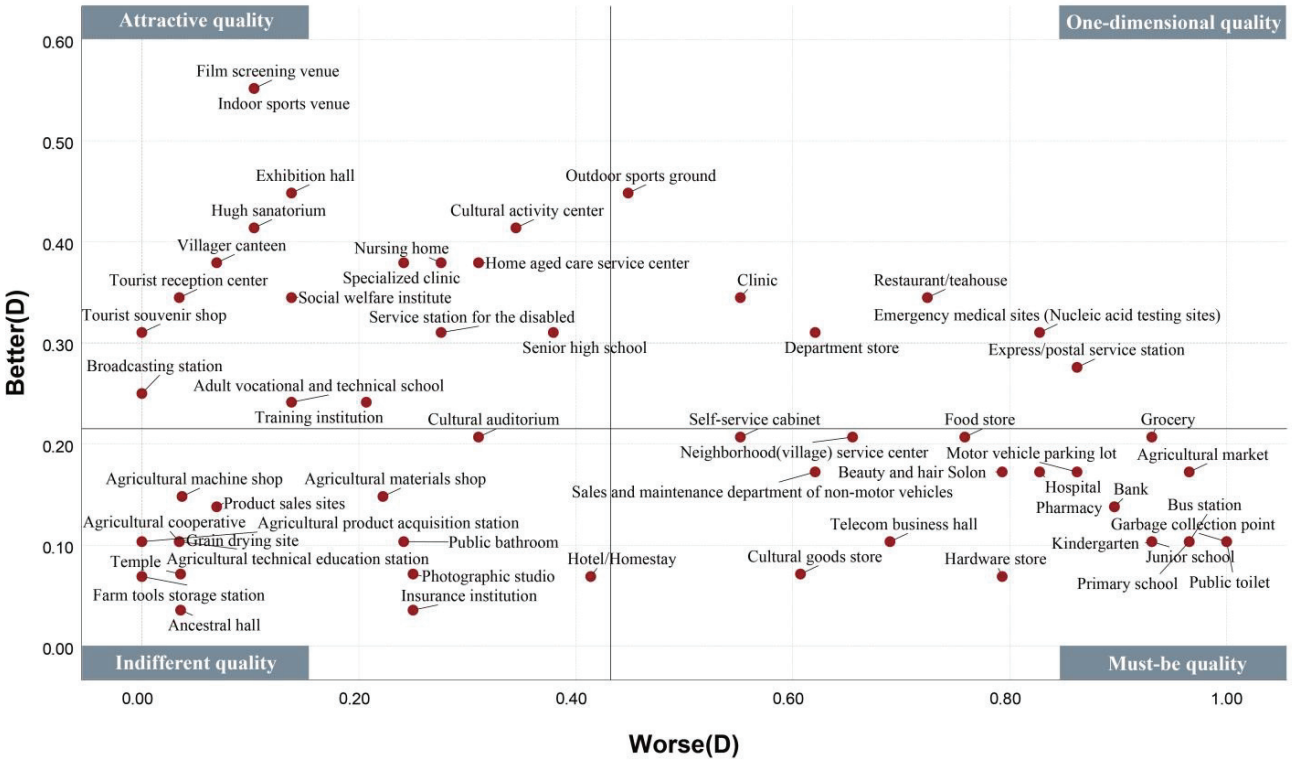



**Figure 12.** Classification of better–worse four-quadrant facility attributes (Group D).

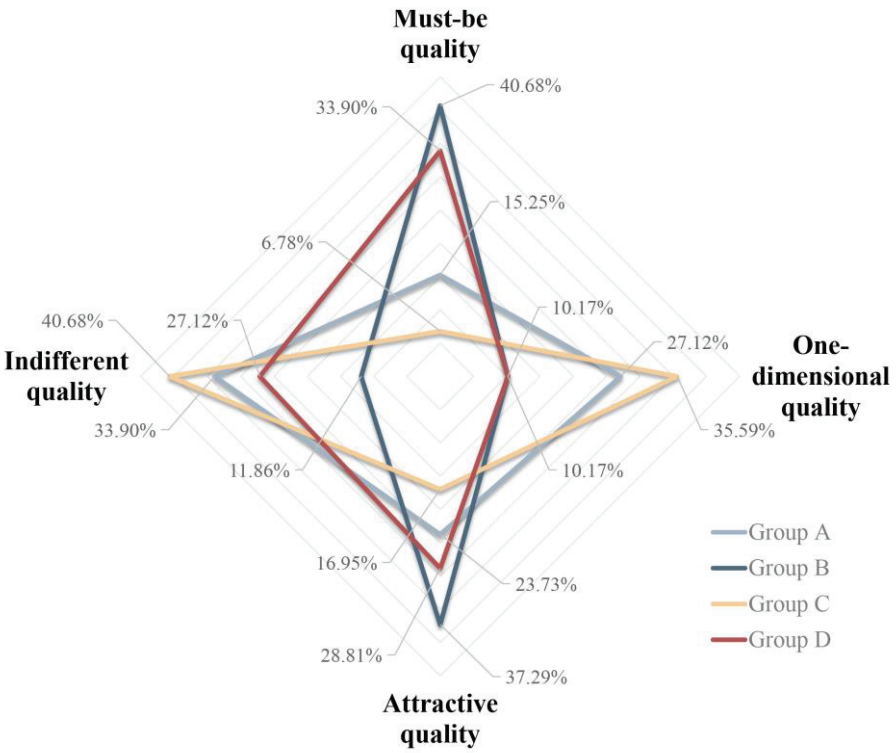



**Figure 13.** Radar chart of the number of facilities according to different cognitive attributes for the four groups.

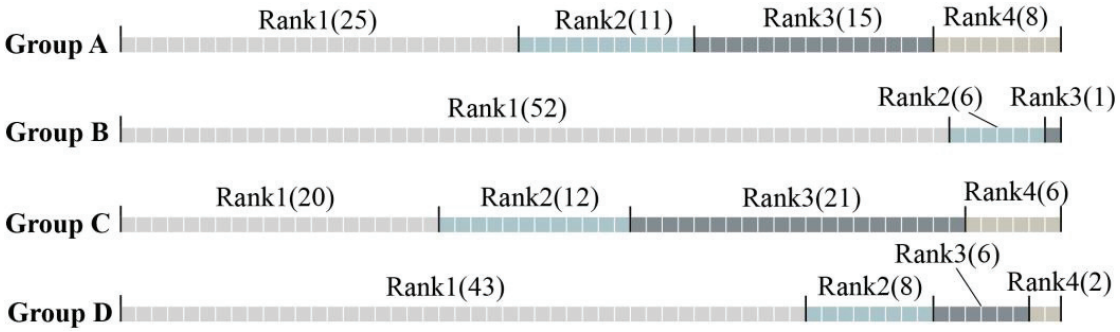



**Figure 14.** Statistics of the four groups' rankings of the urgency of each facility's cognitive attributes.

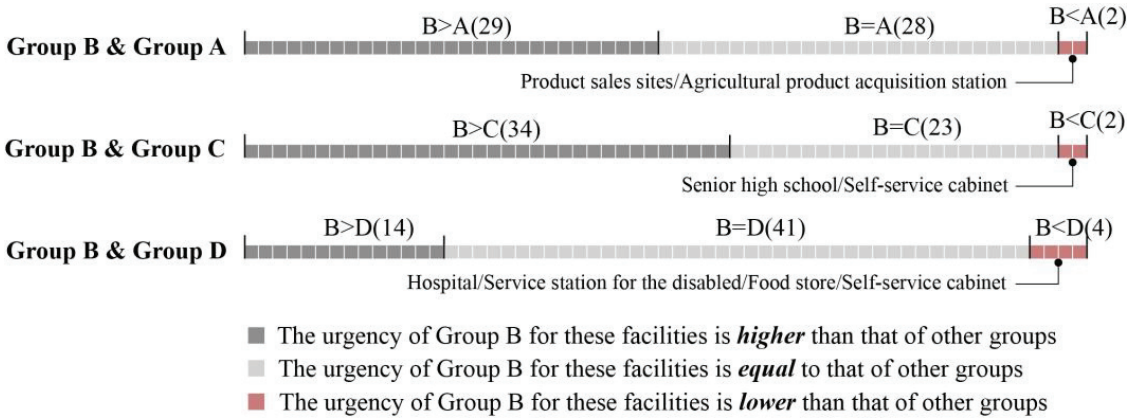



**Figure 15.** Comparative analysis chart of the urgency of Group B's needs versus the other three groups.

### *3.3. Matching Characteristics of the "Residential Area–Residential Facility" Relationship*

According to the chi-square test (Table 6), there was a significant correlation between the individuals' urbanization levels and the type of residential area in which they lived ($p < 0.05$). Proportion analysis (Figure 16A) showed that two groups with lower levels of urbanization (Group A and Group B) tended to live in rural residential areas, while Group D tended to live in urban residential areas. The proportion of these types of residential areas in Group C was roughly equal. Due to the large population base of Group B, the proportion of residents in urban-biased residential areas could not be neglected (26.79%). According to a proportion analysis of the groups in different residential areas (Figure 17), the residents in Groups B, C, and D were the main residents in urban-biased residential areas (accounting for over 94.64% of the total), while those in Groups A, B and C were the main residents in rural-biased residential areas (accounting for over 97.14% of the total). This indicates a relatively matched relationship between the urbanization patterns for residents and residential areas.

**Table 6.** The chi-square test results regarding population attributes.

| Population Attributes | | Option | | Group A | Group B | Group C | Group D | *p* |
|---|---|---|---|---|---|---|---|---|
| (A) Residential Area Type | | A1 | Urban-biased residential area | 17.1% | 33.3% | 52.0% | 86.2% | 0.000 ** |
| | | A2 | Rural-biased residential area | 82.9% | 66.7% | 48.0% | 13.8% | |
| (B) Age Type | | B1 | Youth (18–25) | 2.9% | 3.3% | 9.2% | 3.4% | 0.015 * |
| | | B2 | Middle-aged (25–65) | 54.3% | 63.3% | 66.3% | 89.7% | |
| | | B3 | Seniors (over 65) | 42.9% | 33.3% | 24.5% | 6.9% | |
| (C) Registered Permanent Address | | C1 | Rural | 91.4% | 81.1% | 73.5% | 69.0% | 0.029 * |
| | | C2 | Urban (experienced rural–urban migration) | 8.6% | 6.7% | 4.1% | 3.4% | |
| | | C3 | Urban | 0 | 12.2% | 22.4% | 27.6% | |
| (D) Education Level | | D1 | Did not complete primary School | 11.4% | 3.3% | 12.2% | 0 | 0.028 * |
| | | D2 | Completed primary school | 25.7% | 25.3% | 17.3% | 13.8% | |
| | | D3 | Completed junior school | 14.3% | 26.7% | 19.4% | 34.5% | |
| | | D4 | Completed senior high school | 14.3% | 22.2% | 12.2% | 10.3% | |
| | | D5 | Completed university and above | 34.3% | 22.2% | 38.8% | 41.4% | |
| (E) Employment Status | Whether self-employed | - | No | 94.3% | 80.0% | 88.8% | 69.0% | 0.015 * |
| | | - | Yes | 5.7% | 20.0% | 11.2% | 31.0% | |
| | Whether farming | - | No | 80.0% | 75.6% | 88.8% | 100.0% | 0.006 ** |
| | | - | Yes | 20.0% | 24.4% | 11.2% | 0 | |

* $p < 0.05$; ** $p < 0.01$.

The age, registered permanent residence, educational level, and employment status (farming or individual business) of the respondents showed a significant correlation with the residents' urbanization stage ($p < 0.05$). Through proportion analysis (Figure 16), it was gleaned that residents with a low level of urbanization tended to have rural household registration, be elderly, have lower levels of education, and primarily engage in agricultural activities. In contrast, residents with a high level of urbanization tended to have urban household registration, be middle-aged or young, have higher levels of education, engage in agricultural activities less frequently, and be self-employed.

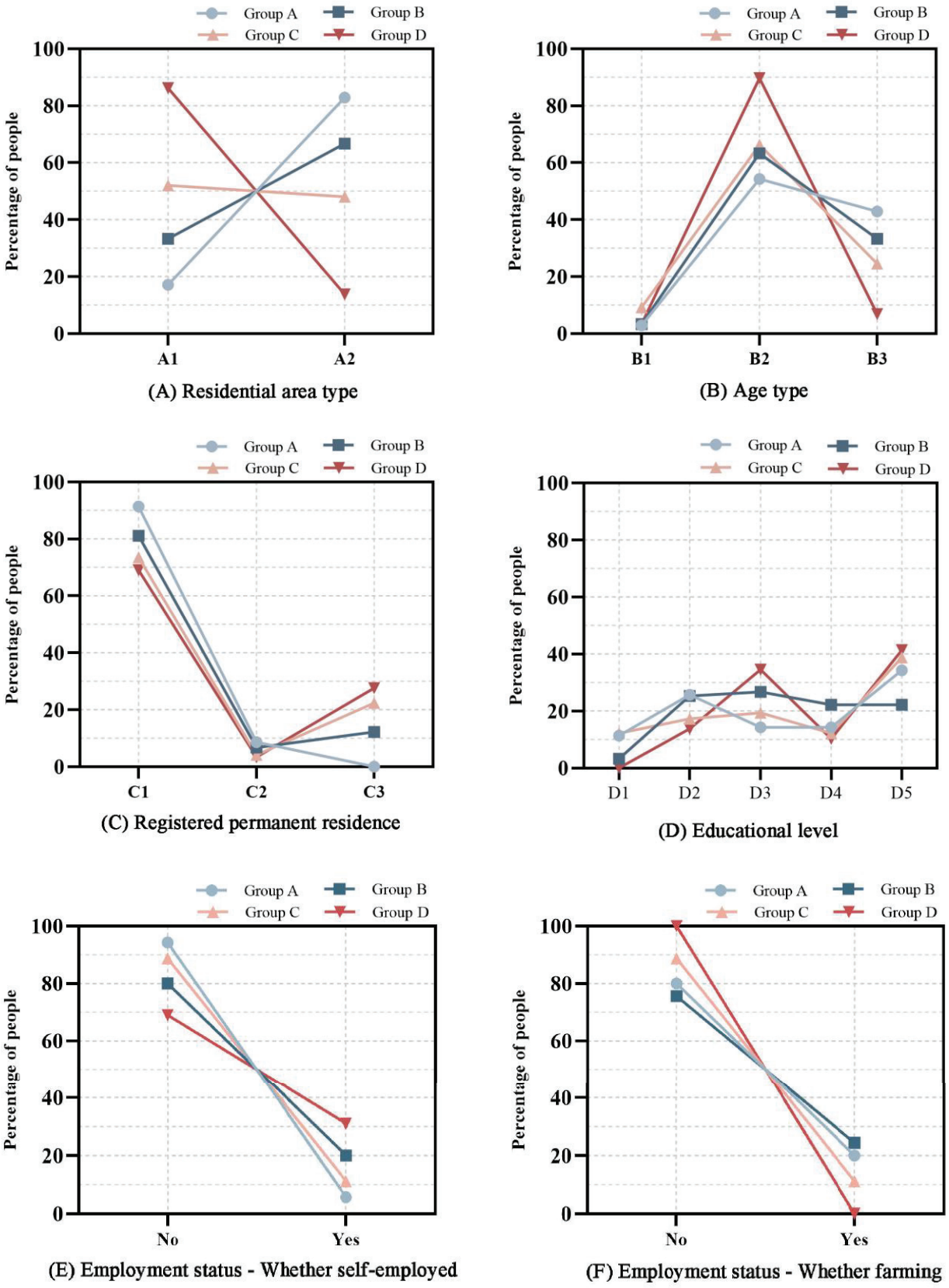



**Figure 16.** Proportion analysis of residents with different population attributes.

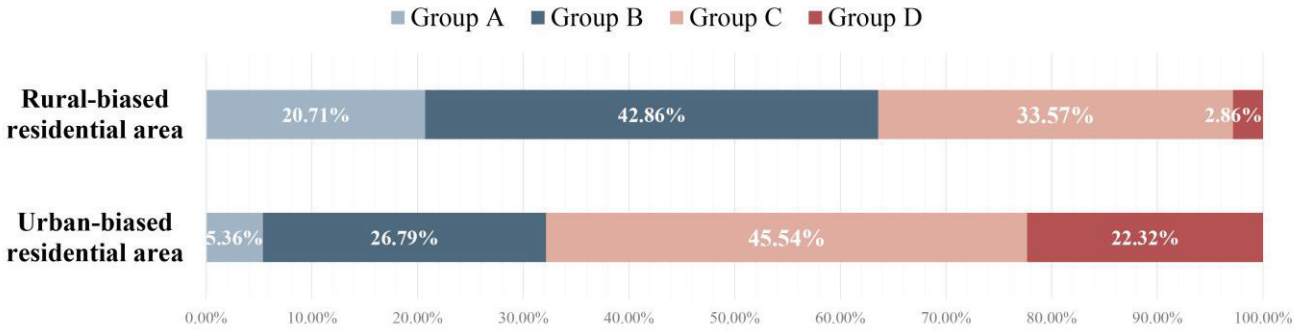



**Figure 17.** Percentage distribution of the four groups of residents in rural- and urban-biased residential areas.

## 4. Discussion

The above analysis clarifies the need characteristics of the different resident groups at different stages of urbanization. However, solely obtaining the demand characteristics of different urbanization stages is not sufficient for directly guiding practical applications. Therefore, the study further combines the needs of multiple groups based on the matching relationship of human–land urbanization patterns and proposes a guidance-control system for facility programming in rural- and urban-biased residential areas. Given the proportion of groups in these two residential areas, the populations of Groups B, C, and D accounted for the majority in urban-biased residential areas, while the populations of Groups A, B, and C accounted for the majority in rural-biased residential areas. To determine the specific levels of required or optional facilities, analytical principles must be developed to combine the three resident groups' cognitive attributes based on their need characteristics.

### *4.1. Guidance-Control Principle of Facility Programming Based on the Characteristics of Residents' Needs*

The core objective of the "control" proposed by the guidance-control system is not to ensure the implementation of the best possible solution but rather the avoidance of the worst-case scenario [59]. Therefore, the goal of organizing "required items" is not to satisfy the needs of all groups simultaneously but to prioritize avoiding dissatisfaction from those with lower service expectations and ensure that their must-be and one-dimensional quality needs are met. "Optional items" consider the must-be and one-dimensional quality needs of residents with high service expectations as well as the attractive quality needs of all groups of residents, helping to prevent dissatisfaction and further enhance overall satisfaction.

Based on the results of the data analysis in Section 3, Group B has an equal or greater level of urgency for most facilities compared with the other three groups. As a group that requires consideration for rural- and urban-biased residential areas, Group B can cover the majority of the other groups' needs. However, for some facilities, Groups A, C, and D also showed a high level of urgency that was not covered by Group B. Therefore, Groups A, C, and D did not have absolutely low service expectations. In fact, each facility had two aspects with high and low levels of service expectations. In this study, the level of service expectations for each facility was screened, and the required and optional items were determined based on the needs of different groups with varying levels of service expectations. The establishment of the guidance-control system is based on the principle of progressively avoiding population dissatisfaction and progressively improving population satisfaction at each level. The specific steps are as follows.

Assume that the cognitive attributes of the three groups for n facilities are $X_{n1}$, $X_{n2}$, and $X_{n3}$ ($n \in [1, 59]$, $X \in [1, 4]$). Define the attributes of a facility recognized by a group with high service expectations using the following formula:

$$X_{ni} = \min [X_{n1}, X_{n2}, X_{n3}]. \quad (3)$$

The attributes of a facility are recognized by two groups with low service expectations according to the following formula:

$$X_{nj} = \max [X_{n1}, X_{n2}, X_{n3}] \text{ and} \quad (4)$$

$$X_{nk} = X_{n1} + X_{n2} + X_{n3} - X_{ni} - X_{nj}. \quad (5)$$

If a facility receives an unsatisfactory rating from residents with low service expectations because of its absence, it should be categorized as "Level 1: Required Items" (either $X_{nj}$ or $X_{nk}$ is one or two). The next level should meet the needs of the residents with high service expectations. Facilities that may result in dissatisfaction if not provided to this group should be designated as "Level 2: Optional Items 1" ($X_{ni}$ is one or two). After addressing dissatisfaction due to the absence of certain facilities among the different resident groups, the facilities that can further enhance satisfaction for the three groups of residents should be designated as "Level 3: Optional Items 2" ($X_{ni}$, $X_{nj}$, and $X_{nk}$ are all neither one nor two but three). In addition, there are types of facilities toward which all three groups have an indifferent attitude. These facilities transcend or fall behind the current production and living needs of residents and can thus be temporarily excluded from consideration. In this study, they are designated as "Level 4: Optional Items 3" ($X_{ni}$, $X_{nj}$, and $X_{nk}$ are all equal to four). The specific process is shown in Figure 18.

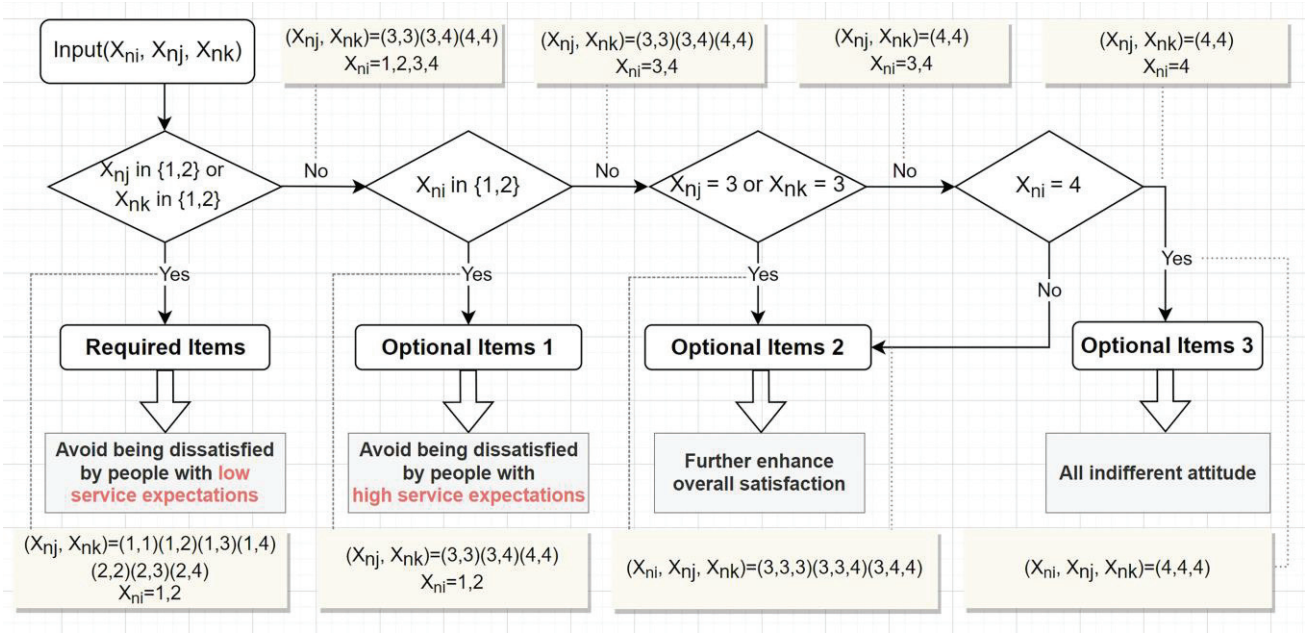



**Figure 18.** Flow chart of guidance-control principle.

In practical applications, the implementation of facility levels can be conducted according to the order of funding input, with required items being implemented first, followed by Optional Items 1 and 2. Required items refer to the facility levels that must be implemented. Optional Items 1 is recommended for implementation if economic conditions permit because such items can prevent dissatisfaction among all the groups. If funding conditions are sufficient, Optional Items 2 can be implemented.

### *4.2. Programming Guidance-Control System of Public Service Facilities in Small Towns Based on the Pattern of Human–Land Urbanization*

In this section, based on the guidance-control principle, the classification and guidance of facility programming in rural and urban-biased residential areas are conducted, the order of facility programming is clarified, and a guidance-control system of "required + optional item" public service facilities is developed (Table 7).

**Table 7.** The "required + optional item" public service facility guidance-control system for rural- and urban-biased residential areas.

| The Relationship between Human–Land Urbanization Patterns | | Differentiation Items (Rural-Biased Residential Area) | Common Items | Differentiation Items (Urban-Biased Residential Area) |
|---|---|---|---|---|
| | | **Land ≈ Human/Land (Urban-Biased Residential Area) > Human (Elderly, Low Education Level, Rural Household Registration, Engaged in Farming)** | | |
| | | | **Land ≈ Human/Land (Urban-Biased Residential Area) < Human (Young, High Education Level, Urban Household Registration, Self-Employed)** | |
| Required Items | Medical | | Clinic, Hospital, Emergency medical site (Nucleic-acid-testing site) | |
| | Education | | Kindergarten, Primary school, Junior school | Senior high school |
| | Cultural and sports | Cultural auditorium | | Outdoor sports ground |
| | Social welfare | | Home aged care service center | |
| | Administration | | Neighborhood (village) service center | |
| | Commerce | | Agricultural market, Grocery, Food store, Pharmacy, Bank, Telecom business hall, Beauty and hair salon, Department store, Sales and maintenance department of non-motor vehicles, Express/postal service station, Restaurant/teahouse | Cultural goods store, Hardware store, Self-service cabinet |
| | Infrastructure | | Bus station, Motor vehicle parking lot, Public toilet, Garbage collection point | |
| | Productive Service | Agricultural machine shop, Agricultural materials shop | | |

**Table 7.** *Cont.*

| The Relationship between Human–Land Urbanization Patterns | | Differentiation Items (Rural-Biased Residential Area) | Common Items | Differentiation Items (Urban-Biased Residential Area) |
|---|---|---|---|---|
| | | **Land ≈ Human/Land (Urban-Biased Residential Area) > Human (Elderly, Low Education Level, Rural Household Registration, Engaged in Farming)** | | |
| | | | **Land ≈ Human/Land (Urban-Biased Residential Area) < Human (Young, High Education Level, Urban Household Registration, Self-Employed)** | |
| Optional Items 1 | Education | Senior high school | | |
| | Cultural and sports | Outdoor sports ground | | Cultural auditorium |
| | Commerce | Cultural goods store, Hardware store, Self-service cabinet | | |
| | Productive Service | Product sales site, Agricultural product acquisition station | Hotel/Homestay | Agricultural machine shop, Agricultural materials shop |
| Optional Items 2 | Medical | | Specialized clinic, Hugh sanatorium | |
| | Education | | Training institution, Adult vocational and technical school | |
| | Cultural and sports | | Indoor sports venue, Cultural activity center, Exhibition hall, Ancestral hall, Temple, Film-screening venue, Broadcasting station | |
| | Social welfare | | Nursing home, Social welfare institute | Service station for the disabled |
| | Commerce | | Villager canteen, Public bathroom | |
| | Productive Service | | Tourist reception center, Tourist souvenir shop, Agricultural technical education station, Agricultural cooperative | Agricultural product acquisition station |

**Table 7.** *Cont.*

| | | Differentiation Items (Rural-Biased Residential Area) | Common Items | Differentiation Items (Urban-Biased Residential Area) |
|---|---|---|---|---|
| **The Relationship between Human–Land Urbanization Patterns** | | **Land ≈ Human/Land (Urban-Biased Residential Area) > Human (Elderly, Low Education Level, Rural Household Registration, Engaged in Farming)** | | |
| | | | **Land ≈ Human/Land (Urban-Biased Residential Area) < Human (Young, High Education Level, Urban Household Registration, Self-Employed)** | |
| Optional Items 3 | Social welfare | Service station for the disabled | | |
| | Commerce | | Insurance institution, Photographic studio | |
| | Productive Service | | Grain-drying site, Agricultural product storage station, Farm tool storage station | Product sales site |

In the practical programming of public service facilities in small towns, it is important to note that not all residential areas have matching levels of human–land urbanization. Therefore, the first step should be to assess the degree of urbanization for the residential areas and their residents, based on which an appropriate programming scheme can be selected. There are three possibilities in the matching relationship of human–land urbanization: first, a high degree of matching between the urbanization of residential areas and residents (land ≈ human), as is the case in the sample in this study; second, the residential area's urbanization is occurring faster than the residents' urbanization (land > human), which is more common in apartment resettlement areas; and third, the residential area's urbanization is lagging behind the level of residents' urbanization (land < human), which is more common in economically developed rural areas. Thus, for urban-biased residential areas whose urbanization is faster than that of their residents, facilities should be constructed according to the program of rural residential areas, as the residents tend to be elderly, have lower levels of education and rural household registration, and still be engaged in farming. Meanwhile, for rural-biased residential areas whose urbanization lags behind that of their residents, facilities should be constructed according to the needs of urban residential areas, as the residents tend to be younger, possess higher levels of education, generally have urban household registration, and be engaged in self-employment activities.

Unlike previous studies, this study employed the Kano model as a methodological approach to identify facility-related cognitive attributes among individual residents and different urbanization-stage groups. In previous surveys conducted using the Likert scale method, it was observed that individuals with a high level of service expectation generally displayed a positive attitude towards most items. However, it is not necessarily the case that all items exhibiting a positive attitude should be given the highest priority for these individuals. When using the negative questions of the Kano model, it was found that interviewees actually responded with "I can live with it if it is not satisfied" instead of "dissatisfied" for certain positive attitude items. Conversely, for individuals with low service expectations, although they generally exhibited a negative attitude towards most items, some items were still considered "dissatisfied" when the negative question of the Kano model was asked. Therefore, the Kano model can mitigate the bias in survey results caused by overly positive or negative attitudes, effectively reflecting objective facts and accurately identifying cognitive attributes. This holds substantial significance when establishing the guidance-control hierarchy of public service facility programming. The rational selection of methods ensures that the results have certain distinctions compared to other studies. While some studies generally qualitatively propose a "guidance-oriented" approach to the programming of public service facilities in small towns, such as preserving certain rural-specific facilities for residents undergoing nearby urbanization [32], this study systematically categorized rural and nonrural facility types. It quantitatively determined the required or optional levels of different facility types based on the needs of residents at different stages of urbanization. As a result, this study provides directly applicable guidance and control strategies.

## 5. Conclusions

As an intermediary link in the "city–town–village" system, small towns serve as crucial support for the promotion of nearby urbanization. Compared with "remote urbanization", which entails the relocation of a rural population to a distant urban area, "nearby urbanization" alleviates the problem of "hollow villages" in rural areas caused by labor outflows. Additionally, nearby urbanization helps enhance rural residents' rights to public services and establish a connection to social security. However, nearby urbanization has resulted in small towns having complex urbanization patterns that differ greatly from those of cities and rural areas. This makes it difficult to determine the programming of public service facilities using rigid indicators. Therefore, this study introduced the concept of "guidance and control", proposing a suitable programming method that incorporates rigid

control and a certain degree of flexibility based on residents' needs, aiming to overturn the current "one-size-fits-all" facility allocation approach.

This study suggests that the level of need for rural and nonrural facilities reflects the different stages of residents' urbanization. Therefore, rural and nonrural facility types were distinguished, and a "rural and nonrural" facility need coupling model was constructed to classify residents into four different urbanization stages. The need systems and population attribute characteristics of each group were analyzed. Furthermore, this study considered the feasibility of implementing its results in other small towns to avoid the complex steps required for decision-makers to identify urbanization types and proportions of residents. Thus, this study not only explored the needs of different stages of urbanization but also deduced the "residential area–resident facility" matching relationship. The study clarified the analyzed residents' urbanization characteristics under the patterns of rural- and urban-biased residential areas and summarized the programming guidance-control system for public service facilities within this relationship.

This study also has certain limitations. Firstly, as a pioneering study on the suitability of public service facilities programming in small towns, this study divided residential areas into two categories based on their degrees of urbanization, namely, rural- and urban-biased areas. However, it did not address specific types of residential areas. Future studies may further explore the relationship between the human–land urbanization characteristics of various types of residential areas and develop a more comprehensive and refined facility programming system. Secondly, the selected sample in this study exhibits a matched urbanization pattern between human and land. Based on the results, we derived guidance-control schemes for "required + optional" public service facility provisions under two mismatched scenarios: "land > human" and "land < human". Future studies should consider selecting samples that represent other human–land urbanization pattern mismatches to further validate and refine the guidance-control system. Thirdly, this study focused on the functional aspect of facility programming, addressing the question of "what to construct." However, a practical application process also involves the implementation of spatial aspects, addressing the question of "where to construct", which requires the cross-functional integration of the different types of residential areas and the determination of accessibility and the corresponding life cycle of facilities. Therefore, the programming path for the suitability of public service facilities in small towns requires further exploration. While this study examined only one aspect of facility programming, it offers valuable insights for local governments and planning and construction departments with respect to developing and revising technical specifications, standards, and guidelines and updating public service facilities through a combination of rigid and flexible approaches.

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