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The Impact of Social and Ecological Factors on Coupled Human-Environment Systems

Edited by
Ying Wang, Weiwen Wang and Bin Yang

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Article

Quantifying the Relationship between Land Use Intensity and Ecosystem Services' Value in the Hanjiang River Basin: A Case Study of the Hubei Section

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Abstract: An increased land use intensity due to rapid urbanization and socio-economic development would alter the structure and function of regional ecosystems and cause prominent environmental problems. Revealing the impact of land use intensity on ecosystem services (ES) would provide guidance for more informed decision making to promote the sustainable development of human and natural systems. In this study, we selected the Hanjiang River Basin (HRB) in Hubei Province (China) as our study area, explored the correlation between land use intensity and ecosystem Services' Value (ESV), and investigated impacts of natural and socio-economic factors on ESV variations based on the Geographical Detector Model (GDM) and Geographically Weighted Regression (GWR). The results show that (1) from 2000 to 2020, land use intensity in HRB generally showed an upward trend, with a high spatial agglomeration in the southeast and low in the northwest; (2) the total ESV increased from 295.56 billion CNY in 2000 to 296.93 billion CNY in 2010, and then decreased to 295.63 CNY in 2020, exhibiting an inverted U-shaped trend, with regulation services contributing the most to ESV; (3) land use intensity and ESV had a strong negative spatial correlation, with LH (low land use intensity vs. high ESV) aggregations mainly distributed in the northwest, whereas HL (high land use intensity vs. low ESV) aggregations were located in the southeast; (4) natural factors, including annual mean temperature, the percentage of forest land, and slope were positively associated with ESV, while socio-economic factors, including GDP and population density, were negatively associated with ESV. To achieve the coordinated development of the socio-economy and the environment, ES should be incorporated into spatial planning and socio-economic development policies.

Keywords: ecosystem services' value (ESV); land use intensity; spatiotemporal characteristics; spatial correlations; driving factors; Hanjiang River Basin (HRB)

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1. Introduction

Land provides space for human activities and supports terrestrial ecosystem services (ES) that are essential for human survival and development. ES are the goods (e.g., food, water, etc.) and services (e.g., air purification, waste treatment, etc.) that ecosystems provide to human society, which can be broadly classified into four categories, i.e., supply services, regulation services, support services, and cultural services [1,2]. During the process of rapid urbanization and industrialization, humans have drastically transformed the landscape from natural surfaces (such as forest land and water areas) to surfaces employed for artificial uses (such as cultivated land and built-up areas), and the land use intensity has substantially increased, which greatly weakens the provision of vital ES by ecosystems [3,4]. In light of this, promoting the coordination between humans and ecosystems has become a hot topic for both governments and academia. For example, the United Nations identified Goal 7: Ensure environmental sustainability as an indicator of the Millennium Development Goals and suggested that it be incorporated into country policies and programs to reverse the loss of ES. Faced with prominent environmental issues, the 18th National Congress of the Communist Party of China (CPC) in 2012 proposed the ecological civilization construction strategy, which emphasized harmony between human and nature [5].

Research on ES has begun to flourish since Costanza et al. (1997) published the famous paper, "The Value of the World's Ecosystem Services and Natural Capital", which classified the global ES into 17 types and estimated their economic values [1]. Xie et al. (2003 and 2008) [6,7] built upon Costanza et al. (1997) and proposed an evaluation method suitable for assessing the economic value of terrestrial ES in China based on surveys of over 200 Chinese ecologists [8]. Much of the literature on ES has focused on the evaluation of ES value (ESV) [9–11], the driving mechanism of ES variation [12–14], the integration of ES in landscape planning and decision making [15,16], and analysis of ES synergies and trade-offs [17,18]. Recent research has begun to investigate the coupling coordinative relationship between ES and socio-economic development, such as sustainable development [19,20], human activities' intensity [21], urbanization [22], etc.

From the perspective of land use, Xi, et al. [23] analyzed the spatiotemporal characteristics of the ESV of island cities based on land use/cover and predicted future ESV. Rahman and Szabó [24] analyzed the impact of land use/cover change (LUCC) on the value of urban ES in Dhaka, Bangladesh, and found that water areas contributed the most to ESV. However, less attention has been drawn to the relationship between land use intensity and ESV. Land use intensity reflects the extent to which land has been developed and utilized by human activities. Some studies take it as an indicator of land use efficiency [25], while others use it to measure the development of regional land parcels [26]. This study uses it to measure the degree to which different land uses are developed by human beings. The existing research on land use intensity has been widely studied in the literature, including the intensity of cultivated land use [27], the response of land use intensity to urbanization [26], and the relationship between land use intensity, the ecological environment [28], and biodiversity [29]. In this study, we aim to explore spatial correlations between land use intensity and ESV.

According to previous studies on the driving mechanism of ES change, the evolution of regional ES is affected by a combination of natural and human factors [30]. Natural factors include precipitation, temperature, and vegetation coverage [31]. The anthropogenic aspect comprises the effects of human-induced climate change and LUCC, as well as the effects of economic development and human activities [32,33]. The selected anthropogenic factors primarily consist of population, urbanization rate, GDP, etc. The impacts of these factors vary widely due to regional differences [34,35]. Understanding the influencing factors and driving mechanisms of regional ES in different locations is essential for targeted plans and measures to achieve environmental protection and sustainable development [36].

As the largest tributary of the Yangtze River, the socio-economic position of the Hanjiang River Basin (HRB) is crucial for the Yangtze River Basin. With the development of the Yangtze River Economic Belt, especially the opening of the middle route of the South-to-North Water Diversion Project, the ecosystem of the Hanjiang River is under great threat [37]. The reduction in the water volume and the destruction of vegetation in the upper reaches of the Hanjiang River directly affect the water quality and hydrological conditions in the middle and lower reaches, i.e., the HRB in Hubei Province. The Danjiangkou Reservoir in Hubei Province is the core water source of the middle route of the South-to-North Water Diversion Project [38], and the water transfer has a great impact on the production and ecology of the middle and lower reaches of the Hanjiang River. Furthermore, the HRB in Hubei Province plays a very important role in the development of the province, with more than 50% of its population and GDP being distributed in the HRB. Hence, decision makers attach great importance to the development and implementation of policy in Hubei Section of HRB. Over the past two decades, rapid urbanization and over-reclamation of cultivated land have resulted in an imbalance of land use structure in the HRB of Hubei Province.

This imbalance is primarily manifested by the continuous expansion of built-up land at the expense of high-quality cultivated land, forest land, and water area, resulting in resource depletion and environmental pollution [39]. Due to increased human activities, the ability of ecosystems in HRB to self-regulate has degraded.

Some scholars have investigated the ES of the HRB. For example, Li, et al. [40] took the upper Hanjiang River as their study area and examined the changes of water-related ES, such as soil conservation and flood control services, as a result of climate change. Qi et al. [41] explored the role of forest restoration in ES in the HRB and found a positive impact. Yu, et al. [42] explored the evolution of the social-ecological system in the Hubei Section of the HRB and found that resources and the economy were important driving forces of the change in social-ecological systems, and that human activity played a leading role in its evolution. Existing studies in the HRB have focused on a single type of ES from a micro perspective, and the majority of the study areas are located in the upper reaches. Few studies have examined the overall ES in the basin and the correlation between land use intensity and ES, as well as the driving force of ES, particularly in the middle and lower HRB reaches. Additionally, as one of the most representative human activities, the South-to-North Water Diversion Project has put great pressure on the environment and society in the middle and lower reaches of the Hanjiang River. Our study period ranged from 2000 to 2020, which allowed us to examine changes in the regional environmental conditions before and after the implementation of the South-to-North Water Diversion Project in 2014. It is of great value to investigate the relationship between land use intensity and ES in this region for the sustainable development of human and the environment. Thus, in this study, we selected the HRB in Hubei Province as our study area to investigate the responses of ESV to changes in land use intensity. This study has four specific research objectives: (1) to identify the spatiotemporal changes of land use intensity, (2) to assess the spatiotemporal evolution of ESV, (3) to analyze the spatial correlations between land use intensity and ESV, and (4) to reveal the driving factors affecting ESV changes in the Hubei section of the HRB from 2000 to 2020.

2. Materials and Methods

2.1. Study Area

The Hanjiang River originates in the Qinling Mountains; flows primarily through Shaanxi, Henan, and Hubei provinces, and has a total length of 1567 km and a total area of 15.9×10^4 km^2. It joins the Yangtze River from west to east and is the largest tributary of the Yangtze River. The landform of the HRB descends a total of 1964 m from mountains to plains [43]. Located in the subtropical monsoon climate zone, the HRB has an annual average precipitation of 700–1800 mm, an annual average temperature of 14 °C, and a relatively high vegetation coverage rate [44]. After passing through Baihe County, the Hanjiang River enters Hubei Province from Yunxi County, turns southeast at Danjiangkou, and passes through Xiangyang, Yicheng, Zhongxiang, and other counties on its way to Wuhan City, where it joins the Yangtze River. The HRB in Hubei Province, encompassing nearly the middle and lower reaches of the Hanjiang River, was selected as our study area (Figure 1).

2.2. Data Sources

The land use raster dataset with a 100 m resolution for the years 2000, 2010, and 2020 was downloaded from the Data Center for Resources and Environmental Sciences, at the Chinese Academy of Sciences (RESDC) (http://www.resdc.cn, accessed on 5 May 2022). Annual mean temperature, annual mean precipitation, slope, GDP, and population density were also obtained from RESDC. The distances to the county center, water system, and road system were calculated using the Euclidean distance tool in ArcGIS 10.3 software (ESRI, Environmental Systems Research Institute, Redlands, CA, USA). ArcGIS 10.3 was also used to calculate the area of different land use types in each county. All datasets were converted into the same coordinate system and the same pixel size (100 m × 100 m).

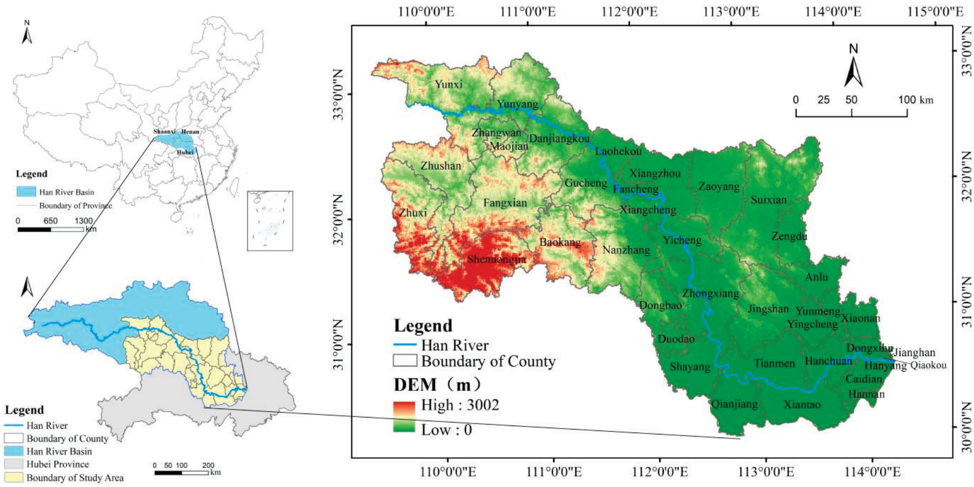

Figure 1. Location of the study area.

2.3. Methods

2.3.1. Calculation of Land Use Intensity

Land is the material basis for the survival and development of human society. Land use intensity reflects the extent to which land resources are developed and utilized by human beings [45]. Referring to the method of land use intensity proposed by Zhuang et al. [46] and the graded assignments of land use type (Table 1), the land use intensity can be calculated with the following formula:

$$L = 100 \times \sum_{i=1}^{n} R_i \times A_i / A_t \tag{1}$$

where L is the land use intensity, n is the number of land use types, R_i is the grade factor of the i-th land use type, A_i is the area of the i-th land use type, and A_t is the total area of all land use types.

Table 1. Graded assignments of land use intensity.

Types and Grades	Unused Land	Forest, Grassland, and Water Land	Agricultural Land	Urban Settlement Land
Land use types	Unused land	Forest land, Grassland, Water area	Cultivated land, Garden Land, Artificial grassland	Towns, residential areas, industrial and mining, transportation land
Grade factor	1	2	3	4

2.3.2. Assessment of Ecosystem Services' Value

The evaluation method proposed by Costanza et al. [1] and adapted by Xie et al. [6,7] for China's ecosystems has been widely adopted due to its high operability and convenient method of data acquisition [8]. In general, ES is classified into four categories, i.e., supply services, regulation services, support services, and cultural services, which can be further divided into nine subtypes (Table 2). Based on the equivalent value per-unit area of ES proposed by Xie et al. in 2008, we adjusted the economic value of a standard equivalent factor and calculated the ESV of the study area. According to the functions and characteristics of land use types, we matched forest land with forest in Xie et al.'s classification system, cultivated land with farmland, water area with rivers/lakes, unused land with desert, and assigned built-up land an ESV of zero [47]. It should be noted that the economic value of a standard equivalent factor equals 1/7 of the average market value of grain production. Considering the grain yield per-unit area of the study area and the average grain prices in 2000, 2010, and 2020, the equivalent factor value was calculated as 1881.45 CNY/hm^2. The formula for estimating the total ESV in the study area is as follows:

$$\mathrm{ESV} = \sum \mathrm{k} \cdot \mathrm{E_i} \times \mathrm{A_i} \tag{2}$$

where k is the equivalent factor value of ES; E_i is the ESV per-unit area of the i-th land use type; A_i is the area of the i-th land use type.

Table 2. Equivalent value per-unit area of ES by land use type in the HRB of Hubei Province (Unit: CNY/hm^2).

Categories of ES	Subtypes	Cultivated Land	Forest Land	Grassland	Water Area	Unused Land	Built-Up Land
Supply services	Food production	1881.45	620.88	809.02	997.17	37.63	0.00
	Raw material production	733.77	5606.72	677.32	658.51	75.26	0.00
Regulation services	Gas regulation	1354.64	8127.87	2822.18	959.54	112.89	0.00
	Climate regulation	1825.01	7657.51	2935.06	3875.79	244.59	0.00
	Hydrological regulation	1448.72	7695.14	2859.81	35314.84	131.70	0.00
	Waste disposal	2615.22	3236.10	2483.52	27,939.55	489.18	0.00
Support services	Soil conservation	2765.73	7563.43	4214.45	771.39	319.85	0.00
	Biodiversity	1919.08	8485.34	3518.31	6453.38	752.58	0.00
Cultural services	Aesthetic landscape	319.85	3913.42	1636.86	8353.64	451.55	0.00

2.3.3. Hot Spot Analysis

Getis–Ord Gi* is an index of local spatial autocorrelation used to explore the spatial clustering of high values (hot spots) or low values (cold spots) of spatial variables [48]. The output can be represented with Z-score, p-value, and confidence level. We used the Getis–Ord Gi* tool in ArcGIS 10.3 software to analyze the hot spots and cold spots of ESV in the study area. See Appendix A.1.1 for more detailed description of the hot spot analysis method.

2.3.4. Bivariate Spatial Autocorrelation Model

Spatial autocorrelation refers to the statistical correlation of a certain attribute value of geographic objects with spatial location differences. Generally, the closer the two values are, the greater the correlation. Spatial autocorrelation analysis is an important indicator to measure the aggregation or discrete distribution of spatial elements, and is generally described by global Moran's *I* and local Moran's *I* [49]. The global autocorrelation tests the spatial vergence pattern of the spatial variables over the entire research range, while the local spatial autocorrelation captures the correlation of the variables in different regional units [50]. In this study, the bivariate spatial autocorrelation model was used to investigate the spatial correlation between land use intensity and ESV using GeoDa 1.18 software. Moran scatter plots and LISA cluster maps were adopted to analyze local spatial correlation and reflect the significance level of spatial correlation. See Appendix A for a more detailed description of the spatial autocorrelation model (Appendix A.1.2).

2.3.5. Analysis of the Driving Mechanism

It is well-established in the literature that changes in ES are driven by both natural and human factors. The natural dimension includes climate factors (e.g., temperature and precipitation), topography (e.g., slope), and vegetation (e.g., the proportion of forest land), which are found to directly affect ES supply and demand [51]. Human activities can be represented by socio-economic factors, including GDP, population density, and percentage of built-up land [35], which are often used to measure regional economic development and urbanization level. In general, the higher the GDP, population density, and percentage of built-up land, the higher the degree of human interference with the ecosystem. In addition, geographic locations, such as distance to the county center, road, and water system, also have impacts on ES, mainly affecting the spatial patterns of ESV [52].

Based on the above analyses, ten driving factors were selected as potential drivers of ESV change (Table 3). Then, Geographical detector model (GDM) and Geographically Weighted Regression (GWR) were used to detect and analyze the driving forces that affect the ESV. GDM can detect not only the influence of driving factors but also their interactions. The GWR model can be used to explore the directions and spatial distributions of the impacts of each driving factor.

Table 3. Details of the driving factors.

Factors Type	Indicator	Description	Calculation	Reference
Natural	Temperature (X1)	Annual mean temperature (°C)	ArcGIS raster statistics	[51]
	Precipitation (X2)	Annual mean precipitation (mm)	ArcGIS raster statistics	
	Slope (X3)	Slope (°)	ArcGIS raster statistics	
	Percentage of forest land (X4)	The percentage of forest land (%)	Forest land area/total land area	
	Distance to water system (X5)	Distance to the water system (m)	ArcGIS raster statistics and Euclidean Distance	[52]
Socio-economic	GDP (X6)	GDP per unit area (10^4 CNY/km^2)	ArcGIS raster statistics	[51]
	Population density (X7)	Number of people per square kilometer (person/km^2)	ArcGIS raster statistics	
	Distance to the county center (X8)	Distance to the county center (m)	ArcGIS raster statistics and Euclidean Distance	[52]
	Distance to road (X9)	Distance to road (m)	ArcGIS raster statistics and Euclidean Distance	
	Percentage of built-up land (X10)	The percentage of built-up land (%)	Built-up land area/total land area	[35]

Geographical Detector Model

GDM is comprised of risk detection, factor detection, ecological detection, and interactive detection, which can be used to detect spatial variation and identify potential influencing factors [53]. The GDM has been widely used in many fields, including social-economy and the ecological environment [51,54]. See Appendix A.1.3 for a more detailed description of the GDM.

Geographically Weighted Regression

GWR is an extension of the traditional regression analysis method that can estimate data with spatial autocorrelation and reflect the spatial heterogeneity of parameters [55]. The GWR can reveal the direction and magnitude of influence of each factor in different locations [56]. See Appendix A.1.3 for more detailed description of the GWR model.

The flow chart of the study is illustrated in Figure 2.

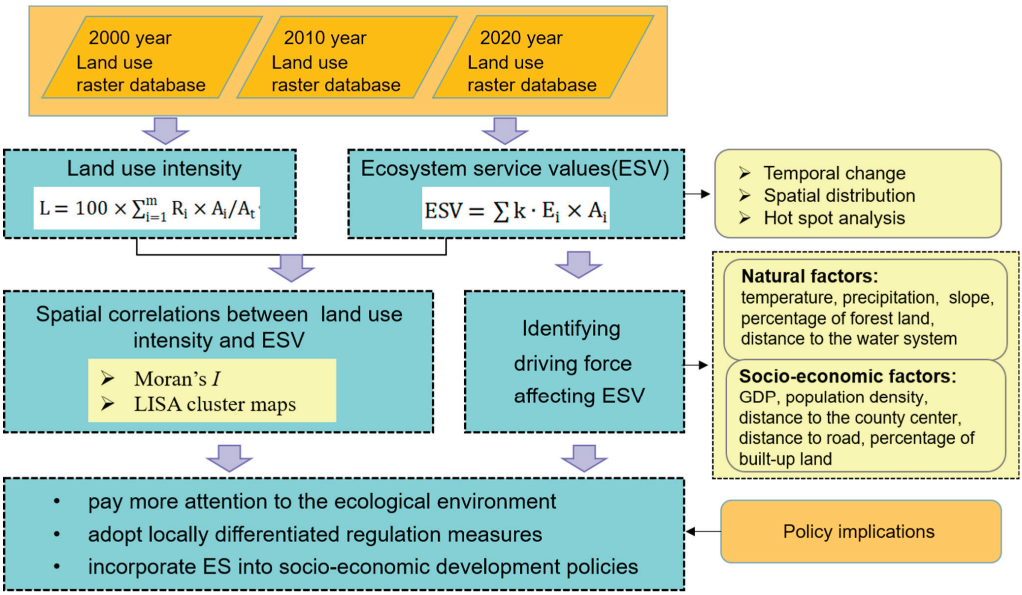

Figure 2. The framework of this study.

3. Results

3.1. Spatiotemporal Characteristics of Land Use Intensity

Figure 3 depicts the land use intensity for each county in the HRB in Hubei Province from 2000 to 2020. High-value areas of land use intensity were primarily concentrated in the southeast, where economic development was relatively advanced, whereas low-value areas were primarily distributed in the northwest, where the ecological environment was superior and development was relatively lagging. This result indicates that land use intensity has a spatial pattern of "centralized distribution". A high-value central area was formed by Jianghan, Hanyang, and Qiaokou districts of Wuhan City. Other counties close to the high-value area also had higher levels of land use intensity. The land use intensity decreased gradually from the county center to the county periphery as the distance increased.

Overall, land use intensity showed a slight upward trend from 2000 to 2020. The counties with the most notable increases were located in the southeast of the study area. For example, the land use intensity of Caidian District changed from weak to medium, and Hanyang District and Qiaokou District changed from strong to strongest. In addition, the disparity in land use intensity between counties was narrowing, and land use intensity in the whole study area remained relatively stable.

3.2. Spatiotemporal Characteristics of ESV

3.2.1. Temporal Change of ESV

Forest land and cultivated land in the study area constituted the largest share of the landscape, accounting for 48.88% and 38.71% of the total area in 2020, respectively, followed by water area and grassland (Table 4). From 2000 to 2020, the area of cultivated land and forest land decreased the most, by 1119.04 km^2 and 245.83 km^2, respectively. The total ESV of the HRB in Hubei Province was 2955.62 $\times$ 10^8 CNY, 2969.34 $\times$ 10^8 CNY, and 2956.30 $\times$ 10^8 CNY in 2000, 2010, and 2020, respectively (1 CNY = 0.1450 US dollar in 2020), with an inverted U-shaped trend of first increasing and then decreasing. Overall, the total ESV increased by 68 million CNY, representing a change rate of 0.02%. Table 4 shows that the ESV of forest land accounted for the largest proportion, greater than 70% throughout the study period, followed by cultivated land and water area, with the highest proportions in 2000 and 2020, respectively, being 16.24% and 12.14%.

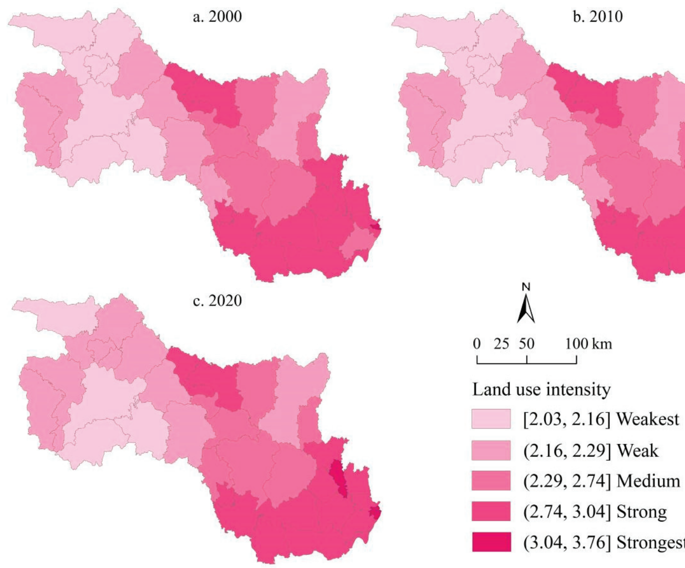

Figure 3. The spatial pattern of land use intensity in the HRB of Hubei Province for (**a**) 2000; (**b**) 2010; (**c**) 2020.

Table 4. ESV of different land use types in the HRB of Hubei Province from 2000 to 2020.

Land Use Types		Cultivated Land	Forest Land	Grassland	Water Area	Unused Land	Built-Up Land	Total
2000	Areas (km^2)	32,289.44	39,609.20	2364.14	3843.85	87.14	2336.39	80,530.16
	ESV (10^8 CNY)	479.93	2095.58	51.91	327.97	0.23	0.00	2955.62
2010	Areas (km^2)	31,786.21	39,546.33	2357.83	4132.90	86.27	2620.62	80,530.16
	ESV (10^8 CNY)	472.45	2092.25	51.77	352.63	0.23	0.00	2969.34
2020	Areas (km^2)	31,170.40	39,363.37	2334.04	4207.03	84.04	3371.28	80,530.16
	ESV (10^8 CNY)	463.30	2082.57	51.25	358.96	0.22	0.00	2956.30
2000–2010	Areas (km^2)	−503.23	−62.87	−6.31	289.05	−0.87	284.23	0.00
	ESV (10^8 CNY)	−7.48	−3.33	−0.14	24.66	0.00	0.00	13.72
2010–2020	Areas (km^2)	−615.81	−182.96	−23.79	74.13	−2.23	750.66	0.00
	ESV (10^8 CNY)	−9.15	−9.68	−0.52	6.33	−0.01	0.00	−13.04
2000–2020	Areas (km^2)	−1119.04	−245.83	−30.10	363.18	−3.10	1034.89	0.00
	ESV (10^8 CNY)	−16.63	−13.01	−0.66	30.99	−0.01	0.00	0.68

Figure 4 exhibits the changes in the ESV of different categories of ES in the study area from 2000 to 2020. These changes were minor, and the structure of the ESV remained relatively stable. The regulation services provided the largest value, reaching up to 1589.89 $\times 10^8$ CNY in 2020. The ESV of cultural services was the lowest, at only 203.02 $\times 10^8$ CNY in the same year. Among the nine subtypes of ES, the value of hydrological regulation services was the largest, at 503.32 $\times 10^8$ CNY in 2020, followed by biodiversity, soil conservation, and climate regulation services, with values of 429.25 $\times 10^8$ CNY, 397.04 $\times 10^8$ CNY, and 381.49 $\times 10^8$ CNY, respectively. During the study period, the hydrological regulation and waste disposal services increased by 9.23 $\times 10^8$ CNY and 6.35 $\times 10^8$ CNY, respectively, whereas all other types of ES showed a slight decline.

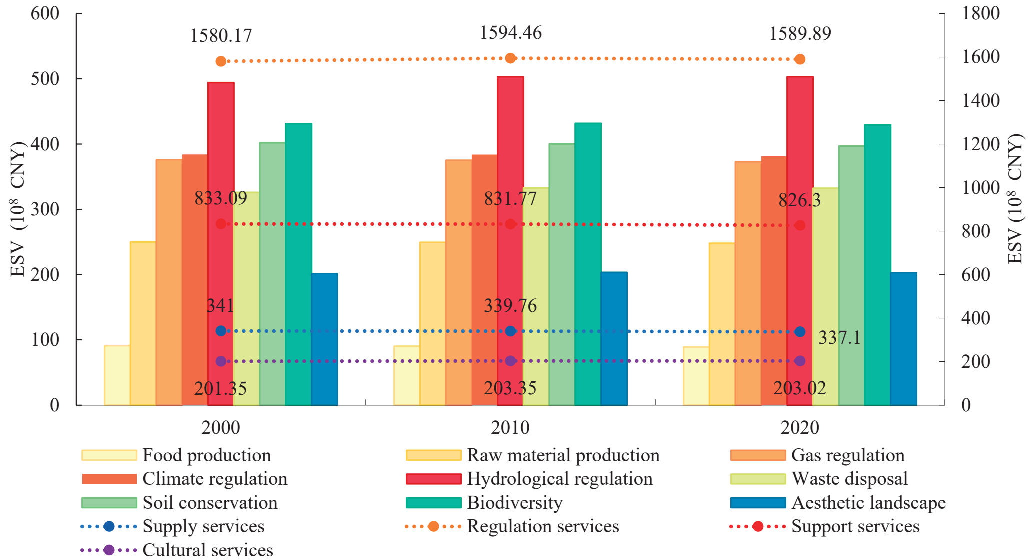

Figure 4. ESV of different ecosystem service types from 2000 to 2020.

3.2.2. Spatial Distribution Characteristics of ESV

We used the ArcGIS 10.3 software to spatially visualize ESV and then classified it into five grades using the natural breaks method. As shown in Figure 5, the ESV exhibited clear spatial differentiation. From 2000 to 2020, the high-value areas of ESV were mainly distributed in the west and northwest of the study area, especially in Maojian, Fangxian, Baokang, and Shennongjia. The higher value of ESV was the result of the presence of water bodies, forests, and vegetation in these counties. The low-value areas were mainly distributed in the southeastern areas, where cultivated land and the economically developed areas were concentrated. Overall, the spatial distribution of ESV was high in the northwest and low in the southeast. Figure 5d depicts the spatial distribution of ESV change rates from 2000 to 2020, indicating that the ESV decreases in the majority of counties within the study area, with change rates ranging from −3.18% to 0.80%. The Qiaokou, Jianghan, and Hanyang districts experienced the largest declines in ESV, with respective change rates of −17.92%, −14.53%, and −12.75%; Xiantao witnessed the largest growth in ESV, which was up to 14.23%. The spatial distribution of the ESV change rates was closely related to the land use structures and regulation policies of different counties.

Based on a hot spot analysis, we further revealed the spatial agglomeration characteristics and evolution of ESV in the HRB of Hubei from 2000 to 2020 (Figure 6). The spatial agglomeration of ESV was insignificant in nearly two-thirds of the study area, and the significant regions were mainly distributed in the northwest and southeast. The high-value (hot spot) agglomeration areas of ESV were mainly distributed in the northwest, whereas the low-value (cold spot) agglomeration areas were mainly distributed in the southeast, forming the spatial pattern of high in the northwest and low in the southeast. From 2000 to 2020, the range of hot spot and cold spot agglomerations remained stable, with the confidence level of hot spots for several counties reducing from 99% to 95%, while the strength of the significance weakened.

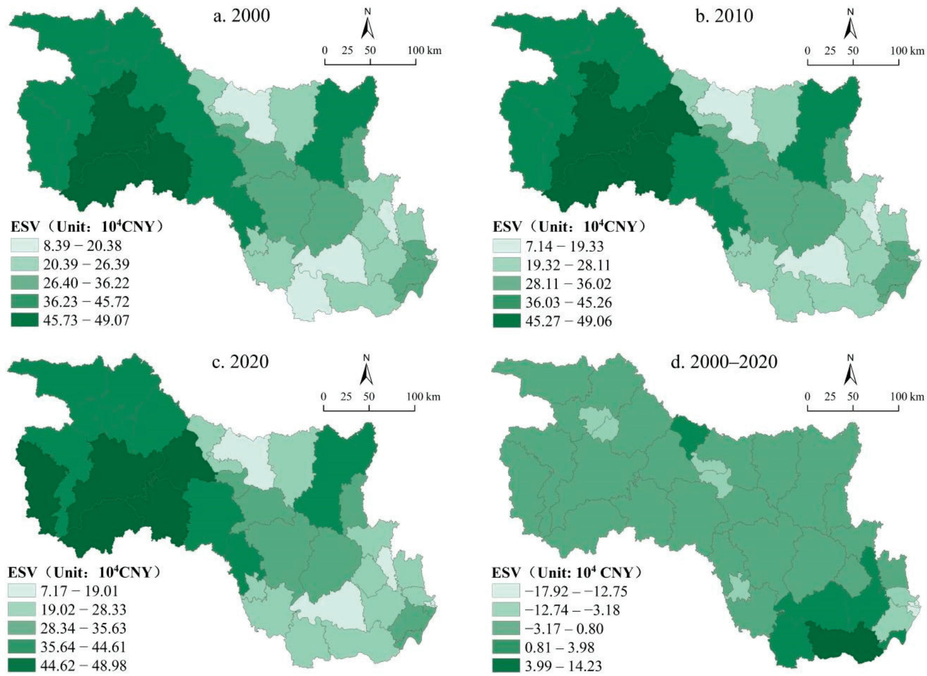

Figure 5. Spatial distribution of ESV (**a**–**c**) and the change rates (**d**) in the HRB of Hubei Province for 2000, 2010, and 2020.

3.3. Spatial Correlations between Land Use Intensity and ESV

The results from the global bivariate Moran's I revealed significant negative spatial correlations between land use intensity and ESV, regardless of the ES type (all Moran's I values < 0) (Figure 7). The global bivariate Moran's I in 2000, 2010, and 2020 was −0.63, −0.65, and −0.66 respectively; the majority of the values are in the second and fourth quadrants. The absolute values of Moran's I from 2020 to 2020 also indicated that the negative correlation was becoming increasingly stronger. This strongly demonstrates that the deepening of land use intensity will lead to the decrease in ESV in the HRB. Figure 8 presents the bivariate local spatial autocorrelation LISA aggregation maps between land use intensity and ESV at the county level for the years 2000, 2010, and 2020. The clustering pattern of the correlation between land use intensity and ESV was obvious, and there were only two types of spatial correlations between the two, namely, LH (low land use intensity vs. high ESV) and HL (high land use intensity vs. low ESV). The LH areas were mainly concentrated in the northwest of the study area, and the HL areas were in the southeast. During the study period, the spatial correction between land use intensity and ESV exhibited a slight shift in its clustering pattern. From 2000 to 2010, both Qianjiang and Xiantao cities changed from HL to insignificant, and the changes in Shayang County and Qiaokou District exhibited the opposite change pattern (Figure 8a,b). Tianmen City changed from HL to not-significant land use during 2010–2020 (Figure 8c).

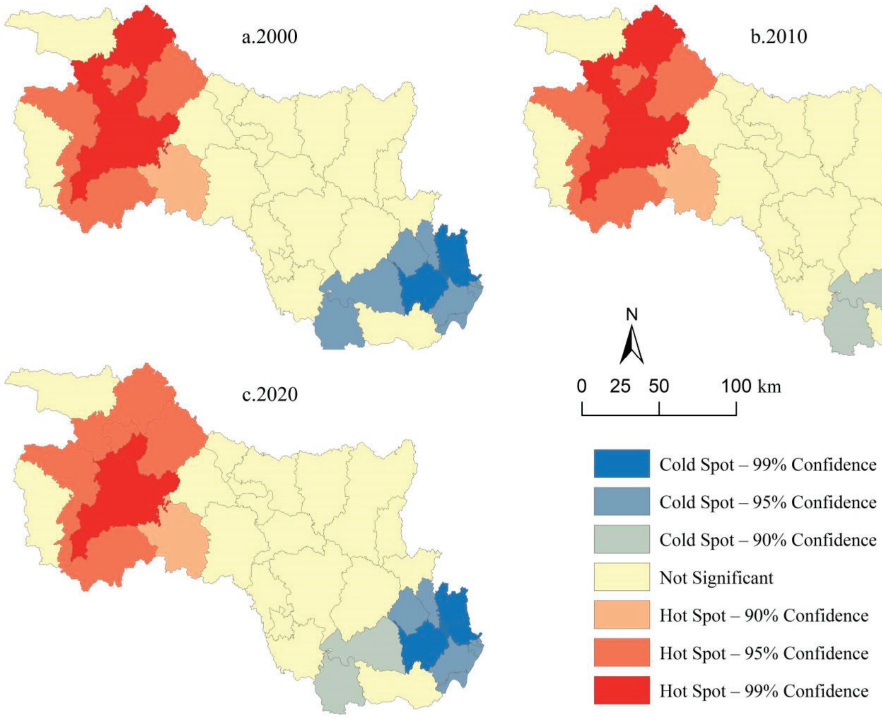

Figure 6. Spatial agglomeration characteristics of ESV in the HRB of Hubei Province for (**a**) 2000, (**b**) 2010, and (**c**) 2020.

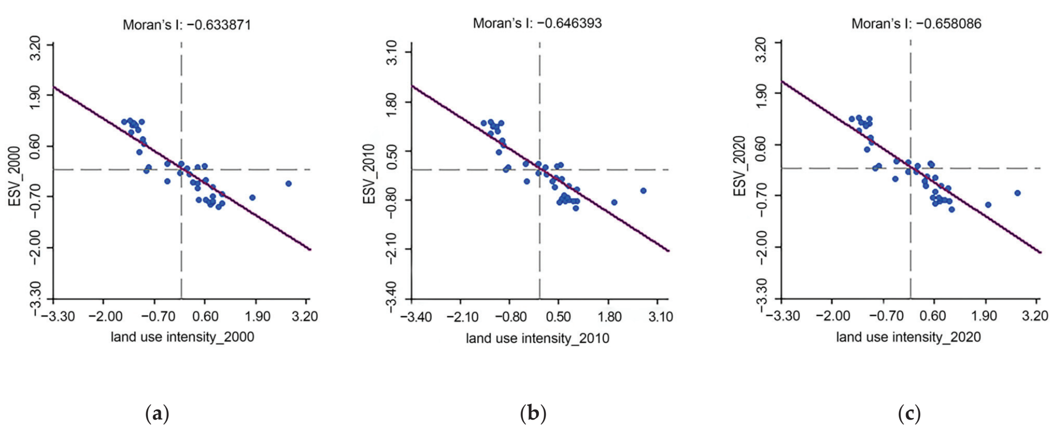

Figure 7. Moran scatter plots of land use intensity with ESV in the HRB of Hubei Province for (**a**) 2000, (**b**) 2010, and (**c**) 2020.

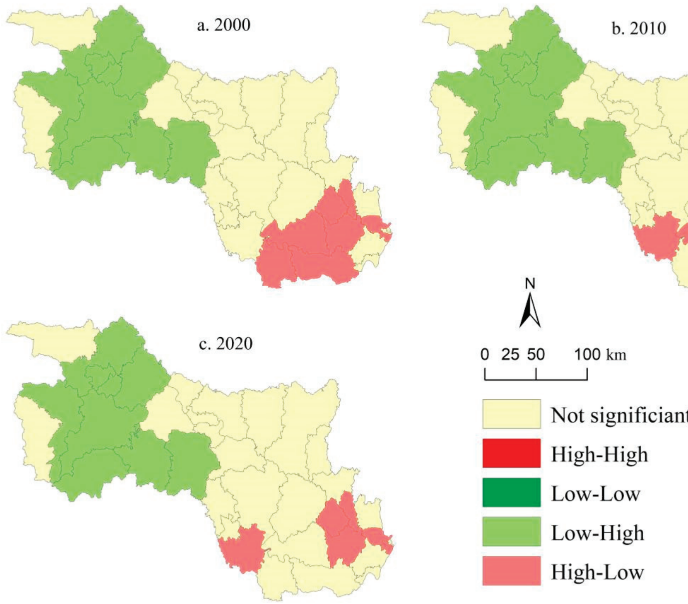

Figure 8. LISA cluster maps between land use intensity and ESV in the HRB of Hubei Province for (**a**) 2000, (**b**) 2010, and (**c**) 2020.

3.4. Spatial Variability of Driving Factors on ESV Changes

3.4.1. Results of GDM

The factor detection module of the GDM was used to quantify the impacts of natural and socio-economic factors on ESV (Table 5). Among the natural factors, the percentages of forest land (X4) and slope (X3) had the greatest explanatory power (with q values of 0.87 and 0.81, respectively) for ESV spatial variation. Regarding the socio-economic factors, the explanatory power of the percentage of built-up land (X10) and GDP (X6) on ESV variations was 0.74 and 0.65, respectively, and both were significant at the 1% level. Only the precipitation (X2) and distance to the water system (X5) did not have significant effects on ESV.

Table 5. Factor detection results of driving factors of ESV.

	X1	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**X8**	**X9**	**X10**
q statistic	0.75	0.19	0.81	0.87	0.27	0.65	0.55	0.41	0.50	0.74
p value	0.00 ***	0.37	0.00 ***	0.00 ***	0.13	0.00 ***	0.00 ***	0.03 **	0.00 ***	0.00 ***
rank	3	10	2	1	9	5	6	8	7	4

Note: *** and ** represent that *p* is significant at the 0.01 and 0.05 levels, respectively.

According to the results of the interaction detector (Table 6), there was no mutual weakening in the 45 pairs of interaction combinations, indicating that the impact of multiple driving factors on ESV is greater than that of a single factor. Except for the interaction results of the precipitation (X2) and the distance to a water system (X5), which are of the nonlinear enhancement type, the interaction results of the other bivariate combinations were enhanced. For example, the interaction between the percentage of forest land (X4) and the distance to a road (X9) explained the ESV changes with the greatest explanatory power (q value = 0.94), followed by the interaction between the percentage of forest land (X4) and the distance to a water system (X5), as well as the percentage of forest land (X4) and GDP (X6), with a q value of 0.92. The results of the interactive detection further verify that the percentage of forest land played a leading role in the spatial distribution of regional ESV changes.

Table 6. Interaction detection results of driving factors of ESV.

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
X1	0.75									
X2	0.84	0.19								
X3	0.83	0.84	0.81							
X4	0.83	0.60	0.89	0.87						
X5	0.87	0.75 #	0.87	0.92	0.27					
X6	0.86	0.80	0.89	0.92	0.81	0.65				
X7	0.88	0.69	0.89	0.90	0.61	0.82	0.55			
X8	0.83	0.64	0.85	0.90	0.65	0.83	0.66	0.41		
X9	0.78	0.69	0.85	0.94	0.80	0.82	0.76	0.71	0.50	
X10	0.86	0.79	0.90	0.90	0.85	0.85	0.75	0.83	0.80	0.74

Note: # denotes nonlinear enhancement of any two factor; without # denotes enhancement of any two factor.

3.4.2. Results of GWR

Table 7 depicts the performance parameters of the GWR and the ordinary least squares regression (OLS) model, which suggest that the GWR model has a better predictive ability than the OLS, as it had higher R^2 and adjusted R^2 values, and a lower AICc value.

Table 7. Statistic coefficients for GWR and OLS.

	R^2	Adjusted R^2	AICc
GWR	0.93	0.90	49.52
OLS	0.88	0.84	248.48

Since the GDM found that precipitation (X2) and the distance to a water system (X5) have no significant impact on ESV, we removed these two factors and only explored the spatial distribution of regression coefficients for the remaining eight factors. As illustrated in Figure 9, each driving factor had an obvious spatial heterogeneity, indicating that the same factor had different impacts on the ESV at different spatial locations, and there was a significant spatial non-stationarity. Among the natural factors, ESV had a significant positive correlation with temperature, slope, and the percentage of forest land, with a higher correlation coefficient in the southeast and a lower correlation coefficient in the northwest (Figure 9a–c). This indicates that the enhancement of these factors contributes to the improvement of ESV. In terms of socio-economic factors, the regression coefficients of GDP and population density were both negative, demonstrating that an increase in these factors will weaken the ESV. The distance to the county center and the distance to a road had negative correlations with ESV in most regions, and only a few counties in the southeast had a positive correlation. The absolute values of the influence of GDP and percentage of built-up land were consistent, with high values in the southeast and low values in the northwest, which were spatially similar to the driving forces of natural factors. The effects of population density, distance to county center, and distance to a road on ESV were not only consistent in their correlation but were also similar in distribution, showing values of high in the northwest and low in the southeast (Figure 9d–h). In conclusion, the order for the size of the impacts of the eight driving factors on ESV was as follows: percentage of forest land > population density > percentage of built-up land > slope > temperature > GDP > distance to a road > distance to the county center (Figure 9).

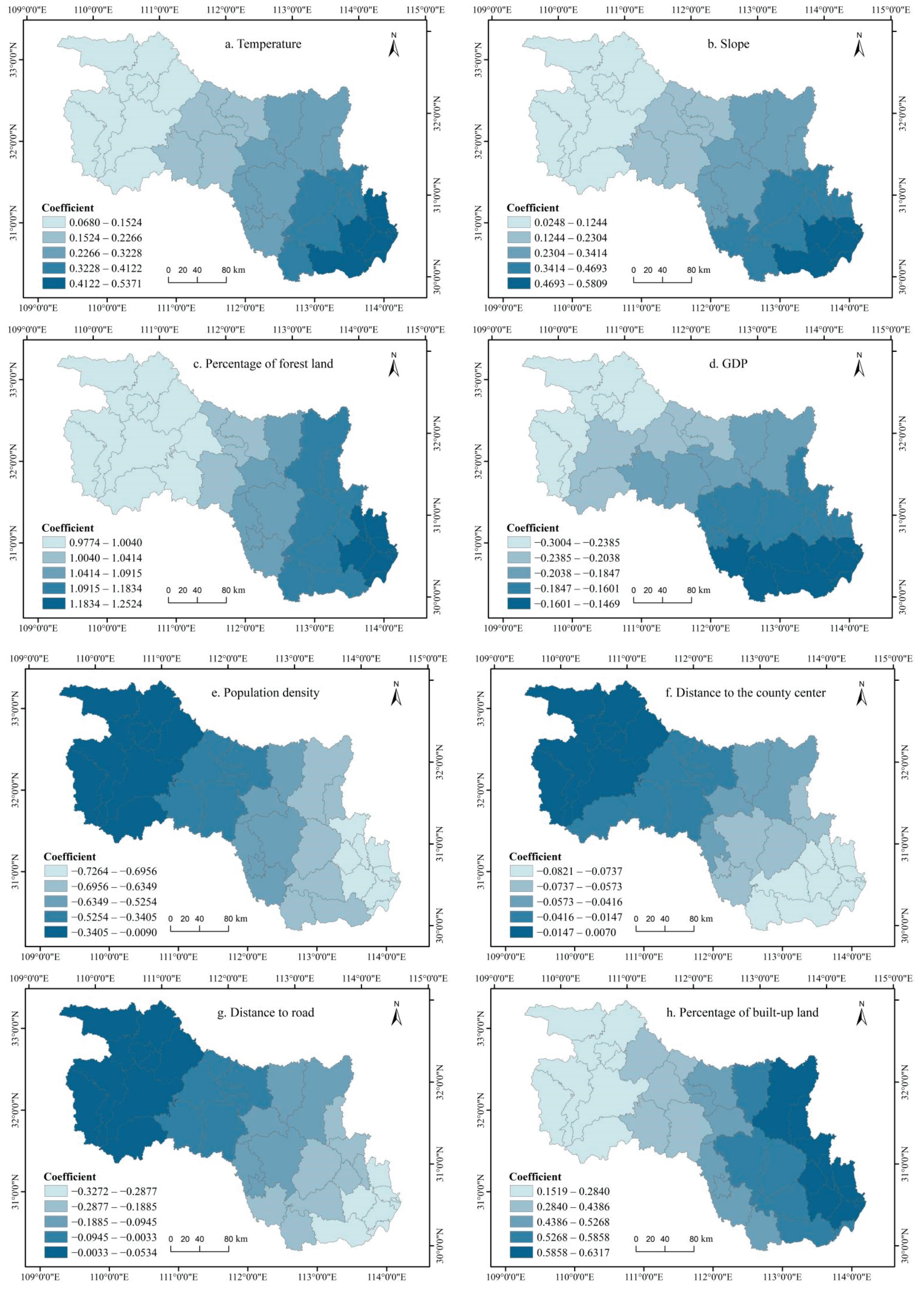

Figure 9. Spatial distribution of regression coefficients in GWR.

4. Discussion

4.1. Spatial Relationship between Land Use Intensity and ESV

From 2000 to 2010, ESV experienced an inverted U-shaped trend. The changes in ESV were mainly due to unreasonable land use planning and low land utilization rate, which led to the rapid growth of built-up land at the expense of forest land, cultivated land, and grassland. Land use intensity has a significant negative relationship with ESV [57]. Socioeconomic development led to dramatic changes in land use structure, and the increase in land use intensity was the direct cause of ESV degradation [58,59]. To further explore the characteristics of the spatial correlation between land use intensity and ESV, we used the bivariate spatial autocorrelation method to study the spatial relationship between the two. During the study period, the Moran's *I* was entirely negative, and its absolute value showed a trend of increasing (Figure 7). This indicated that the negative correlation between land use intensity and ESV in the study area had become more pronounced over time, which was in line with prior studies on the relationship between LUCC and ESV [60,61]. The intensification of land use was mainly manifested in the increasing expansion of built-up land; the continuous occupation of cultivated land, forest land, and grassland; the extensive land utilization; and the low land utilization. Consequently, the ES provided by ecosystems was deteriorating. The LISA cluster maps revealed a significant spatial correlation between land use intensity and ESV (Figure 8). The LH areas were mainly distributed in the hilly and mountainous areas with higher terrain and steeper slopes in the northwest of the study area (such as the Shennongjia Mountain, Wudang Mountain, etc.), while HL areas were mainly distributed in the middle and lower reaches of the Yangtze River with flat terrain and dense lakes in the southeastern part of the study area, particularly in Wuhan—which is known as the "city of a thousand lakes"—and the surrounding cities. This was due to the mountainous and hilly terrain in the northwest region, which made land development difficult and costly. In addition, the area of forest land in this region is large, which provides human society with crucial ES such as biodiversity maintenance, climate regulation, and ecological conservation; thus, the ESV was high. The situation in the southeast was the opposite of that in the northwest. The unique natural environment created the conditions for high-density population agglomeration and high-intensity land development, resulting in the disorderly spread of built-up land and the occupation of ecological lands, especially water bodies and cultivated land; thus, the ESV in this region was at a low level.

For the ecosystem in the HRB of Hubei Province, the middle route of the South-to-North Water Diversion Project is undoubtedly one of the most representative human activities. The opening of the project had a great impact on the aquatic ecological environment, climate conditions, and people's production and life in this area. Due to the reduction in the water volume in the basin, there are problems such as the decline in the water purification capacity, the reduction of aquatic organisms, the decrease in aquatic environmental carrying capacity, and the deterioration of the aquatic ecological environment. At the same time, the industrial and agricultural sectors—with a great demand for water—are facing a water shortage, and the industrial structure is changing, which will affect the production and lifestyles of people in the region [62]. The construction of the project also brought about the problem of immigration. The change from farmland to settlement and the establishment of new residential areas for immigrants are among the reasons for the expansion of built-up land and the reduction of cultivated land and forest land [63].

4.2. Identifying Driving Factors Affecting ESV

According to the Geographical Detector Model (GDM) (Tables 5 and 6), the percentage of forest land had the largest positive effect on ESV, which was consistent with previous studies where regions with a large forest area provided greater regulation and support services and had higher ESV [64,65]. Thus, strengthening the protection of forest land and increasing the forest coverage rate of each county is of great significance for promoting regional climatic improvement and alleviating the greenhouse and heat island effect. The results of the Geographically Weighted Regression (GWR) analysis further revealed the dominant role of natural factors with respect to ESV and the growing trend of socio-economic factors (Figure 9). Natural factors had positive impacts on ESV and the regions with more favorable natural conditions had larger ESVs. However, the areas with high driving coefficients of natural factors were concentrated in the economically developed counties in the southeast. This was because better economic conditions in many regions come at the expense of environmental degradation. Therefore, if the protection of the natural environment of counties in this region is enhanced, based on the same input conditions, the increase in ESV must be much higher than those of the regions with relatively poor socio-economic conditions but a superior ecological environment. This can also explain the "high in the northwest and low in the southeast" distribution of socio-economic factors such as GDP. Nevertheless, not all socio-economic factors had the same distribution of driving forces as GDP. For example, the distribution of the driving coefficients of population density, the distance to the county center, and the distance to a road was "low in the northwest and high in the southeast". This indicated that the improvement of socio-economic conditions had less of an effect on the ESV of the undeveloped counties in the northwest. For these regions, the improvement in socio-economic conditions would not result in a substantial decrease in ESV. However, for the more economically developed and densely populated southeastern regions, the lack of environmental protection would increase regional environmental pressure and lead to a rapid decline in ESV [66]. The influence of the distance to the county center and the distance to a road on ESV was predominantly negative, except for a few northwest counties.

In conclusion, ESV was influenced by both natural and socio-economic factors in an interactive way [67]. Although multiple types of ES are provided by natural systems to maintain human welfare, human activities have altered the structure and function of ecosystems, which further affect the provision of vital ES by ecosystems [68]. Therefore, it is important to protect and restore the crucial ecosystems through landscape planning, regulative policies, and environmental programs.

4.3. Policy Implications

The increased land use intensity during rapid urbanization and social-economic development has inevitably degraded the ecological environment [69,70], as evidenced by the reduction of forest land and cultivated land, air pollution, severe climate change, waste of land resources, etc. The existing land use planning and policies have not adequately recognized the negative impact of land use intensification on ESV [71]. With a greater emphasis on the sustainable development of humans and the environment in the future, the protection of ecosystems will inevitably become the core of social and economic development. Therefore, we should adhere to the developmental idea of "ecological priority" and attach importance to the rational use of land to enhance ESV. This study proposes the following practical policy recommendations for the Hanjiang River Basin in Hubei Province. First, since the study area is a river basin, its regulation and support services are particularly prominent. Therefore, the sustainability of the river basin should be based on the protection of forest land and water areas [72,73]. Decision makers should increase the vegetation coverage of river basins through forest restoration and reforestation programs, increase the supervision of the aquatic environment, and moderately restore farmland to forests and grasslands. Second, due to the imbalanced regional development, counties with varying levels of socio-economic development should adopt locally differentiated regulation policies and regulation measures. For mountain counties, ecological compensation policies should be implemented to improve local economic and social conditions, while for plain counties, it is necessary to strictly control the expansion of built-up land and strengthen the protection of ecological land. It is possible to establish a long-term cross-regional ecological compensation and monitoring mechanism between mountain and plain counties. Third, to achieve the coordinated development of the socio-economy and the environment, future decision-making should incorporate ES into spatial-planning and socio-economic development policies. The ESV should be evaluated before projects progress to construction to mitigate the negative effects of human activities on ecosystems.

4.4. Limitations and Future Work

This study has several limitations. First, due to the opening of the middle route of the South-to-North Water Diversion Project, the natural and socio-economic environment of the HRB has been greatly affected by the change in water resources. However, the impacts of the project on local ecosystems could not be fully revealed in this study. The ESV in this study was estimated based on land use/cover data and their equivalent values proposed by Xie et al. (2003 and 2008). The change in land use/cover area cannot fully reflect the impact of the South-to-North Water Diversion Project on the ecosystem. Second, this study mainly evaluated the ecosystem as a whole, without considering the in-depth analysis of the primary and secondary services of the ecosystem. Furthermore, driving factors were selected at the macro level, such as the annual mean temperature, slope, and GDP, without considering the interactions with micro factors such as soil, the sediment concentration, microelements, etc. Our future research will improve the assessment method of ESV and evaluate ESV at the township level or grid scale [74], and the land types will be subdivided to obtain a more accurate estimation of ESV.

5. Conclusions

The change in ESV is the result of the joint action of natural and human forces. Exploring the temporal and spatial variation of ESV and revealing its driving factors is crucial for promoting the harmonious coexistence between human and nature. Our study analyzed how ESV changed over time due to the change in land use intensity. From 2000 to 2020, the area of built-up land increased from 2336.39 km^2 to 3371.28 km^2, while the area of cultivated land, grassland, and forest land decreased. The ESV of the Han River Basin in Hubei Province experienced an inverted U-shaped trend, with an increase followed by a decrease, and had the spatial distribution characteristics of high in the northwest and low in the southeast. The counties with larger forest land and water areas tended to have higher ESVs. Additionally, there was a significant negative correlation between land use intensity and ESV, which was most prominent in the northwest (LH type) and southeast (HL type) of the study area. From the analysis of the driving forces, it was found that the interaction between driving factors had a greater impact on the spatial variability of ESV than that of single factors. The spatial regression results indicated that natural factors, such as the percentage of forest land, temperature, and slope, have positive impacts on ESV, and their influence gradually increased from northwest to southeast. There was a significant spatial differentiation between socio-economic factors, i.e., both positive and negative relationships existed, and the spatial distributions of the influence coefficients were opposite to those of natural factors. In general, the influence of natural factors on ESV was greater and more significant than that of socio-economic factors, while the impact and spatial heterogeneity of socio-economic factors on ESV tended to increase. The findings in this study could provide implications for spatial planning towards promoting the sustainable development of ecosystems.

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

Appendix A.

The detailed description of the methods used in this study can be found in Appendix A.

Appendix A.1. Methods

Appendix A.1.1. Hot Spot Analysis

Getis–Ord *Gi** is an index of local spatial autocorrelation used to explore the spatial clustering of high values (hot spots) or low values (cold spots) of spatial variables [48]. The output can be represented with the Z-score, *p*-value, and confidence level. We used the Getis–Ord *Gi** tool in the ArcGIS 10.3 software to analyze the hot spots and cold spots of ESV in the study area. The expression is as follows [75]:

$$G^* = \frac{\sum_{j=1}^{n} W_{ij}X_j - \overline{X}\sum_{i=1}^{n} W_{ij}}{\sqrt[s]{\left[n\sum_{j=1}^{n} W_{ij}{}^2 - \left(\sum_{j=1}^{n} W_{ij}\right)^2\right]/(n-1)}} \tag{A1}$$

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{A2}$$

$$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n} X_i{}^2 - \frac{1}{X^2}} \tag{A3}$$

where G^* is the Z-score; n is the number of units; X_i and X_j represent the observations of variable X in i and j space units, respectively; W_{ij} is a spatial weight matrix; and $\overline{X}$ and s are the average value and standard deviation, respectively. The higher the Z-score, the denser the high-values (hot spots) are, which means the higher the attribute value around the unit, and vice versa.

Appendix A.1.2. Bivariate Spatial Autocorrelation Model

Spatial autocorrelation refers to the statistical correlation of a certain attribute value of a geographic object with spatial location differences. Generally, the closer the two values are, the greater the correlation. Spatial autocorrelation analysis is an important indicator to measure the aggregation or discrete distribution of spatial elements, and is generally described by global Moran's *I* and local Moran's *I* [49]. The Moran's *I* value is expressed as follows:

$$\text{Moran's } I = \frac{n\sum_{i=1}^{n}\sum_{j\neq 1}^{n} W_{ij}\cdot(X_i - \overline{X})\cdot(X_j - \overline{X})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)\sum_{i=1}^{n}(X_i - \overline{X})^2} \tag{A4}$$

where n is the number of the geographic unit (i.e., 39 counties in this study); X_i and X_j denote the actual attribute values in the sampling plots i and j, respectively; $\overline{X}$ is the average value of X; and W_{ij} is a spatial weight matrix. When Moran's $I < 0$, it indicates a negative correlation; when Moran's $I = 0$, it indicates no correlation; and when Moran's $I > 0$, it indicates a positive correlation. The greater the value, the larger the correlation between the observed values in the spatial distribution and the stronger the aggregation.

The global autocorrelation tests the spatial vergence pattern of the spatial variables over the entire research range, while the local spatial autocorrelation captures the correlation of the variables in different regional units [50]. The formula is as follows:

$$I_{kl}^{i} = z_k^i \sum_{j=1}^{n} W_{ij} z_l^j \tag{A5}$$

where $z_k^i = \frac{X_k^i - \overline{X_k}}{e_k}$, $z_l^j = \frac{X_l^i - \overline{X_l}}{e_l}$; X_k^i is the value of attribute k of sampling plot i; X_l^j is the value of attribute l of sampling plot j; $\overline{X_k}$ and $\overline{X_l}$ is the average values of attributes k and l, respectively; and e_k and e_l are the variances of attributes k and l, respectively.

Appendix A.1.3. Analysis of the Driving Mechanism

Geographical Detector Model

The GDM comprises risk detection, factor detection, ecological detection, and interactive detection, which can be used to detect spatial variation and identify potential influencing factors [53]. The GDM has been widely used in many fields, including social economy and ecological environments [51,54]. The expression of the GDM is as follows:

$$q = 1 - \frac{1}{N\sigma^2}\sum_{j=1}^{L} N_j\sigma_j^2 \tag{A6}$$

where q represents the explanatory ability of the independent variable (including natural and socio-economic factors) towards the dependent variable (ESV), and $q \in [0, 1]$; N is the total sample size in the study area; σ^2 is the variance; and j represents partition (j = 1,2, . . . , L). When q is closer to 1, it indicates that the driving factor has a greater impact on the independent variable and that the spatial heterogeneity is stronger, and vice versa.

Geographically Weighted Regression

The GWR is an extension of the traditional regression analysis method that can estimate data with spatial autocorrelation and reflect the spatial heterogeneity of parameters [55]. The GWR can reveal the direction and magnitude of influence of each factor in different locations [56]. The expression is as follows:

$$y_k = \beta_0(u_k, v_k) + \sum_{i=1}^{n} \beta_i(u_k, v_k)x_{ki} + c_k \tag{A7}$$

where y_k is the weighted regression value of k-th sample; β_0 is the intercept; (u_k, v_k) is the geographic center coordinate of the k-th sample; $\beta_0(u_k, v_k)$ is the constant term; $\beta_i(u_k, v_k)$ is the coefficient of the k-th independent variable of i-th driving factor; x_{ki} is the i-th independent variable of the k-th sample; and c_k is the error term. In this study, ESV is the dependent variable, and natural and socio-economic factors are the independent variables.

References

1. Costanza, R.; dArge, R.; deGroot, R.; Farber, S.; Grasso, M.; Hannon, B.; Limburg, K.; Naeem, S.; Oneill, R.V.; Paruelo, J.; et al. The value of the world's ecosystem services and natural capital. *Nature* **1997**, *387*, 253–260. [CrossRef]
2. Daily, G.C. Nature's Services: Societal Dependence on Natural Ecosystems (1997). In *The Future of Nature: Documents of Global Change*; Libby, R., Sverker, S., Paul, W., Eds.; Yale University Press: New Haven, CT, USA, 2013; pp. 454–464.
3. Hasan, S.; Shi, W.Z.; Zhu, X.L. Impact of land use land cover changes on ecosystem service value—A case study of Guangdong, Hong Kong, and Macao in South China. *PLoS ONE* **2020**, *15*, e231259. [CrossRef] [PubMed]
4. Tolessa, T.; Senbeta, F.; Kidane, M. The impact of land use/land cover change on ecosystem services in the central highlands of Ethiopia. *Ecosyst. Serv.* **2017**, *23*, 47–54. [CrossRef]
5. Zhu, S.; Huang, J.; Zhao, Y. Coupling coordination analysis of ecosystem services and urban development of resource-based cities: A case study of Tangshan city. *Ecol. Indic.* **2022**, *136*, 108706. [CrossRef]
6. Xie, G.D.; Lu, C.X.; Xiao, Y.; Zheng, D. Ecological assets valuation of the Tibetan Plateau. *J. Mt. Sci.* **2003**, *21*, 50–55. [CrossRef]
7. Xie, G.D.; Zhen, L.; Lu, C.X.; Xiao, Y. Expert knowledgy based valuation method of ecosystem services in China. *J. Nat. Resour.* **2008**, *23*, 911–919.
8. Zheng, L.; Wang, Y.; Li, J. How to achieve the ecological sustainability goal of UNESCO Global Geoparks? A multi-scenario simulation and ecological assessment approach using Dabieshan UGGp, China as a case study. *J. Clean. Prod.* **2021**, *329*, 129779. [CrossRef]
9. Ge, Q.Q.; Xu, W.J.; Fu, M.C.; Han, Y.X.; An, G.Q.; Xu, Y.T. Ecosystem service values of gardens in the Yellow River Basin, China. *J. Arid. Land* **2022**, *14*, 284–296. [CrossRef]
10. Su, K.; Wei, D.Z.; Lin, W.X. Evaluation of ecosystem services value and its implications for policy making in China—A case study of Fujian province. *Ecol. Indic.* **2020**, *108*, 105752. [CrossRef]

11. Zhao, H.; Zhang, H.L.; Wang, F.Q.; Kang, P.P.; Lu, S.B. Service value of wetland ecosystem in Sanmenxia Reservoir area. *Glob. Glob. Nest J.* **2020**, *22*, 463–470. [CrossRef]
12. Wang, F.; Yuan, X.Z.; Zhou, L.L.; Liu, S.S.; Zhang, M.J.; Zhang, D. Detecting the Complex Relationships and Driving Mechanisms of Key Ecosystem Services in the Central Urban Area Chongqing Municipality, China. *Remote Sens.* **2021**, *13*, 4248. [CrossRef]
13. Xiao, Z.L.; Liu, R.; Gao, Y.H.; Yang, Q.Y.; Chen, J.L. Spatiotemporal variation characteristics of ecosystem health and its driving mechanism in the mountains of southwest China. *J. Clean. Prod.* **2022**, *345*, 131138. [CrossRef]
14. Zhang, K.L.; Liu, T.; Feng, R.R.; Zhang, Z.C.; Liu, K. Coupling Coordination Relationship and Driving Mechanism between Urbanization and Ecosystem Service Value in Large Regions: A Case Study of Urban Agglomeration in Yellow River Basin, China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 7836. [CrossRef]
15. De Groot, R.S.; Alkemade, R.; Braat, L.; Hein, L.; Willemen, L. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. *Ecol. Complex.* **2010**, *7*, 260–272. [CrossRef]
16. Elmqvist, T.; Setala, H.; Handel, S.N.; van der Ploeg, S.; Aronson, J.; Blignaut, J.N.; Gomez-Baggethun, E.; Nowak, D.J.; Kronenberg, J.; de Groot, R. Benefits of restoring ecosystem services in urban areas. *Curr. Opin. Environ. Sustain.* **2015**, *14*, 101–108. [CrossRef]
17. Pan, J.H.; Wei, S.M.; Li, Z. Spatiotemporal pattern of trade-offs and synergistic relationships among multiple ecosystem services in an arid inland river basin in NW China. *Ecol. Indic.* **2020**, *114*, 106345. [CrossRef]
18. Ran, C.; Wang, S.J.; Bai, X.Y.; Tan, Q.; Zhao, C.W.; Luo, X.L.; Chen, H.; Xi, H.P. Trade-Offs and Synergies of Ecosystem Services in Southwestern China. *Environ. Eng. Sci.* **2020**, *37*, 669–678. [CrossRef]
19. Chen, W.; Zeng, J.; Zhong, M.; Pan, S. Coupling Analysis of Ecosystem Services Value and Economic Development in the Yangtze River Economic Belt: A Case Study in Hunan Province, China. *Remote Sens.* **2021**, *13*, 1552. [CrossRef]
20. Yang, Z.; Zhan, J.; Wang, C.; Twumasi-Ankrah, M.J. Coupling coordination analysis and spatiotemporal heterogeneity between sustainable development and ecosystem services in Shanxi Province, China. *Sci. Total. Environ.* **2022**, *836*, 155625. [CrossRef]
21. Sun, Y.X.; Liu, S.L.; Shi, F.N.; An, Y.; Li, M.Q.; Liu, Y.X. Spatio-temporal variations and coupling of human activity intensity and ecosystem services based on the four-quadrant model on the Qinghai-Tibet Plateau. *Sci. Total Environ.* **2020**, *743*, 140721. [CrossRef]
22. Wang, J.L.; Zhou, W.Q.; Pickett, S.T.A.; Yu, W.J.; Li, W.F. A multiscale analysis of urbanization effects on ecosystem services supply in an urban megaregion. *Sci. Total Environ.* **2019**, *662*, 824–833. [CrossRef]
23. Xi, H.H.; Cui, W.L.; Cai, L.; Chen, M.Y.; Xu, C.L. Evaluation and Prediction of Ecosystem Service Value in the Zhoushan Islands Based on LUCC. *Sustainability* **2021**, *13*, 2302. [CrossRef]
24. Rahman, M.; Szabó, G. Impact of Land Use and Land Cover Changes on Urban Ecosystem Service Value in Dhaka, Bangladesh. *Land* **2021**, *10*, 793. [CrossRef]
25. Yang, J.; Zeng, C.; Cheng, Y.J. Spatial influence of ecological networks on land use intensity. *Sci. Total Environ.* **2020**, *717*, 137151. [CrossRef] [PubMed]
26. Xu, F.; Wang, Z.; Chi, G.; Zhang, Z. The impacts of population and agglomeration development on land use intensity: New evidence behind urbanization in China. *Land Use Policy* **2020**, *95*, 104639. [CrossRef]
27. Ye, S.; Ren, S.; Song, C.; Cheng, C.; Shen, S.; Yang, J.; Zhu, D. Spatial patterns of county-level arable land productive-capacity and its coordination with land-use intensity in mainland China. *Agric. Ecosyst. Environ.* **2022**, *326*, 107757. [CrossRef]
28. Zhang, Y.J.; Song, W.; Fu, S.; Yang, D.Z. Decoupling of Land Use Intensity and Ecological Environment in Gansu Province, China. *Sustainability* **2020**, *12*, 2779. [CrossRef]
29. Ge, B.M.; Zhou, J.; Yang, R.P.; Jiang, S.H.; Yang, L.; Tang, B.P. Lower land use intensity promoted soil macrofaunal biodiversity on a reclaimed coast after land use conversion. *Agric. Ecosyst. Environ.* **2021**, *306*, 107208. [CrossRef]
30. Wu, X.; Liu, S.; Zhao, S.; Hou, X.; Xu, J.; Dong, S.; Liu, G. Quantification and driving force analysis of ecosystem services supply, demand and balance in China. *Sci. Total Environ.* **2019**, *652*, 1375–1386. [CrossRef]
31. Liu, S.N.; Lei, Y.; Zhao, J.S.; Yu, S.X.; Wang, L. Research on ecosystem services of water conservation and soil retention: A bibliometric analysis. *Environ. Sci. Pollut. Res.* **2021**, *28*, 2995–3007. [CrossRef]
32. Zhou, Y.K.; Zhang, X.Y.; Yu, H.; Liu, Q.Q.; Xu, L.L. Land Use-Driven Changes in Ecosystem Service Values and Simulation of Future Scenarios: A Case Study of the Qinghai-Tibet Plateau. *Sustainability* **2021**, *13*, 4079. [CrossRef]
33. Song, F.; Su, F.L.; Mi, C.X.; Sun, D. Analysis of driving forces on wetland ecosystem services value change: A case in Northeast China. *Sci. Total Environ.* **2021**, *751*, 141778. [CrossRef] [PubMed]
34. Luo, Q.L.; Zhou, J.F.; Li, Z.G.; Yu, B.L. Spatial differences of ecosystem services and their driving factors: A comparation analysis among three urban agglomerations in China's Yangtze River Economic Belt. *Sci. Total Environ.* **2020**, *725*, 138452. [CrossRef]
35. Shao, M.; Wu, L.F.; Li, F.Z.; Lin, C.S. Spatiotemporal Dynamics of Ecosystem Services and the Driving Factors in Urban Agglomerations: Evidence From 12 National Urban Agglomerations in China. *Front. Ecol. Evol.* **2022**, *10*, 804969. [CrossRef]
36. Chen, T.T.; Peng, L.; Liu, S.Q.; Wang, Q. Spatio-temporal pattern of net primary productivity in Hengduan Mountains area, China: Impacts of climate change and human activities. *Chin. Geogr. Sci.* **2017**, *27*, 948–962. [CrossRef]
37. Yin, X.; Zhang, J.Y.; Chen, J. The Impact of Multi-Projects on the Alteration of the Flow Regime in the Middle and Lower Course of the Hanjiang River, China. *Water* **2020**, *12*, 2301. [CrossRef]
38. Liu, C.X.; Wu, X.L.; Wang, L. Analysis on land ecological security change and affect factors using RS and GWR in the Danjiangkou Reservoir area, China. *Appl. Geogr.* **2019**, *105*, 1–14. [CrossRef]

39. Ren, W.; Zhang, X.; Peng, H. Evaluation of Temporal and Spatial Changes in Ecological Environmental Quality on Jianghan Plain From 1990 to 2021. *Front. Environ. Sci.* **2022**, *10*, 884440. [CrossRef]
40. Li, X.P.; Zhang, L.W.; O'Connor, P.J.; Yan, J.P.; Wang, B.; Liu, D.L.; Wang, P.T.; Wang, Z.Z.; Wan, L.W.; Li, Y.J. Ecosystem Services under Climate Change Impact Water Infrastructure in a Highly Forested Basin. *Water* **2020**, *12*, 2825. [CrossRef]
41. Qi, W.H.; Li, H.R.; Zhang, Q.F.; Zhang, K.R. Forest restoration efforts drive changes in land-use/land-cover and water-related ecosystem services in China's Han River basin. *Ecol. Eng.* **2019**, *126*, 64–73. [CrossRef]
42. Yu, G.M.; Li, M.X.; Tu, Z.F.; Yu, Q.W.; Jie, Y.; Xu, L.L.; Dang, Y.F.; Chen, X.X. Conjugated evolution of regional social-ecological system driven by land use and land cover change. *Ecol. Indic.* **2018**, *89*, 213–226. [CrossRef]
43. Yang, N.; Zhang, K.; Hong, Y.; Zhao, Q.H.; Huang, Q.; Xu, Y.S.; Xue, X.W.; Chen, S. Evaluation of the TRMM multisatellite precipitation analysis and its applicability in supporting reservoir operation and water resources management in Hanjiang basin, China. *J. Hydrol.* **2017**, *549*, 313–325. [CrossRef]
44. Wang, Y.G.; Zhang, W.S.; Zhao, Y.X.; Peng, H.; Shi, Y.Y. Modelling water quality and quantity with the influence of inter-basin water diversion projects and cascade reservoirs in the Middle-lower Hanjiang River. *J. Hydrol.* **2016**, *541*, 1348–1362. [CrossRef]
45. Huang, M.; Li, Y.; Xia, C.; Zeng, C.; Zhang, B. Coupling responses of landscape pattern to human activity and their drivers in the hinterland of Three Gorges Reservoir Area. *Glob. Ecol. Conserv.* **2022**, *33*, e01992. [CrossRef]
46. Zhuang, D.F.; Liu, J.Y. Study on the model of regional differention of land use degree in China. *J. Nat. Rescour.* **1997**, *12*, 105–111.
47. Cao, L.; Li, J.; Ye, M.; Pu, R.; Liu, Y.; Guo, Q.; Feng, B.; Song, X. Changes of Ecosystem Service Value in a Coastal Zone of Zhejiang Province, China, during Rapid Urbanization. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1301. [CrossRef]
48. Getis, A.; Ord, J.K. The Analysis of Spatial Association by Use of Distance Statistics. *Geogr. Anal.* **1992**, *24*, 189–206. [CrossRef]
49. Anselin, L.J. Local indicators of spatial association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
50. Zhao, L.L.; Fan, X.C.; Lin, H.; Hong, T.; Hong, W. Impact of Urbanization on the Value of Ecosystem Services in Nanping City, China. *Pol. J. Environ. Stud.* **2021**, *30*, 965–975. [CrossRef]
51. Fang, L.L.; Wang, L.C.; Chen, W.X.; Sun, J.; Cao, Q.; Wang, S.Q.; Wang, L.Z. Identifying the impacts of natural and human factors on ecosystem service in the Yangtze and Yellow River Basins. *J. Clean. Prod.* **2021**, *314*, 127995. [CrossRef]
52. Wang, X.; Wu, J.; Liu, Y.; Hai, X.; Shanguan, Z.; Deng, L. Driving factors of ecosystem services and their spatiotemporal change assessment based on land use types in the Loess Plateau. *J. Env. Manag.* **2022**, *311*, 114835. [CrossRef] [PubMed]
53. Wang, J.; Xu, C.J. Geodetector: Principle and prospective. *Acta Geogr. Sin.* **2017**, *72*, 116–134.
54. Gao, J.B.; Jiang, Y.; Anker, Y. Contribution analysis on spatial tradeoff/synergy of Karst soil conservation and water retention for various geomorphological types: Geographical detector application. *Ecol. Indic.* **2021**, *125*, 107470. [CrossRef]
55. Fotheringham, A.S.; Yang, W.B.; Kang, W. Multiscale Geographically Weighted Regression (MGWR). *Ann. Am. Assoc. Geogr.* **2017**, *107*, 1247–1265. [CrossRef]
56. Lu, B.B.; Charlton, M.; Harris, P.; Fotheringham, A.S. Geographically weighted regression with a non- Euclidean distance metric: A case study using hedonic house price data. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 660–681. [CrossRef]
57. Li, B.W.; Yang, Z.F.; Cai, Y.P.; Xie, Y.L.; Guo, H.J.; Wang, Y.Y.; Zhang, P.; Li, B.; Jia, Q.P.; Huang, Y.P.; et al. Prediction and valuation of ecosystem service based on land use/land cover change: A case study of the Pearl River Delta. *Ecol. Eng.* **2022**, *179*, 106612. [CrossRef]
58. Hu, S.; Chen, L.Q.; Li, L.; Wang, B.Y.; Yuan, L.N.; Cheng, L.; Yu, Z.Q.; Zhang, T. Spatiotemporal Dynamics of Ecosystem Service Value Determined by Land-Use Changes in the Urbanization of Anhui Province, China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 5104. [CrossRef]
59. Zhang, P.Y.; Li, Y.Y.; Jing, W.L.; Yang, D.; Zhang, Y.; Liu, Y.; Geng, W.L.; Rong, T.Q.; Shao, J.W.; Yang, J.X.; et al. Comprehensive Assessment of the Effect of Urban Built-Up Land Expansion and Climate Change on Net Primary Productivity. *Complexity* **2020**, *2020*, 8489025. [CrossRef]
60. Li, N.; Wang, J.Y.; Wang, H.Y.; Fu, B.L.; Chen, J.J.; He, W. Impacts of land use change on ecosystem service value in Lijiang River Basin, China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 46100–46115. [CrossRef]
61. Ye, Y.Q.; Zhang, J.E.; Wang, T.; Bai, H.; Wang, X.; Zhao, W. Changes in Land-Use and Ecosystem Service Value in Guangdong Province, Southern China, from 1990 to 2018. *Land* **2021**, *10*, 426. [CrossRef]
62. Tan, L.; Yang, B.; Xue, Z.B.; Wang, Z.Q. Assessing Heavy Metal Contamination Risk in Soil and Water in the Core Water Source Area of the Middle Route of the South-to-North Water Diversion Project, China. *Land* **2021**, *10*, 934. [CrossRef]
63. Gao, W.; Zeng, Y.; Zhao, D.; Wu, B.; Ren, Z. Land Cover Changes and Drivers in the Water Source Area of the Middle Route of the South-to-North Water Diversion Project in China from 2000 to 2015. *Chin. Geogr. Sci.* **2020**, *30*, 115–126. [CrossRef]
64. Hu, B.A.; Kang, F.F.; Han, H.R.; Cheng, X.Q.; Li, Z.Z. Exploring drivers of ecosystem services variation from a geospatial perspective: Insights from China's Shanxi Province. *Ecol. Indic.* **2021**, *131*, 108188. [CrossRef]
65. Luo, Y.; Lu, Y.H.; Fu, B.J.; Zhang, Q.J.; Li, T.; Hu, W.Y.; Comber, A. Half century change of interactions among ecosystem services driven by ecological restoration: Quantification and policy implications at a watershed scale in the Chinese Loess Plateau. *Sci. Total Environ.* **2019**, *651*, 2546–2557. [CrossRef] [PubMed]
66. Zhang, Z.M.; Gao, J.F.; Fan, X.Y.; Lan, Y.; Zhao, M.S. Response of ecosystem services to socioeconomic development in the Yangtze River Basin, China. *Ecol. Indic.* **2017**, *72*, 481–493. [CrossRef]

67. Li, W.S.; Wang, L.Q.; Yang, X.; Liang, T.; Zhang, Q.; Liao, X.Y.; White, J.R.; Rinklebe, J. Interactive influences of meteorological and socioeconomic factors on ecosystem service values in a river basin with different geomorphic features. *Sci. Total Environ.* **2022**, *829*, 154595. [CrossRef]
68. Zhang, Z.P.; Xia, F.Q.; Yang, D.G.; Huo, J.W.; Wang, G.L.; Chen, H.X. Spatiotemporal characteristics in ecosystem service value and its interaction with human activities in Xinjiang, China. *Ecol. Indic.* **2020**, *110*, 105826. [CrossRef]
69. Guo, P.F.; Zhang, F.F.; Wang, H.Y. The response of ecosystem service value to land use change in the middle and lower Yellow River: A case study of the Henan section. *Ecol. Indic.* **2022**, *140*, 109019. [CrossRef]
70. Long, H.L.; Liu, Y.Q.; Hou, X.G.; Li, T.T.; Li, Y.R. Effects of land use transitions due to rapid urbanization on ecosystem services: Implications for urban planning in the new developing area of China. *Habitat Int.* **2014**, *44*, 536–544. [CrossRef]
71. Du, X.J.; Huang, Z.H. Ecological and environmental effects of land use change in rapid urbanization: The case of hangzhou, China. *Ecol. Indic.* **2017**, *81*, 243–251. [CrossRef]
72. Hou, J.; Qin, T.L.; Liu, S.S.; Wang, J.W.; Dong, B.Q.; Yan, S.; Nie, H.J. Analysis and Prediction of Ecosystem Service Values Based on Land Use/Cover Change in the Yiluo River Basin. *Sustainability* **2021**, *13*, 6432. [CrossRef]
73. Luo, Q.; Luo, L.; Zhou, Q.; Song, Y. Does China's Yangtze River Economic Belt policy impact on local ecosystem services? *Sci. Total Environ.* **2019**, *676*, 231–241. [CrossRef]
74. Shen, J.S.; Li, S.C.; Liu, L.B.; Liang, Z.; Wang, Y.Y.; Wang, H.; Wu, S.Y. Uncovering the relationships between ecosystem services and social- ecological drivers at different spatial scales in the Beijing-Tianjin- Hebei region. *J. Clean. Prod.* **2021**, *290*, 125193. [CrossRef]
75. Tran, D.X.; Pla, F.; Latorre-Carmona, P.; Myint, S.W.; Gaetano, M.; Kieu, H.V. Characterizing the relationship between land use land cover change and land surface temperature. *ISPRS J. Photogramm. Remote Sens.* **2017**, *124*, 119–132. [CrossRef]

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Is There a Spatial Relationship between Urban Landscape Pattern and Habitat Quality? Implication for Landscape Planning of the Yellow River Basin

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Abstract: The extent to which landscape spatial patterns can impact the dynamics and distribution of biodiversity is a key geography and ecology issue. However, few previous studies have quantitatively analyzed the spatial relationship between the landscape pattern and habitat quality from a simulation perspective. In this study, the landscape pattern in 2031 was simulated using a patch-generating simulation (PLUS) model for the Yellow River Basin. Then, the landscape pattern index and habitat quality from 2005 to 2031 were evaluated using the Fragstats 4.2 and the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model. Furthermore, we analyzed the spatial distribution characteristics and spatial spillover effects of habitat quality using spatial autocorrelation analysis. Finally, the spatial association between the landscape pattern index and habitat quality was quantitatively revealed based on a spatial lag model. The simulation results showed that: (1) from 2005 to 2031, the landscape of the Yellow River Basin would be dominated by grassland and unused land, and the areas of construction land and water body will increase significantly, while the area of grassland will decrease; (2) patch density (PD) and Shannon's diversity index (SHDI) show significant increases, while edge density (ED), landscape shape index (LSI), mean patch area (AREA_MN), and contagion index (CONTAG) decrease; (3) from 2005 to 2031, habitat quality would decrease. The high-value areas of habitat quality are mainly distributed in the upper reaches of the Yellow River Basin, and the low-value areas are distributed in the lower reaches. Meanwhile, both habitat quality and its change rate present positive spatial autocorrelation; and (4) the spatial relationships of habitat quality with PD and COHESION are negative, while ED and LSI have positive impacts on habitat quality. Specifically, landscape fragmentation caused by high PD has a dominant negative influence on habitat quality. Therefore, this study can help decision makers manage future landscape patterns and develop ecological conservation policy in the Yellow River Basin.

Keywords: land-use simulation; landscape pattern; habitat quality; spatial autocorrelation; spatial regression; Yellow River Basin

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1. Introduction

Land-use/cover change (LUCC) resulting from the interaction between human activities and the natural environment on temporal-spatial scales is directly expressed in the form of changes in surface landscape patterns [1]. Landscape patterns are defined as the spatial composition and configuration of land use. However, the rapid growth of industrialization and urbanization has intensified changes in land use and ecological issues, such as landscape fragmentation, occupation of natural habitat, environmental pollution, and loss of biodiversity [2], leading to a drastic reduction in habitat quality [3]. Habitat quality refers to the ability of the environment to provide conditions for human sustainable development and is an important support for species diversity and reproduction [4,5]. Numerous studies have shown that landscape pattern changes have a strong effect on habitat quality [6–9]. For example, landscape continuity, which is important for species to exchange materials, information, and energy flows, can lead to an increase in habitat quality. The increase in patches leads to landscape fragmentation, which is detrimental to animal migration and plant pollen dispersal and leads to a decrease in habitat quality. Most studies have utilized only the traditional linear equation approach to examine the influences of landscape pattern changes on regional habitat quality [10], ignoring the spatial autocorrelation and spatial spillover properties of habitat quality. However, spatial regression models are able to solve this problem, which can quantitatively analyze the spatial relationship between habitat quality and landscape pattern by considering spatial autocorrelation. The Yellow River Basin, an important ecological barrier in China's ecological security strategy pattern, plays an important role in biodiversity conservation and healthy ecosystem maintenance. However, rapid socioeconomic development has led to the expansion of construction land and the loss of natural habitats in the Yellow River Basin. Therefore, it is necessary to simulate landscape patterns and analyze the spatiotemporal characteristics of habitat quality. More importantly, quantitative analysis of the spatial relationship between habitat quality and landscape patterns is of great importance for maintaining biodiversity and promoting sustainable development.

In recent years, many assessment methods have been applied to evaluate habitat quality, such Social Values for Ecosystem Services (SolVES), ARtificial Intelligence for Ecosystem Services (ARIES), Multi-scale Integrated Models of Ecosystem Services (MIMES), and Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) [11–15]. Among these models, the InVEST model is becoming a popular tool because it is more mature and easier to operate [16]. For example, Moreira et al. [17] adopted the InVEST model to assess the conservation status of Azorean natural habitats. Nematollahi et al. [18] evaluated the roads' effects on the natural habitats of wild sheep based on the InVEST habitat quality module. Hack et al. [19] used the InVEST model to evaluate the impacts of built-up areas, roads, and water pollution on habitat quality. To conclude, the InVEST model can be applied to evaluate habitat quality in combination with habitat suitability and human activities and provides more detailed information about biodiversity [13,20]. Thus, the InVEST model is used in this study to evaluate the habitat quality of the Yellow River Basin.

Meanwhile, landscape patterns and biodiversity conservation have become one of the most popular issues in landscape ecology. The correlation of land use, landscape patterns, and ecosystems has drawn the attention of international scholars [21]. For example, Zhu et al. [22] used gray correlation analysis to explore the correlation between habitat quality and landscape pattern indexes in the eastern Qinghai-Tibet Plateau. Wu et al. [23] used Pearson's correlation analysis methods to investigate the influential factors of habitat quality and showed that vegetation cover, intensity of human activity, and land-use change can cause a decline in habitat quality. Yushanjiang et al. [24] found that landscape pattern indexes were positively and negatively correlated with the ecosystem value in the Ebinur Lake Basin by using multiple linear regression models. However, most studies have ignored the spatial spillover effects of ecosystems, which are influenced not only by their own unit but also by the habitat quality of neighboring units. This will reduce the validity of conclusions. Noteworthy to mention is that most recent studies have begun to explore the spatial association between landscape patterns and ecosystems [1]. For instance, Zhu et al. [25] explored the effects of urbanization and landscape pattern changes on habitat quality in Hangzhou by using ordinary least squares (OLS) and geographically weighted regression (GWR) models. Chen et al. [26] used a multiscale spatial panel regression analysis approach to explore the impact of landscape patterns on ecosystem services. Thus, research on the mechanism of landscape pattern influence on habitat quality is gradually shifting from traditional linear correlation analysis or regressions to spatial econometric models. Quantitative analyses of the spatial association between landscape pattern and habitat quality can help to better understand the impact of changes in landscape pattern on habitat quality.

The abovementioned studies are very important guidelines for advancing habitat quality research, but they are all from the perspective of the past to analyze the spatiotemporal characteristics of habitat quality in the region. There is a growing need to explore the evolution of habitat quality from a simulation perspective, which can provide insights for ecological conservation planning and sustainable development. Cellular automata (CA) is the basis of many land-use simulation models. Researchers have proposed constrained CA, CA-Markov, the Conversion of Land Use and its Effects at Small regional extent (CLUE-S), and Future Land-Use Simulation (FLUS) models by improving the algorithms and techniques of CA and used these methods to predict habitat quality in the future. For example, Ding et al. [27] used the FLUS model to assess habitat quality changes in Dongying city in 2030 under multiple scenarios. Gomes et al. [28] simulated land use and habitat quality by using CA in Lithuania. Tang et al. [29] combined the CA-Markov and CLUE-S models to predict the evolution of habitat quality in Changli city. Li et al. [30] simulated urban growth and integrated habitat quality by using the SLEUTH model. However, most of the models were simulated based on each meta-cell scale and lacked the ability to simulate the evolution of patches with multiple land-use types. In this study, a patch-generating simulation (PLUS) model developed by Liang et al. [31] is adopted to simulate landscape pattern change. Compared with other CA-based models, PLUS has higher simulation accuracy and more realistic indicators of landscape patterns, which could provide more accurate quantitative assessment of the impact of landscape pattern on habitat quality.

The Yellow River Basin has been an important part of achieving balanced east-west and north-south development in China and plays an irreplaceable role in overall ecosystem health and biodiversity conservation in China. In the context of ecological protection and high-quality development, the evolution characteristics and spatial relationships of the landscape pattern and habitat quality in Yellow River Basin deserve unprecedented attention. Therefore, taking the Yellow River Basin as an example, this study quantitatively analyzes the spatial relationship between landscape pattern and habitat quality using a simulation approach to (1) simulate the future land use of Yellow River Basin based on the PLUS model and analyze the dynamic changes of the landscape pattern; (2) assess the spatiotemporal characteristics of habitat quality in Yellow River Basin using the InVEST model; (3) identify the spatial clusters of habitat quality and its rate of change from 2005 to 2031 based on univariate spatial autocorrelation; and (4) quantitatively evaluate the effect of the landscape pattern index on habitat quality based on the spatial lag model.

2. Materials and Methods

2.1. Study Area

The Yellow River flows through nine provinces (i.e., Qinghai, Sichuan, Ningxia, Gansu, Shaanxi, Shanxi, Inner Mongolia, Henan, and Shandong). Eight of them are included in the boundary of the Yellow River Basin in this study (Figure 1), with Sichuan being excluded. Sichuan is often considered a part of the Yangtze River Economic Belt [32,33]. Generally, the Yellow River Basin has a high topography in the west and a low one in the east, with an average annual precipitation of 200–650 mm. The average altitude of the western headwaters region is above 4000 m, and the altitude of the central region is between 1000–2000 m. The Yellow River Basin is an important population catchment area and ecological security barrier in China. With abundant mineral and energy resources, the Yellow River Basin is one of the key areas of China's socioeconomic development. It also serves as an ecological corridor that connects the Qinghai-Tibet Plateau, Loess Plateau, and North China Plain. Wetland resources are abundant, and species diversity is rich. There are also 12 national key ecological function areas in the region. Exploring the influences of landscape patterns on habitat quality is crucial for protecting biodiversity and improving the high-quality development level in Yellow River Basin.

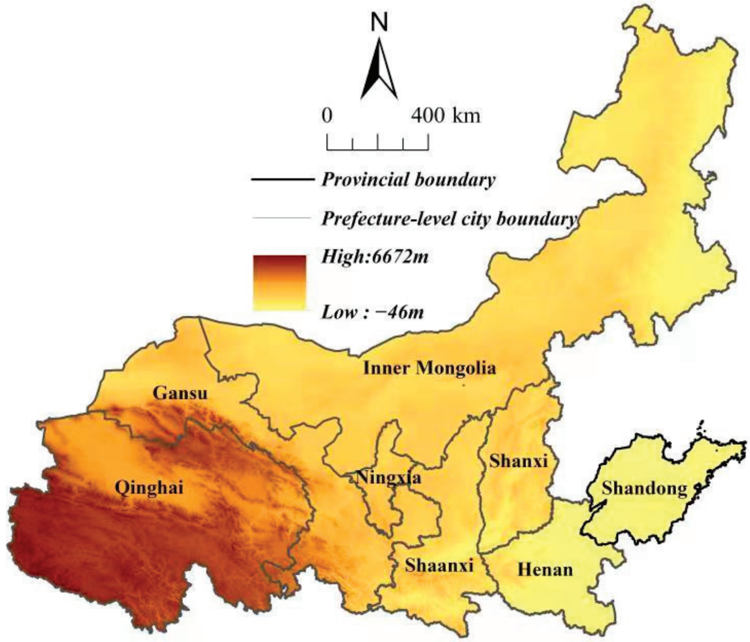

Figure 1. Location of the study area.

2.2. Data Source

The basic data of this study include land-use maps, population density, Gross Domestic Product (GDP), nighttime lights, Digital Elevation Model (DEM), slope, aspect, distance from railway, distance from highway, distance from county center, distance from provincial government, precipitation, temperature, soil type, and Normalized Difference Vegetation Index (NDVI) (Table 1). The land-use data were obtained from the Chinese Academy of Sciences Data Center for Resources and Environmental Sciences (http://www.resdc.cn/, accessed on 12 May 2022), which were generated through remote sensing interpretation and manual visual interpretation from Landsat remote sensing images with an accuracy of 30 m. The landscape was classified into six land-use types, including cultivated land, forest, grassland, water body, construction land, and unused land. The DEM was obtained from the Geospatial Data Cloud platform (http://www.gscloud.cn/, accessed on 12 May 2022) and further used to derive the slope and aspect using the 3D Analyst tool in ArcGIS 10.2. Other data were obtained from the China Statistical Yearbook and the Resource and Chinese Academy of Sciences Data Center for Resources and Environmental Sciences, and all data were extracted as a 1000 × 1000 m raster dataset by using ArcGIS 10.2.

2.3. Methods

2.3.1. Future LUCC Simulation Based on the PLUS Model

The PLUS model is a cutting-edge land-use simulation tool developed by Liang et al. in 2020 that includes two modules: the transformed rule mining framework (LEAS) based on a land expansion analysis strategy and the CA model (CARS) based on a multitype stochastic patch seeding mechanism [31]. It adopts the artificial neural network (ANN) algorithm to integrate natural and socioeconomic driving factors and simulate the suitability probability of each land-use type by combining the base period land-use data. Then, it uses the adaptive inertia competition mechanism based on roulette selection to solve the uncertainty and complexity of the interconversion of each type under the synergistic effects of natural and socioeconomic factors. The land-use demand, neighborhood factor, and conversion cost are set to simulate the land use at a future time point. The LUCC simulation based on the PLUS model involved five major steps.

Table 1. Data information and sources.

Data Type	Data Name	Data Source and Preprocessing
Land-use data	Basic land-use data at 30 m (2005) Basic land-use data at 30 m (2018)	Chinese Academy of Sciences Data Center for Resources and Environmental Sciences (http://www.resdc.cn, accessed on 12 May 2022)
Driving factors Of LUCC	Spatial distribution of population density Spatial distribution of GDP Nighttime light Rainfall Temperature Soil type NDVI	
	DEM	Geospatial Data Cloud (http://www.gscloud.cn/, accessed on 12 May 2022)
	Slope Aspect	Extract from DEM by Using ArcGIS 10.2
	Distance to railway Distance to highway Distance to provincial governments Distance to prefectural governments	Extract by using ArcGIS Euclidean distance function

1. Selection of driving factors for LUCC. The landscape pattern of the Yellow River Basin is affected not only by natural factors but also by socioeconomic and spatial location factors [34–36]. Considering the availability, diversity, and representativeness of the data, 14 driving factors were finally selected in this study, including rainfall, temperature, elevation, slope, aspect, population density, GDP density, nighttime light, soil type, NDVI, and distances to provincial governments, prefectural governments, railways, and highways.
2. Cost matrix and setting of restricted expansion areas. The cost matrix can be used to represent the cost of conversion between different land-use types (see Table S1 in Supplementary Materials). A value of 0 indicates that this land-use conversion is not allowed, while 1 means it is allowed [37]. In this study, the cost matrix and the restricted expansion area were set based on previous studies and realistic conditions. In reality, construction land is rarely converted to other land-use types. Therefore, this study assumes that the conversion of construction land to other land-use types is not allowed. To ensure food security, this study prohibits the conversion of cultivated land to unused land. To promote ecological protection, the 1000 m buffer zone along the main stream of the Yellow River was set as a restricted expansion area, and conversion of landscape types in this area was prohibited.
3. Setting of neighborhood weight parameters. The neighborhood weight parameter indicates the expansion intensity of each land-use type. The parameter ranges from 0 to 1, where values closer to 1 have stronger expansion abilities. In this study, the expansion intensity of each land-use type was determined based on the experience of existing studies and the characteristics of landscape evolution in the Yellow River Basin (see Table S2 in Supplementary Materials).
4. Land-use demand prediction. This study used Markov models to predict the land-use structure in 2031 based on the probability matrix of land-use changes from 2005–2018 and the current land-use development patterns in the Yellow River Basin.
5. Model validation. Based on the land-use data in 2005, we simulated the land use of the Yellow River Basin in 2018 using the model parameters specified above and compared it with the classified land-use map in 2018 from Landsat remote sensing images. The kappa coefficient and figure of merit (FoM) were used to verify the simulation accuracy. The validation results showed that the kappa coefficient and FOM were 0.84 and 0.28, respectively. The simulation accuracy achieved a high level, which indicated that the PLUS model is reliable for future land-use simulations in 2031.

2.3.2. Landscape Pattern Indexes Analysis

The landscape pattern index is an important tool to analyze the spatiotemporal characteristics of landscape patterns by reflecting the composition and spatial configuration of the landscape structure and the evolution of landscape patterns. The study selects landscape pattern indexes based on the diversity, aggregation, and complexity of the landscape space. The selected landscape pattern indexes are patch density (PD), mean patch area (AREA_MN), edge density (ED), landscape shape index (LSI), Shannon's diversity index (SHDI), patch cohesion index (COHESION), and contagion index (CONTAG) [38]. The specific calculation was performed by using Fragstats 4.2 software.

2.3.3. Habitat Quality Evaluation

Stable habitat quality is a crucial basis for sustaining ecosystem biodiversity. In this study, the habitat quality module of the InVEST model was adopted to evaluate habitat quality [39,40]. As the researchers have established, higher levels of land use and socioeconomic activity pose greater threat to habitat conservation and are correlated with lower-quality habitat and vice versa [41]. The model combines the sensitivity of different land-use types to threat factors and with intensity of external threats. Specifically, cultivated land, construction land, and unused land are identified as the threat factors of habitat quality in this study. The model parameters, including the maximum stress distance, weight, type of spatial recession, and sensitivity of LUCC to habitat threat factors, are specified according to the model's manual and expert experience (Table 2) [42,43].

Table 2. Input data used for InVEST model.

Threat Factors	Maximum Duress Distance (km)	Weights	Land-Use Types					
			Cultivated Land	Forest	Grassland	Water Body	Construction Land	Unused Land
			Habitat suitability					
			0.3	1	1	0.7	0.3	0.6
			Threat factors					
Cultivated land	4	0.6	0	0.6	0.8	0.5	0	0.6
Construction land	8	0.4	0.8	0.4	0.6	0.4	0	0.4
Unused land	6	0.5	0.4	0.2	0.6	0.2	0.1	0

The change rate in habitat quality is measured by the percentage change in regional habitat quality at the beginning and the end of a time period, expressed as follows:

$$V = (P_{t1} - P_{t0})/P_{t0} \times 100\% \quad (1)$$

In Equation (1), V is the change rate of habitat quality, with a negative value indicating decreasing habitat quality and vice versa; P_{t0} and P_{t1} are the initial and final values of habitat quality in the *t*-th year, respectively.

2.3.4. Spatial Autocorrelation Analysis

A spatial autocorrelation approach was used to verify the spatial dependence and spatial spillover effects of habitat quality [44]. Univariate spatial autocorrelation analysis includes global and local autocorrelation analysis [45]. Moran's I has been widely used for representing global autocorrelation, i.e., the overall clustering pattern. The value of Moran's I ranges from −1 to 1. A higher Moran's I value suggests a more significant positive spatial autocorrelation of habitat quality. To explore the local spatial association and type of spatial clusters of habitat quality in different prefecture-level cities, we used the local indicator of spatial association (LISA) [46]. In addition, the spatial clusters of habitat quality in this study were classified into four types, i.e., high-high (H-H), low-low (L-L), high-low (H-L), and low-high (L-H). Specifically, the H-H clusters mean that the prefecture-level city and its neighbors all had a high habitat quality that was higher than the average In the Yellow River Basin. The L-L clusters indicate that the prefecture-level city and its neighbors had a low habitat quality that was lower than the average. The H-L clusters indicate that the prefecture-level city and its neighbors had negative spatial autocorrelation of habitat quality. That is, the prefecture-level cities with high habitat quality were surrounded by the prefecture-level cities with low habitat quality and vice versa for the L-H clusters. Thus, the H-H clusters and L-L clusters indicated that the habitat quality of the area was similar to that of its neighbors. The formulas for global Moran's I and local Moran's I are shown as follows:

$$I = \frac{\sum_{P=1}^{K} \sum_{q=1}^{k} W_{pq} \left(Y_P - \overline{Y}\right)\left(Y_q - \overline{Y}\right)}{S^2 \sum_{p=1}^{k} \sum_{q=1}^{k} W_{pq}} \tag{2}$$

$$I_p = \frac{Y_p - \overline{Y}}{S^2} \sum_{q=1}^{k} W_{pq}\left(Y_p - \overline{Y}\right) \tag{3}$$

In Equations (2) and (3), I is the global Moran's I for the whole area, and its value ranges from -1 to 1; I_p is the local Moran's I for prefecture-level city p; Y_p and Y_q are the habitat quality of prefecture-level cities p and q; S^2 is the discrete variance of Y_q; $\overline{Y}$ is the average value of habitat quality; k is the number of prefecture-level cities; W_{pq} is the spatial weight matrix, representing that prefecture-level city p is adjacent to prefecture-level city q, and the value of W_{pq} is 1 if they are adjacent and otherwise 0.

2.3.5. Spatial Regression Analysis

The spatial lag model (SLM) and spatial error model (SEM) are usually used for spatial regression analysis [47,48]. To determine whether SLM or SEM is more appropriate in this study, we used a Lagrange multiplier (LM) test and a robust Lagrange multiplier (RLM) test to verify by using OLS [45]. We found that both LM (lag) and its RLM (lag) are more significant than LM (error) and its RLM (error). Thus, we selected SLM to quantitatively analyze the influence of the landscape pattern indexes on habitat quality in this study. The OLS can be defined as follows:

$$Q_{pt} = \beta L_t + \varepsilon \tag{4}$$

The SLM can be defined as follows:

$$Q_{pt} = \rho \varpi_1 Q_{pt} + \beta L_t + \varepsilon \tag{5}$$

The SEM can be defined as follows:

$$Q_{pt} = \beta L_t + \gamma \varpi_2 + \varepsilon \tag{6}$$

In Equations (4)–(6), Q_{pt} is the habitat quality in prefecture-level city p in the t-th year; ρ, γ is the spatial lag parameter and spatial error parameter; ϖ_1, ϖ_2 is the spatial weight matrix of the lag terms and error terms, respectively; β is the parameter revealing the correlations between habitat quality and landscape pattern indexes; L_t is the landscape pattern index in the t-th year; and ε is a constant.

3. Results

3.1. Spatiotemporal Characteristics of Landscape Patterns from 2005 to 2031

3.1.1. Predicted Land-Use Changes

The simulated land-use pattern of the Yellow River Basin in 2031 using the PLUS model is shown in Figure 2. Landscape change in the Yellow River Basin slows down from 2018 to 2031 compared to 2005–2018 (Table 3). The main landscape types in the Yellow River Basin were grassland and unused land, while construction land and water bodies accounted for the smallest proportion. From 2005 to 2031, landscape changes are mainly characterized by the transformation of cultivated land and grassland into construction land and forest. Specifically, from 2005 to 2018, the areas of cultivated land and grassland decreased, and the highest reduction by 3.10% was observed in grassland. Construction land, forest, water bodies, and unused land were all expanding, with construction land increasing by 37.48%. The predicted trend of landscape change from 2018 to 2031 is similar to that in 2005–2018, with the area of cultivated land and grassland showing a decreasing trend and the area of construction land, forest, water body, and unused land showing an increasing trend.

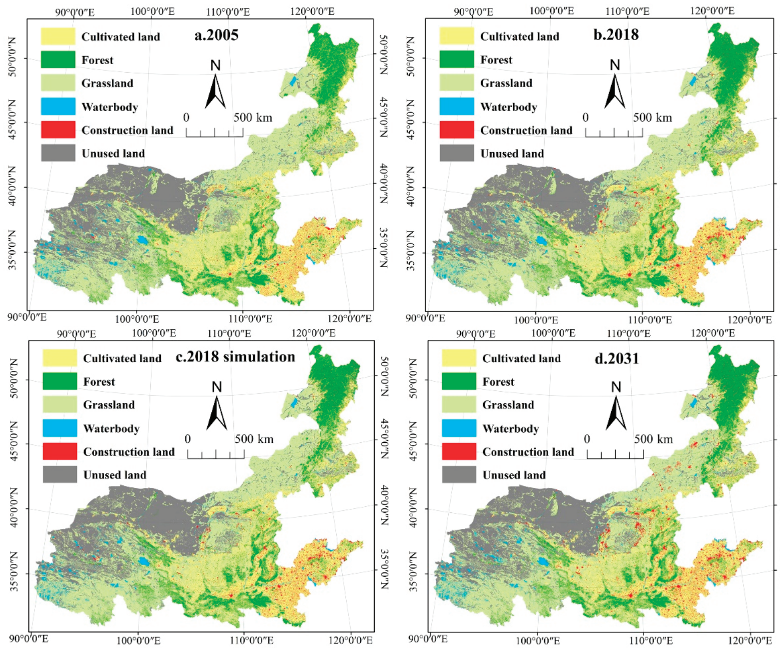

Figure 2. The land-use simulation map of the Yellow River Basin. (**a**). 2005 represents the land use of the Yellow River Basin in 2005; (**b**). 2018 represents the land use of the Yellow River Basin in 2018; (**c**). 2018 simulation represents the simulated land use of the Yellow River Basin in 2018; (**d**). 2031 represents the simulated land use of the Yellow River Basin in 2031.

Table 3. Landscape type structure of the Yellow River Basin from 2005 to 2031 (unit: 10^4 km^2).

Time	Cultivated Land	Forest	Grassland	Water Body	Construction Land	Unused Land
2005	54.46	36.17	120.79	5.84	6.43	75.50
2018	53.88	37.29	117.05	6.42	8.84	75.71
2031	53.75	38.17	113.89	6.94	10.64	75.79
2005–2018	−0.58	1.12	−3.74	0.58	2.41	0.21
2005–2018	−1.07%	3.10%	−3.10%	9.93%	37.48%	0.28%
2018–2031	−0.13	0.88	−3.16	0.53	1.80	0.08
2018–2031	−0.24%	2.36%	−2.70%	8.26%	20.36%	0.11%

3.1.2. Landscape Pattern Metrics

The landscape pattern indexes in the Yellow River Basin show different change trends from 2005 to 2031 (Table 4). In particular, the PD and SHDI increase continuously by 3.23% and 3.76%, respectively, from 2005 to 2031, indicating that the landscape in the Yellow River Basin would become more fragmented. In contrast, the AREA_MN and CONTAG decrease by 3.17% and 6.94%, respectively, which also demonstrates that the landscape would be more heterogenous. According to AREA_MN, the average size of patches within the landscape becomes smaller, indicating increasing fragmentation. The CONTAG index is used to describe the degree of clustering or extension trend of different patch types within the landscape. The reduction of CONTAG indicates that the number of patches with a certain dominant type of connectivity in the landscape is decreasing, and thus, the fragmentation of the landscape is growing. Meanwhile, the ED and LSI indexes slightly decrease by 0.55% and 0.48%, respectively, from 2005 to 2031. The decrease of ED and LSI indicates patches within the landscape are becoming more spatially aggregated. However, the ED and LSI increase from 2018 to 2031, reflecting the trend towards fragmentation and complexity of the landscape pattern change. In addition, the COHESION remains basically unchanged from 2005 to 2031.

Table 4. Landscape pattern indexes of Yellow River Basin.

Landscape Pattern Indexes	2005	2018	2031	2005–2018	2018–2031	2005–2031
PD	0.0526	0.0535	0.0543	1.71%	1.50%	3.23%
ED	5.8669	5.7729	5.8346	−1.60%	1.07%	−0.55%
LSI	257.6114	253.6939	256.3796	−1.52%	1.06%	−0.48%
AREA_MN	1902.8027	1869.4666	1842.4869	−1.75%	−1.44%	−3.17%
CONTAG	34.7186	33.3331	32.3093	−3.99%	−3.07%	−6.94%
COHESION	99.6430	99.6361	99.6225	−0.01%	−0.01%	−0.02%
SHDI	1.4385	1.4696	1.4926	2.16%	1.57%	3.76%

From the perspective of landscape types (see Table S3 in Supplementary Materials), the LSI and PD of construction land, water bodies, unused land, and cultivated land show increasing trends, while the LSI and PD of grassland and forest generally decrease. There were no significant changes in the ED of cultivated land and forestland. The ED of water bodies, construction land, and unused land significantly increases, and the ED of grassland decreases. The AREA_MN and COHESION of water bodies, construction land, and forest increase significantly, and that of grassland and unused land does not change significantly.

3.2. Spatiotemporal Characteristics of Habitat Quality from 2005 to 2031

3.2.1. Temporal Changes of Habitat Quality

Results indicate that the habitat quality in the Yellow River Basin displays a declining tendency from 2005 to 2031. The average habitat quality in the Yellow River Basin decreases by 0.98% and 1.05% from 2005 to 2018 and 2018 to 2031, respectively. From the perspective of landscape types (Table 5), the average habitat quality of forest and construction land remains stable, the average habitat quality of water body and grassland increased, and grassland has the largest increase, with a specific increase of 0.05%. The average habitat quality is highest in forests and grasslands, followed by water bodies and unused lands, and lowest in cultivated land and construction land, which is mainly because of the high habitat suitability of forests, grasslands, and water bodies, which are far from threat sources. Therefore, natural vegetation (i.e., forest, grassland, etc.) plays a vital role in maintaining the habitat quality of the Yellow River Basin.

Table 5. Average habitat quality of landscape types in the Yellow River Basin from 2005–2031.

Landscape Types	2005	2018	2031	Average
Cultivated land	0.2998	0.2997	0.2997	0.2997
Forest	0.9960	0.9960	0.9960	0.9960
Grassland	0.9881	0.9887	0.9886	0.9885
Water body	0.6943	0.6944	0.6947	0.6945
Construction land	0.0000	0.0000	0.0000	0.0000
Unused land	0.5997	0.5996	0.5996	0.5996
Yellow River Basin	0.7388	0.7315	0.7253	0.7319

3.2.2. Spatial Evolution of Habitat Quality

From 2005 to 2031, the spatial distribution pattern of habitat quality in the Yellow River Basin remains stable (Figure 3), and the overall habitat quality is high. In this study, habitat quality is classified as highest (0.8–1.0), high (0.6–0.8), medium (0.4–0.6), low (0.2–0.4), and lowest (0–0.2). Specifically, the highest-level and high-level habitat quality areas are mainly distributed in areas with high vegetation cover, such as the Qinghai-Tibet Plateau and northeastern Inner Mongolia. These areas are important ecological sources for maintaining regional ecological security, and urban expansion should be strictly limited. Medium-level habitat quality areas are concentrated in the Loess Plateau region represented by Ningxia, Gansu, and Shaanxi. Low-level and lowest-level habitat quality areas are mainly distributed in Henan, Shandong, and other provinces downstream of the Yellow River Basin and present a clustered pattern. These areas are the main distribution areas of cultivated land and towns and are also the areas with the highest intensity of human activities in the Yellow River Basin. The contradiction between socioeconomic development and ecological protection is prominent here, and urban development has already produced a strong duress on the surrounding habitats. Therefore, excessive growth of urban space in the future should be limited, especially excessive occupation of ecological land.

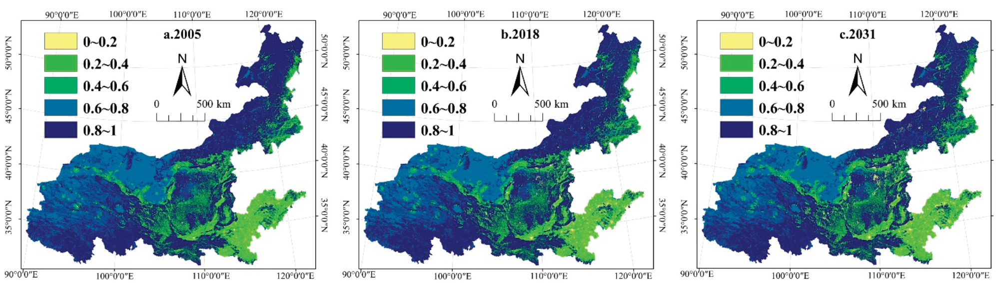

Figure 3. Distribution of habitat quality. (**a**). 2005 represents the habitat quality of the Yellow River Basin in 2005; (**b**). 2018 represents the habitat quality of the Yellow River Basin in 2018; (**c**). 2031 represents the habitat quality of the Yellow River Basin in 2031.

3.3. Spatial Clustering Characteristics and Spatial Relationships

3.3.1. Univariate Spatial Autocorrelation Analysis

(1) Spatial autocorrelation of habitat quality

To analyze the spatial distribution characteristics and spatial spillover effects of habitat quality in the Yellow River Basin, spatial autocorrelation analysis was performed for the habitat quality by using prefecture-level cities as units of analysis. The global Moran's I values of each city in 2005, 2018, and 2031 are greater than 0.82 (0.8217, 0.8322, and 0.8248, respectively), and the p-values are less than or equal to 0.001, indicating that the spatial distribution of habitat quality in the Yellow River Basin exhibits significant positive spatial autocorrelations. In addition, according to the results of local spatial autocorrelation (Figure 4), habitat quality shows a clear bipolar clustering feature in space (i.e., high-high clusters and low-low clusters). The spatial clustering characteristics of habitat quality are similar in 2005, 2018, and 2031. The high-high clusters of habitat quality in the Yellow River Basin are concentrated in the Qinghai-Tibet Plateau, the southern Loess Plateau, and western and eastern Inner Mongolia. The low-low clusters of habitat quality are concentrated in Henan and Shandong in the lower reaches of the Yellow River Basin.

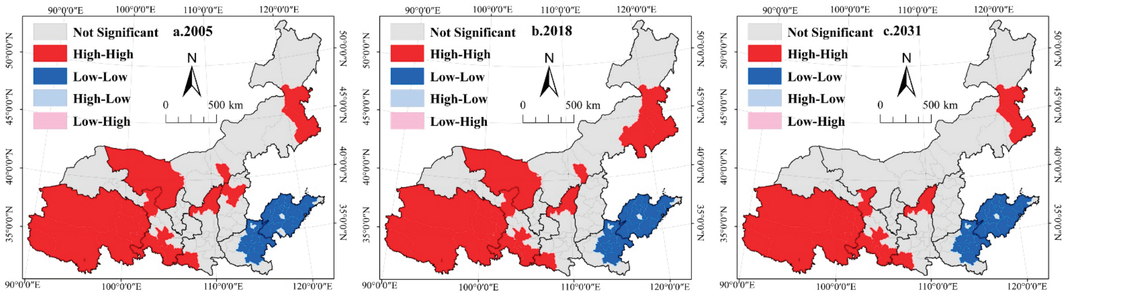

Figure 4. LISA cluster map of habitat quality in the Yellow River Basin. (**a**). 2005 represents the LISA cluster map of habitat quality of the Yellow River Basin in 2005; (**b**). 2018 represents the LISA cluster map of habitat quality of the Yellow River Basin in 2018; (**c**). 2031 represents the LISA cluster map of habitat quality of the Yellow River Basin in 2031.

(2) Spatial autocorrelation of the rate of change in habitat quality

According to the global spatial autocorrelation analysis of the rate of change in habitat quality, the global Moran's I values are 0.4280 and 0.3764 from 2005 to 2018 and 2018 to 2031, respectively. The results show that the spatial distribution of the rate of change in habitat quality in Yellow River Basin presents significant positive spatial autocorrelations from 2018 to 2031 (Figure 5). The H-H clusters of the rate of change in habitat quality in the Yellow River Basin are mainly concentrated in the plateau areas from 2005 to 2031. This result indicates that there is a significant improvement in habitat quality in the plateau region during this period. From 2005–2018, the H-H agglomeration areas of the rate of change in habitat quality are mainly distributed in most areas of Qinghai province and parts of Gansu and Shaanxi provinces. The L-L agglomeration areas of the rate of change in habitat quality are distributed in Shandong and parts of Henan, and there are no areas of H-L clusters. From 2018 to 2031, the H-H agglomeration areas of the rate of change in habitat quality are mainly distributed in most areas of Qinghai, the eastern part of Inner Mongolia, and parts of Gansu and Shaanxi provinces. The L-L agglomeration areas of the rate of change in habitat quality are distributed in Shandong and parts of Henan. The L-H agglomeration areas of the rate of change in habitat quality are distributed in the western part of Inner Mongolia. The H-L agglomeration areas of the rate of change in habitat quality are distributed in the eastern part of Inner Mongolia. From 2005 to 2018, the spatial aggregation characteristics of high or low values of the rate of change in habitat quality in the Yellow River Basin are closely related to human activities, land-use policies, and ecosystem protection engineering projects. From 2018 to 2031, the spatial aggregation characteristics of habitat quality change rates are also influenced by the specification of cost matrix and restricted areas in the land-use simulation. The results can provide data support for biodiversity conservation and ecological priority area setting in the Yellow River Basin.

3.3.2. Spatial Regression Analysis

The above analysis confirmed the spatial autocorrelation of habitat quality. Therefore, we can further explore the spatial spillover effect of habitat quality and its influential factors by using a spatial regression model. In this study, the habitat quality of 95 prefecture-level cities in the Yellow River Basin was included in the model as the dependent variable, while the independent variables in the model were the landscape pattern indexes. In addition, multicollinearity diagnosis of landscape pattern indexes was used to eliminate the presence of multicollinearity in multiple landscape pattern indexes by using IBM SPSS Statistics. Four factors with VIF < 8 were selected as independent variables of the model: PD, ED, LSI, and COHESION.

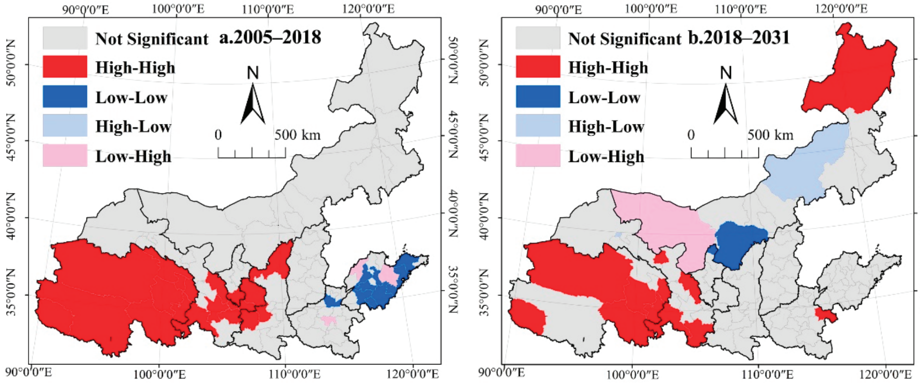

Figure 5. LISA cluster map of the rate of habitat quality change in the Yellow River Basin. (**a**). 2005–2018 represents the LISA cluster map of the rate of habitat quality change in the Yellow River Basin in 2005–2018; (**b**). 2018–2031 represents the LISA cluster map of the rate of habitat quality change in the Yellow River Basin in 2018–2031.

As can be seen, the log likelihood of the spatial lag model is larger than that of the OLS model (AIC and SC values are smaller than those of the OLS model) (see Table S4 in Supplementary Materials), which indicates that the fitting degree of the spatial lag model is better than that of the OLS model. Almost all the independent variables in the spatial lag model (Table 6) are significant ($p < 0.05$) from 2005 to 2031. The spatial lag regression results demonstrate that the spatial relationships between habitat quality and PD as well as COHESION are negative, while ED and LSI had a positive impact on habitat quality. Meanwhile, a 1% increase in PD led to decreases of 4.622%, 3.926%, and 4.041% in habitat quality in 2005, 2018, and 2031, respectively. The impact of ED is positive, but its effect size decays over time, as a 1% increase in ED can lead to increases of 0.031%, 0.036%, and 0.002% in habitat quality in 2005, 2018, and 2031, respectively. The impact of LSI fluctuates over time and increases substantially from 2018 to 2031, e.g., a 1% increase in LSI can lead to increases of 0.005%, 0.003%, and 0.038% in habitat quality in 2005, 2018, and 2031, respectively. In addition, the impact of COHESION on habitat quality is negative and decreases over time. The results show that PD is the dominant driving factor of the decrease in habitat quality with the largest magnitude of effect. As displayed in Table 6, the PD increases during the study period, demonstrating that the landscape in the Yellow River Basin would become more fragmented. Specifically, the PD of water bodies and cultivated land increases. Therefore, landscape fragmentation due to higher PD has a strong influence on ecosystem structure, ecological processes, and biodiversity and causes degradation of habitat quality.

Table 6. Regression results of SLM.

Variable	2005		2018		2031	
	Habitat Quality	p	Habitat Quality	p	Habitat Quality	p
PD	−4.6219 ***	0.0000	−3.9258 ***	0.0000	−4.0412 ***	0.0000
ED	0.0313 ***	0.0002	0.0362 **	0.0018	0.0024 *	0.0471
LSI	0.0046 ***	0.0000	0.0026 *	0.0335	0.0381 **	0.0014
COHESION	−0.0381 ***	0.0000	−0.0184 *	0.0233	−0.0170 *	0.0366
CONSTANT	4.1951 ***	0.0000	2.1218 **	0.0100	1.9812 *	0.0170
Spatial lag term	0.2734 ***	0.0000	0.4368 ***	0.0000	0.4349 ***	0.0000
Measures of fit						
Log likelihood	91.1599		63.5760		61.8309	
AIC	−170.3200		−115.1520		−111.6620	
SC	−154.9970		−99.8288		−96.3386	
R2	0.7814		0.6449		0.6328	

Note: *** $p \leq 0.001$, ** $p \leq 0.01$, and * $p \leq 0.05$. AIC, Akaike information criterion; SC, Schwartz's.

4. Discussion

4.1. Spatiotemporal Characteristics of Habitat Quality and Landscape Pattern

In this study, we examined spatiotemporal evolution characteristics of landscape pattern and its impact on regional habitat quality and then combined the PLUS and InVEST models to predict future habitat quality levels in the Yellow River Basin. The evaluation of current habitat quality and projection of future habitat quality in the Yellow River Basin are of great significance for ecological protection and high-quality development in the Yellow River Basin.

In general, the landscape of the Yellow River Basin was dominated by grassland and unused land. The area of construction land in the east was significantly larger than that in the west. From 2005 to 2018, the area of arable land and grassland decreased, while the area of construction land, forest, water body, and unused land increased. Meanwhile, PD and SHDI increased significantly in the Yellow River Basin, while ED, LSI, AREA_MN, and CONTAG decreased, and COHESION remained basically unchanged. The predicted trend of landscape pattern changes from 2018 to 2031 is basically the same as it was from 2005 to 2018. Although the proportion of built-up land area in the total landscape area of the Yellow River Basin is low, the expansion of built-up land in recent decades has caused the destruction of forest, grassland, water, and other habitat landscapes. This phenomenon is more obvious in the population and economic agglomeration areas in the lower reaches of the Yellow River Basin (e.g., Henan and Shandong, etc.). This is because areas with more intensified human activities and massive land-use changes have rapid population and economic growth and great demands for housing, transportation, and public facilities, leading to the occupation of many natural resources such as grasslands, water bodies, and forests and increasing the degree of landscape diversity and fragmentation.

In addition, we assessed habitat quality in the Yellow River Basin. It was found that the habitat quality of the western and northern Yellow River Basin along the Qinghai-Tibet–Inner Mongolia was relatively high. The main reason is that the region has good natural endowment and less construction occupation. It has also gradually established a nature reserve management system with national parks as the main body, nature reserves as the basis, and various nature parks as supplements. More importantly, due to the intervention of afforestation, water conservation, and other ecological protection measures, the number of forests and water bodies with high habitat quality in this area continues to increase. However, habitat quality was at a low level in the middle and lower reaches of the Yellow River Basin. The population and economic agglomeration effect is more obvious in this region. The urban expansion continues to occupy natural resources, leading to the degradation of habitat quality. The influence of the continuous expansion of construction land on the degradation of habitat quality is mainly the reduction of cultivated land, forest, and other landscape land area [49]. At the same time, severe landscape fragmentation reduces landscape connectivity and affects the overall regional habitat, which is particularly critical to the quality of regional habitat.

4.2. Impact of Landscape Pattern Change on Habitat Quality

The results showed that the influence of landscape pattern change on regional habitat quality could not be ignored, and its impact direction and magnitude vary largely in different regions. Therefore, it is of great significance to analyze the effect of landscape pattern on habitat quality for regional landscape planning and ecological sustainable development. Spatial regression was used to quantitatively analyze the correlation between landscape pattern index and habitat quality in the Yellow River Basin. The results showed that the change of landscape pattern had an important effect on habitat quality in the Yellow River Basin. Landscape pattern indices (PD, ED, LSI, and cohesion) had significant effects on habitat quality. The regression coefficients for LSI and ED were both positive, indicating that increased LSI and ED improved habitat quality, while the regression coefficients for PD and cohesion were negative, indicating that increased PD and cohesion resulted in decreased habitat quality. Despite the positive contribution of LSI and ED to habitat quality, both LSI and ED values fluctuated during the study period. There was the greatest negative impact of PD on habitat quality, and the PD value increased over time, which was a major factor in the decline of habitat quality in the Yellow River Basin. In general, the effect of PD on habitat quality reduction was greater than that of LSI and ED enhancement, and the increase of PD implied that the landscape was more fragmented, and the landscape connectivity was weakened, which was related to the decrease of biodiversity and habitat quality. Some relevant studies support our findings. For example, Hu et al. used Geographically and Temporally Weighted Regression (GTWR) and Multiscale Geographic Weighted Regression (MGWR) methods to analyze the driving mechanisms of landscape patterns on habitat quality and found that an increase in landscape connectivity in the urban center of Nanjing significantly improved habitat quality, while an increase in fragmentation in high habitat areas reduced habitat quality [50].

As part of spatial planning and land-use construction in the Yellow River Basin, it is necessary to coordinate the relationship between development and protection to improve regional habitat quality. It is important for the government to maintain the landscape integrity of natural habitats (such as forests, rivers, and wetlands) as much as possible, arrange agricultural landscapes reasonably, and improve the landscape diversity of urban construction areas [25]. Specific measures can be adopted, including delineating ecological protection red lines and delimiting permanent primary farmland, managing high- and low-quality areas of ecological space [51], and establishing pocket parks and green corridors.

4.3. Strengths and Limitations

In this study, the PLUS model was used to simulate the LUCC of the Yellow River Basin in 2031, with 2018 as the base period. Numerous studies adopting the CA-based model have focused mainly on improving technical modeling procedures rather than simulating the detailed patches of multiple land-use types that evolve over time. The PLUS model developed by Liang et al. [31] has a powerful ability to simulate the evolution of land-use types at patch scale. It has been confirmed that the PLUS model has higher simulation accuracy and landscape pattern indicators that were closer to the real landscape than the other CA-based models. This is essential for accurate quantitative assessment of the impact of future landscape patterns on habitat quality and thus the development of policies to manage future land use and landscape patterns in the Yellow River.

At the same time, spatial autocorrelation models and spatial regression models are used to analyze the spatiotemporal characteristics of habitat quality and its response to landscape pattern changes. Various ecological processes often lead to nonrandom spatial distributions of land use, landscape, and biodiversity and show some dependence on spatial patterns. Thus, spatial autocorrelation analysis is crucial for understanding how ecological variables are related and vary in time and space, which can then be used to understand and predict ecological processes and functions. In addition to traditional factors, spatial autocorrelation is also an important factor that influences habitat quality and landscape pattern, but this factor is often overlooked. In previous studies, linear models are often used to analyze the relationship between landscape pattern and habitat quality, which cannot capture the spatial dependence and spillover effects due to spatial autocorrelation. Spatial regression models and spatial autocorrelation models are used to overcome this shortcoming in this study.

However, there are several limitations in this study. First, the InVEST model was used to evaluate the habitat quality of the Yellow River Basin by accumulating the effects of threat factors. Despite this, InVEST does not take into account the interaction between the threat factors, as their cumulative impact on habitat quality is not the same as their simple accumulation [29]. Second, this study only analyzed the impact of seven landscape pattern indexes that were recognized as significant, while other related landscape pattern indexes were not comprehensively considered.

5. Conclusions

This study analyzes the spatiotemporal characteristics of landscape patterns and habitat quality, explores the spatial association between the landscape pattern indexes and habitat quality, and proposes reasonable suggestions to protect and improve habitat quality from the perspective of landscape pattern protection.

Firstly, the results showed that the landscape of the Yellow River Basin is dominated by grassland and unused land, and the area of construction land in the east is significantly greater than that in the west. From 2005 to 2031, the areas of cultivated land and grassland decreased, while the areas of construction land, forest, water bodies, and unused land increased. Then, it was found that a significant increase in PD and SHDI will occur in the Yellow River Basin, while ED, LSI, AREA_MN, and CONTAG will decrease, and COHESION remains almost unchanged. In general, landscape heterogeneity increases, and landscape connectivity decreases. In addition, the habitat quality in the Yellow River Basin shows a continuous decrease trend during the study period, but the change is not drastic. This is because the landscape pattern evolution has both enhanced and diminished effects on habitat quality, which offset each other to a certain extent. Forests, grasslands, and water bodies have the highest habitat quality among landscape types, while construction lands have the lowest. Finally, a spatial lag regression model was further applied to quantitatively assessed the effects of the landscape pattern on habitat quality. The results show that PD and COHESION have significant negative impacts on habitat quality, whereas ED and LSI have significant positive impacts. Landscape fragmentation due to high PD exerts the most significant negative effect on habitat quality. Therefore, we should consider enhancing the connectivity of habitats in landscape planning and limiting the fragmentation of ecological land caused by the uncontrolled expansion of construction land in order to achieve biodiversity conservation and ecological sustainability.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijerph191911974/s1, Table S1: Conversion cost matrix; Table S2: Neighborhood weight parameters for different land use types; Table S3: Landscape pattern indexes of landscape types in Yellow River Basin; Table S4: Regression results of the ordinary least-squares (OLS) method.

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References

1. Zhang, X.; Song, W.; Lang, Y.; Feng, X.; Yuan, Q.; Wang, J. Land use changes in the coastal zone of China's Hebei Province and the corresponding impacts on habitat quality. *Land Use Policy* **2020**, 99. [CrossRef]
2. Wang, Y.; Li, X.; Zhang, Q.; Li, J.; Zhou, X. Projections of future land use changes: Multiple scenarios -based impacts analysis on ecosystem services for Wuhan city, China. *Ecol. Indic.* **2018**, *94*, 430–445. [CrossRef]

3. Zlinszky, A.; Heilmeier, H.; Balzter, H.; Czucz, B.; Pfeifer, N. Remote Sensing and GIS for Habitat Quality Monitoring: New Approaches and Future Research. *Remote Sens.* **2015**, *7*, 7987–7994. [CrossRef]
4. Ye, X.P.; Skidmore, A.K.; Wang, T.J. Within-patch habitat quality determines the resilience of specialist species in fragmented landscapes. *Landsc. Ecol.* **2013**, *28*, 135–147. [CrossRef]
5. Ahmadi Mirghaed, F.; Souri, B. Relationships between habitat quality and ecological properties across Ziarat Basin in northern Iran. *Environ. Dev. Sustain.* **2021**, *23*, 16192–16207. [CrossRef]
6. Fu, B.; Chen, L.; Wang, J.; Meng, Q.; Zhao, W. Land use structure and ecological processes. *Quat. Sci.* **2003**, *23*, 249–254.
7. Goldstein, J.H.; Caldarone, G.; Duarte, T.K.; Ennaanay, D.; Hannahs, N.; Mendoza, G.; Polasky, S.; Wolny, S.; Daily, G.C. Integrating ecosystem-service tradeoffs into land-use decisions. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, 7565–7570. [CrossRef]
8. Gong, J.; Xie, Y.; Cao, E.; Huang, Q.; Li, H. Integration of InVEST-habitat quality model with landscape pattern indexes to assess mountain plant biodiversity change: A case study of Bailongjiang watershed in Gansu Province. *J. Geogr. Sci.* **2019**, *29*, 1193–1210. [CrossRef]
9. McKinney, M.L. Urbanization, biodiversity, and conservation. *Bioscience* **2002**, *52*, 883–890. [CrossRef]
10. Mengist, W.; Soromessa, T.; Feyisa, G.L. Landscape change effects on habitat quality in a forest biosphere reserve: Implications for the conservation of native habitats. *J. Clean. Prod.* **2021**, *329*, 129778. [CrossRef]
11. Robele Gari, S.; Newton, A.; Icely, J.D. A review of the application and evolution of the DPSIR framework with an emphasis on coastal social-ecological systems. *Ocean. Coast. Manag.* **2015**, *103*, 63–77. [CrossRef]
12. Boumans, R.; Roman, J.; Altman, I.; Kaufman, L. The Multiscale Integrated Model of Ecosystem Services (MIMES): Simulating the interactions of coupled human and natural systems. *Ecosyst. Serv.* **2015**, *12*, 30–41. [CrossRef]
13. Sallustio, L.; De Toni, A.; Strollo, A.; Di Febbraro, M.; Gissi, E.; Casella, L.; Geneletti, D.; Munafo, M.; Vizzarri, M.; Marchetti, M. Assessing habitat quality in relation to the spatial distribution of protected areas in Italy. *J. Environ. Manag.* **2017**, *201*, 129–137. [CrossRef] [PubMed]
14. Sun, X.; Jiang, Z.; Liu, F.; Zhang, D. Monitoring spatio-temporal dynamics of habitat quality in Nansihu Lake basin, eastern China, from 1980 to 2015. *Ecol. Indic.* **2019**, *102*, 716–723. [CrossRef]
15. Sherrouse, B.C.; Semmens, D.J.; Clement, J.M. An application of Social Values for Ecosystem Services (SolVES) to three national forests in Colorado and Wyoming. *Ecol. Indic.* **2014**, *36*, 68–79. [CrossRef]
16. Aneseyee, A.B.; Noszczyk, T.; Soromessa, T.; Elias, E. The InVEST Habitat Quality Model Associated with Land Use/Cover Changes: A Qualitative Case Study of the Winike Watershed in the Omo-Gibe Basin, Southwest Ethiopia. *Remote Sens.* **2020**, *12*, 1103. [CrossRef]
17. Moreira, M.; Fonseca, C.; Vergilio, M.; Calado, H.; Gil, A. Spatial assessment assessment of habitat conservation status in a Macaronesian island based on the InVEST model: A case study of Pico Island (Azores, Portugal). *Land Use Policy* **2018**, *78*, 637–649. [CrossRef]
18. Nematollahi, S.; Fakheran, S.; Kienast, F.; Jafari, A. Application of InVEST habitat quality module in spatially vulnerability assessment of natural habitats (case study: Chaharmahal and Bakhtiari province, Iran). *Environ. Monit. Assess.* **2020**, *192*, 1–17. [CrossRef]
19. Hack, J.; Molewijk, D.; Beissler, M.R. A Conceptual Approach to Modeling the Geospatial Impact of Typical Urban Threats on the Habitat Quality of River Corridors. *Remote Sens.* **2020**, *12*, 1345. [CrossRef]
20. Terrado, M.; Sabater, S.; Acuna, V. Identifying regions vulnerable to habitat degradation under future irrigation scenarios. *Environ. Res. Lett.* **2016**, *11*, 21. [CrossRef]
21. Zhang, X.R.; Zhou, J.; Li, G.N.; Chen, C.; Li, M.M.; Luo, J.M. Spatial pattern reconstruction of regional habitat quality based on the simulation of land use changes from 1975 to 2010. *J. Geogr. Sci.* **2020**, *30*, 601–620. [CrossRef]
22. Zhu, J.; Gong, J.; Li, J. Spatiotemporal change of habitat quality in ecologically sensitive areas of eastern Qinghai-Tibet Plateau: A case study of the Hehuang Valley, Qinghai Province. *Resour. Sci.* **2020**, *42*, 991–1003. [CrossRef]
23. Wu, L.; Sun, C.; Fan, F. Estimating the Characteristic Spatiotemporal Variation in Habitat Quality Using the InVEST Model-A Case Study from Guangdong-Hong Kong-Macao Greater Bay Area. *Remote Sens.* **2021**, *13*, 1008. [CrossRef]
24. Yushanjiang, A.; Zhang, F.; Yu, H.; Kung, H.-t. Quantifying the spatial correlations between landscape pattern and ecosystem service value: A case study in Ebinur Lake Basin, Xinjiang, China. *Ecol. Eng.* **2018**, *113*, 94–104. [CrossRef]
25. Zhu, C.; Zhang, X.; Zhou, M.; He, S.; Gan, M.; Yang, L.; Wang, K. Impacts of urbanization and landscape pattern on habitat quality using OLS and GWR models in Hangzhou, China. *Ecol. Indic.* **2020**, *117*, 106654. [CrossRef]
26. Chen, W.; Zeng, J.; Chu, Y.; Liang, J. Impacts of Landscape Patterns on Ecosystem Services Value: A Multiscale Buffer Gradient Analysis Approach. *Remote Sens.* **2021**, *13*, 2551. [CrossRef]
27. Ding, Q.L.; Chen, Y.; Bu, L.T.; Ye, Y.M. Multi-Scenario Analysis of Habitat Quality in the Yellow River Delta by Coupling FLUS with InVEST Model. *Int. J. Environ. Res. Public Health* **2021**, *18*, 2389. [CrossRef] [PubMed]
28. Gomes, E.; Inacio, M.; Bogdzevic, K.; Kalinauskas, M.; Karnauskaite, D.; Pereira, P. Future scenarios impact on land use change and habitat quality in Lithuania. *Environ. Res.* **2021**, *197*, 111101. [CrossRef]
29. Tang, F.; Fu, M.; Wang, L.; Zhang, P. Land-use change in Changli County, China: Predicting its spatio-temporal evolution in habitat quality. *Ecol. Indic.* **2020**, *117*, 106719. [CrossRef]
30. Li, F.X.; Wang, L.Y.; Chen, Z.J.; Clarke, K.C.; Li, M.C.; Jiang, P.H. Extending the SLEUTH model to integrate habitat quality into urban growth simulation. *J. Environ. Manag.* **2018**, *217*, 486–498. [CrossRef]

31. Liang, X.; Guan, Q.F.; Clarke, K.C.; Liu, S.S.; Wang, B.Y.; Yao, Y. Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China. *Comput. Environ. Urban Syst.* **2021**, *85*, 14. [CrossRef]
32. Ma, H.; Xu, X. High-Quality Development Assessment and Spatial Heterogeneity of Urban Agglomeration in the Yellow River Basin. *Econ. Geogr.* **2020**, *40*, 11–18.
33. Zhao, J.; Liu, Y.; Zhu, Y.; Qin, S.; Wang, Y.; Miao, C. Spatiotemporal differentiation and influencing factors of the coupling and coordinated development of new urbanization and ecological environment in the Yellow River Basin. *Resour. Sci.* **2020**, *42*, 159–171. [CrossRef]
34. Hu, C.; Ran, G.; Li, G.; Yu, Y.; Wu, Q.; Yan, D.; Jian, S. The effects of rainfall characteristics and land use and cover change on runoff in the Yellow River basin, China. *J. Hydrol. Hydromech.* **2021**, *69*, 29–40. [CrossRef]
35. Li, J.; Sun, W.; Li, M.; Meng, L. Coupling coordination degree of production, living and ecological spaces and its influencing factors in the Yellow River Basin. *J. Clean. Prod.* **2021**, *298*, 126803. [CrossRef]
36. Omer, A.; Ma, Z.; Yuan, X.; Zheng, Z.; Saleem, F. A hydrological perspective on drought risk-assessment in the Yellow River Basin under future anthropogenic activities. *J. Environ. Manag.* **2021**, *289*, 112429.
37. Liu, X.P.; Liang, X.; Li, X.; Xu, X.C.; Ou, J.P.; Chen, Y.M.; Li, S.Y.; Wang, S.J.; Pei, F.S. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landsc. Urban Plan.* **2017**, *168*, 94–116. [CrossRef]
38. Li, H.B.; Wu, J.G. Use and misuse of landscape indices. *Landsc. Ecol.* **2004**, *19*, 389–399. [CrossRef]
39. Lin, Y.; Lin, W.; Wang, Y.; Lien, W.; Huang, T.; Hsu, C.; Schmeller, D.S.; Crossman, N.D. Systematically designating conservation areas for protecting habitat quality and multiple ecosystem services. *Environ. Model. Softw.* **2017**, *90*, 126–146. [CrossRef]
40. Leh, M.D.K.; Matlock, M.D.; Cummings, E.C.; Nalley, L.L. Quantifying and mapping multiple ecosystem services change in West Africa. *Agric. Ecosyst. Environ.* **2016**, *221*, 285. [CrossRef]
41. Fu, B.; Xu, P.; Wang, Y.K.; Yan, K.; Chaudhary, S. Assessment of the ecosystem services provided by ponds in hilly areas. *Sci. Total Environ.* **2018**, *642*, 979–987. [CrossRef] [PubMed]
42. Terrado, M.; Sabater, S.; Chaplin-Kramer, B.; Mandle, L.; Ziv, G.; Acuna, V. Model development for the assessment of terrestrial and aquatic habitat quality in conservation planning. *Sci. Total Environ.* **2016**, *540*, 63–70. [CrossRef] [PubMed]
43. Zhang, X.; Zhou, J.; Li, M. Analysis on spatial and temporal changes of regional habitat quality based on the spatial pattern reconstruction of land use. *Acta Geogr. Sin.* **2020**, *75*, 160–178.
44. Ruiz, A.R.; Pascual, U.; Romero, M. An exploratory spatial analysis of illegal coca cultivation in Colombia using local indicators of spatial association and socioecological variables. *Ecol. Indic.* **2013**, *34*, 103–112. [CrossRef]
45. Yang, Y.; Li, J.; Zhu, G.B.; Yuan, Q.Q. Spatio-Temporal Relationship and Evolvement of Socioeconomic Factors and PM2.5 in China During 1998–2016. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1149. [CrossRef] [PubMed]
46. Xia, C.; Yeh, A.G.; Zhang, A. Analyzing spatial relationships between urban land use intensity and urban vitality at street block level: A case study of five Chinese megacities. *Landsc. Urban Plan.* **2020**, *193*, 103669. [CrossRef]
47. Griffith, D.A. Spatial Econometrics: Methods and Models. *Econ. Geogr.* **2016**, *65*, 160–162. [CrossRef]
48. Chi, G.; Zhu, J. Spatial Regression Models for Demographic Analysis. *Popul. Res. Policy Rev.* **2008**, *27*, 17–42. [CrossRef]
49. Bai, L.M.; Xiu, C.L.; Feng, X.H.; Liu, D.Q. Influence of urbanization on regional habitat quality:a case study of Changchun City. *Habitat Int.* **2019**, *93*, 102042. [CrossRef]
50. Hu, J.; Zhang, J.; Li, Y. Exploring the spatial and temporal driving mechanisms of landscape patterns on habitat quality in a city undergoing rapid urbanization based on GTWR and MGWR: The case of Nanjing, China. *Ecol. Indic.* **2022**, *143*, 109333. [CrossRef]
51. Xu, X.B.; Tan, Y.; Yang, G.S.; Barnett, J. China's ambitious ecological red lines. *Land Use Policy* **2018**, *79*, 447–451. [CrossRef]

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Allocation of Land Factors in China Looking Forward to 2035: Planning and Market

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Abstract: Land factors are natural resources with fundamental and strategic significance in the achievement of China's 2035 modernization goals. Dilemmas caused by market-oriented or planning-oriented allocation of land factors urgently call for new theoretical guidance and mode. After conducting a systematic review of the literature, this paper built a new framework from the perspective of production–living–ecological spaces to facilitate a better understanding of China's land factors allocation looking forward to 2035. Inductive and deductive methods were both used to interpret the applications of planning and market in land factors allocation. Our results show that: (1) The allocation of land factors for production space is truth-oriented and needs the guidance of market efficiency. The essential feature of "production" as the driving force in production space requires that the allocation of land factors in production space must "respect rules, give play to the agglomeration effect, and rationally carry out regional economic layout". (2) For the allocation of land factors for living space, it is necessary to pursue a kindness-oriented approach and establish a reasonable housing supply system based on people. Among them, the ordinary commercial housing and improving housing should rely on market forces to achieve multi-subject supply, while affordable housing should be ensured through government intervention in a multi-channel way. (3) For the allocation of land factors in ecological space, aesthetic-oriented planning should follow the rule of territorial differentiation and realize the transformation of ecological function into ecological value through market mechanisms. Top-down planning and bottom-up market represents the logic of overall and individual rationality, respectively. The effective allocation of land factors requires the utilization of both planning and market forces. However, the intersection needs be guided by boundary selection theory. This research indicates that "middle-around" theory could be a possible theoretical solution for future study.

Keywords: territorial space planning; land market; factors allocation; production–living–ecological spaces; modernization

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1. Introduction

Modernizing China's governance system for territorial space and capacity is an important part of China's efforts to achieve the strategic goal of socialist modernization by 2035 [1]. Looking backward, China's rapid development in the past 40 years was mainly driven by the factors represented by land. In particular, the successful reform of land factors from total planning allocation to market allocation supported the rise of China's industrial manufacturing industry, the improvement of people's living conditions, the large-scale construction of urban infrastructure, and the accumulation of social wealth [2]. However, since Rittle and Webber introduced the concept of planning as a thorny problem in the 1970s, today, in the 21st century, scholars are still baffled by the problem of planning for complex urban environments [3]. The core of the complexity of planning comes from human behavior, whether it is the behavior of supply producers or consumers, which will often form feedback loops. Good planning is, first of all, rational and should conform to the balance of market supply and demand [4].

As a traditional agricultural country, China is trying to embrace industrial civilization in the process of becoming a modern country. However, facing the basic national conditions of more people with less land, China's modernization process must achieve high-quality development of production, satisfy people's demand for a better life and at the same time protect the fragile ecological environment to ensure the sustainability of modern development, which requires China's modern development to be guided by ecological civilization. In this regard, China's central government has put forward the overall requirements for land and space development of "intensive and efficient production space, livable and moderate living space, and beautiful ecological space". However, China's relatively lagging territorial space governance system and reform capacity do not adapt to the huge changes surrounding land factors. In the process of rapid urbanization and industrialization in China, many contradictions have arisen due to the uncoordinated planning and market means in the allocation of land factors. Disordered competition and interest conflicts among local governments and departments have led to extensive land use. The existence of the dual structure of urban and rural land has led to the dilemma that the urbanized agricultural population is facing insufficient urban housing security and difficulties in realizing rural land property rights. The regional division of development strategy lacks the support of a flexible planning mechanism for the allocation of land factors, resulting in a lack of necessary incentives and funds for ecological and environmental protection, which makes it difficult to truly achieve the goal of ecological civilization construction.

In 2019, China announced the establishment of a new spatial planning system, which integrates the traditional functional zoning planning, land use planning, and urban and rural planning [5]. This new system provides basic principles for various development and protection activities and provides a sustainable spatial development guide for realizing the strategic goal of national modernization by 2035. However, the realization of these grand development strategies requires the removal of the contradictions accumulated in the previous development stage. Central to this problem is to straighten out the relationship between planning and market in the allocation of land factors [6]. Existing theoretical research either focuses on the guiding role of government planning [7,8], or focuses on the regulating role of market allocation [9], or emphasizes that both are indispensable [10], which does not reveal enough about the boundary selection theory between the two. Therefore, this paper aims to address the achievement of effective allocation of land factors looking toward 2035 by exploring a new framework and theoretical guidance.

2. Literature Review

2.1. The Allocation of Land Factors as Quasi-Public Goods

Public goods refer to the products and services consumed by the whole society, such as national defense, public transportation, urban disaster prevention facilities, etc. Public goods are characterized by high input, low return, and social necessities [11,12]. According to the different degree of competition and exclusivity, public goods can be divided into pure public goods and quasi-public goods. Generally, it is the responsibility of governments to provide purely public goods such as defense and security. Quasi-public goods, however, can be provided in a more flexible and diversified way according to their different degrees of publicity [13]. Land resources have typical characteristics of quasi-public goods, which need market and planning allocation in the real world. On the one hand, land is an important factor of production, and market mechanism is a panacea to achieve the sustainability of land supply [14]. Gebre and Demsis [15] surveyed public-private partnerships in Ethiopia's road sector, citing the lack of government funding, the inability of the public sector to shoulder all project risks, social pressures on people due to poor road infrastructure, the need for private sector skills and experience, and the need to improve service levels as the main reasons for their cooperation. The results of the study provide solutions to problems related to the delivery of road infrastructure [15]. On the other hand, land resources are quasi-public goods, whose allocation needs government intervention. This is because weak competition environment (Cournot competition) can bring more public benefits than strong competition environment (Bertrand competition) [16]. For instance, Rohman evaluated the role of the government in the public-private partnership toll road project in Indonesia [17]. In the consideration of land public goods, some governments gradually attract the private sector to provide infrastructure through public-private partnership. In addition, land use has externalities. For the negative externalities of environmental pollution, Li Sufeng et al. [18] built a dynamic game model and analyzed the evolution and development law of carbon emission reduction between governments and enterprises. It is believed that carbon trading, as one of the effective market tools combining planning and market, can promote the smooth implementation of the "dual carbon" goal [18].

2.2. Planning Allocation of Land Factors

Keynesianism believes that due to market failure, the government must actively intervene to correct the defects of the market mechanism, and planning is one of the most important and effective ways for the government to intervene in the allocation of land resources [19]. Although many countries began to carry out territorial planning in succession from the early 20th century, most western countries did not begin to take effective steps to regulate and intervene in regional development until after the Second World War. Since the 1960s, due to the rapid industrial development and accelerated urbanization in Western countries, the problems of population, resources and environment have become prominent, especially the imbalance of regional development has become increasingly serious. Among them, the development problem of backward areas is very prominent, while some prosperous core areas, such as Paris in France, the United Kingdom and the southeast area centered around London, appear the problem of excessive concentration. in order to overcome the phenomenon of "over-density" (over-concentration) and "over-sparse" (low level of development) of the national industry in the region and realize the balanced development of national economy, France [20], Britain [21] and other developed countries have respectively adopted relevant policies to strengthen the planning and guidance of regional development. Even in the United States, which has the most developed market economy, planning as a public policy plays an important role in resource allocation [22].

From the general experience of developed countries in the world, space planning, as an important public policy, is an important means for the government to conduct space governance. The International Habitat Conference II has set "adequate housing for all" as the core goal of the Habitat Agenda [23], and the right to housing is listed as a part of the "right to a minimum standard of living" in the Universal Declaration of Human Rights [24]. Therefore, planning should first meet peoples' housing needs. Later, the New Urban Agenda of Habitat III re-established the core status of cities in the world human settlement environment, and pointed out that the planning should focus on the whole urban system rather than a single urban element, that is to say, not only the planning of a single element such as the road network structure, but also the solution of many complex problems [25]. These complex issues include resilient cities, housing issues, food issues, etc. For example, Sadegh Sabouri et al. explored the national practice of linking and coordinating transportation and land use planning in the United States. The ultimate goals of these projects were found to be similar throughout the case studies, namely to reduce suburban sprawl and the associated need for road construction, and to create more livable, sustainable, walkable, cyclable and passable communities within the region [26]. When it comes to China, in the deep development period of urbanization from "extension type" to "concursive type", spatial planning focuses on solving urban life problems such as dislocation of employment and housing, traffic congestion, environmental pollution, insufficient supporting public facilities and unbalanced development with surrounding areas [27]. In addition, government planning and allocation of land is a multi-objective public management activity, which can be in line with the 2030 Sustainable Development Goals (SDGs). In the 2030 Development Agenda, 17 Sustainable Development Goals and

169 targets are divided into three dimensions, namely "economic development", "environmental well-being", and "social inclusion". Domestic and foreign scholars have studied the integration strategies of urban planning and resource management from the perspectives of social stability and development as well as ecological environmental protection [28–33].

2.3. Market Allocation of Land Factors

The neoliberalism represented by Hayek criticized the government failure of Keynesian intervention. Hayek believed that the "invisible hand" of the market was highly capable of self-regulation and risk prevention in complex market economic activities [34]. Since the late 20th century, the global society has been influenced by the neoliberal theory, which has also penetrated the land factors allocation. The marketization mechanism of land resource allocation is to follow the rule of value, the law of competition, the law of supply and demand and other market laws to spontaneously reach the optimal allocation state. Under the condition of market mechanism, land rights holders will utilize land resources in accordance with the principle of profit maximization and promote intensive land use. Whether any land is developed for commercial, residential or public services, market needs, and development interests will usually give the best choice [35]. In developed capitalist economies, it can be seen that there is a "market" model represented by the United States, in which the allocation of housing resources largely depends on the incentive of information channels and price mechanisms [36]. Deegen and Halbritter [37] analyzed the problem of pure land allocation under certain market conditions when land use changes have different impacts on commodity prices and production factor prices, and proposed three different models: a completely open economy, a closed economy and an economy in which selection prices are determined externally [37]. China, with its socialist market economy system, is no exception. The transformation of urban land from planned allocation to market-oriented allocation is an important part of China's market-oriented economic reform, and the marketization of land transfer can significantly promote economic growth in the long run [38].

3. Allocation of Land Factors in China: Modes and Dilemmas

3.1. Planning-Oriented Allocation Mode and Its Performance

Planning is future-oriented, statutory, and holistic. As a government action, it can make up for the failure and absence of market allocation and correct the disadvantages of market allocation such as external diseconomy and information asymmetry. As a resource in the planning system, the allocation of land factors is regarded as a part of China's macro-control, and it is also regarded as a policy tool of state governance. In the allocation of land factors, planning mainly plays a leading and controlling role. Since China's reform and opening-up in 1978, the central government has given full play to the leading and controlling role of planning in the allocation of land factors through the preparation of land use planning. The law guarantees the effective implementation of the plan. In the compilation of China's first round of overall land use planning (Outline of the National Land Use Planning (1986–2000)), indicators and zoning are two policy tools that constitute the overall land use plan. Specifically, it first analyzes and evaluates the utilization suitability of all land factors, and then it divides the available land factors into cultivated land indicators and construction land indicators. After that, it allocates them among different regions, departments, and industries, to ensure land factors better serve the various needs of national economic development. However, on the one hand, the lack of science and public participation in the overall land use plan compiled, and the persistent pursuit of the perfection of the planning results lead to a disconnect between the overall land use plan and the actual needs of social and economic development. On the other hand, under the impact of China's market economy reform, the lack of constraints and flexibility of land use planning have led to a serious loss of cultivated land resources in China. Therefore, in the preparation of the second round of overall land use planning (Outline of the National Land Use Planning (1997–2010)), the protection of valuable cultivated land resources has become the primary goal. The cultivated land protection indicators approved by the central government are allocated from top to bottom among local governments at different levels, to realize the guidance and containment of development demand from supply side of land factors. However, in practice, the relationship between the protection pressure of cultivated land and the expansion of construction land demand has not been effectively coordinated, which has challenged the forward-looking planning. In the preparation of the third round of overall land use planning (Outline of the National Land Use Planning (2006–2020)), the practice of local governments on the relationship between protection and development in land use provided valuable information for the preparation of overall land use planning. In this stage, land use control has become the most distinctive feature of China's land use planning system. This system has played an important role in ensuring the realization of multi-dimensional goals of ecological environment protection, dynamic balance of cultivated land resources, and intensive use of construction land.

3.2. Market-Oriented Allocation Mode and Its Performance

As a resource in the market system, market allocation tools should play a fundamental and decisive role in land factors. Land is the spatial carrier for human economic and social activities and the basic resource to be used. The increasingly diversified demands for land resources from population growth, urban expansion, and social development objectively require the market mechanism to play its role of allocating scarce land resources. From a micro perspective, the market promotes the effective conversion of land resources between different uses through the price mechanism, competition mechanism, and supply and demand mechanism, and maximizes the use value of land resources. From a macro perspective, as a factor commodity in national economic and social development, the improvement of its overall allocation efficiency still requires clear property rights and reduced market transaction costs as a prerequisite [39]. As the reform and opening up, the market allocation of rural land has greatly contributed to the increase of agricultural production and provided capital and labor accumulation for industrialization and urbanization. The marketization of urban land lease has significantly contributed to China's economic growth in the long term through two major channels: the financing effect and the resource allocation effect. The construction of industrial parks and real estate development in the context of urban land market allocation has led to the rapid development of industrialization and urbanization in China. The activation of the capital properties of land has given rise to the land finance driven urban development and management mode, which on the one hand has accumulated wealth for urban development, but on the other hand, the drawbacks of the land finance mode have become increasingly evident [40].

3.3. Dilemmas from the Unclear Boundary between Planning and Market Allocation

In general, the planning role of land factor allocation emphasizes "top-down", which has the disadvantage of over-idealized planning allocation and often generates unavoidable conflicts between the rigidity of planning and the uncertainty and complexity of reality [3]. When planning allocation is dominant, distortion and misallocation of land factors arises. In addition, institutional factors, such as the lack of public participation and supervision, may make it difficult for the planning to allocate land factors as expected. It is foreseeable that the increasingly improved territorial spatial planning system will overcome the drawbacks of "multiple planning", promote the role of planning tools in land factors allocation, and promote the modernization of territorial spatial governance system and governance capacity, but this requires a more flexible, effective, and adequate interface between planning intervention and market adjustment [41]. In contrast, the market role of land factor allocation emphasizes "bottom-up". However, market allocation tends to focus on short-term interests and there are external diseconomies in the market mechanism, which leads to disorder and imbalance when market allocation is dominant, manifesting in extensive use of industrial land, duplication of construction and overcapacity, high housing prices and inadequate housing security, local debt and land financial risks, and environmental pollution problems.

The effective combination of market mechanism and government planning is an indispensable basis for realizing the Pareto optimization of land factors allocation. With the increasing complexity and suddenness of human economic and social development, the effective integration of the two becomes more important than ever. However, in the current allocation of land factors, the boundary between planning and market is not clear, which has created hurdles for their effective integration. Therefore, how to draw the boundary between the two is the most significant issue.

4. Allocation of Land Factors from the Perspective of Production-Living-Ecological Spaces

Production–living–ecological spaces is a classification perspective of land factors allocation (Figure 1). Firstly, Production is a driving force. Production space is truth-oriented, a philosophy between people and things, which follows rules and emphasizes agglomeration effect. Secondly, Living is goal. Living space is kindness-oriented, a philosophy between people and people, which follows the logic of people-oriented and emphasizes livability. Thirdly, Ecology is the bottom line. Ecological space is aesthetic-oriented, a philosophy between people and God, which needs to respect nature and stresses the guidance of green development. Based on the above reasons, this study will explore the synergistic application of planning and market in land factors allocation from the perspective of production–living–ecological spaces.

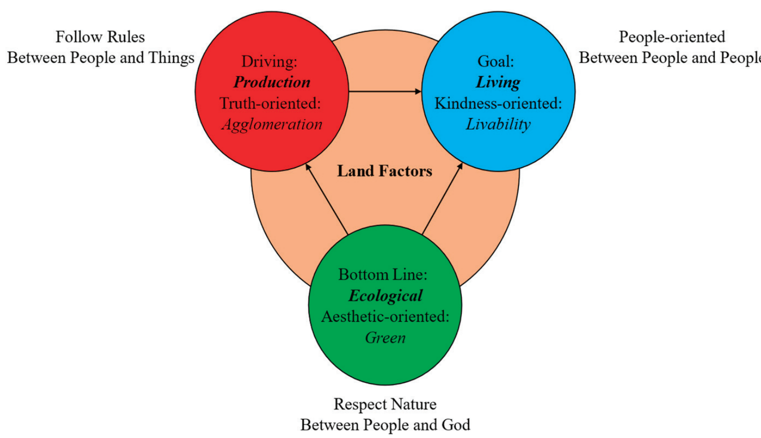


Figure 1. Allocation of land factors from the perspective of production-living-ecological spaces.

4.1. Allocation of Land Factors for Production Space

The market-based reform of land allocation can unleash huge potential for economic development and is of great significance to achieving steady and high-quality economic growth. The land factor allocation oriented by market efficiency is firstly reflected in the agglomeration of population and various production factors in geographical space, and behind this agglomeration of factors is the agglomeration of industries. Take Dongguan City in Guangdong province as an example. In 2020, the total population of the city reached 10.47 million, and the global market share of the computer mouse, keyboards and capacitors had reached 70%. For this concentration of market allocation, Adam Smith opened the Wealth of Nations with an example of making paper clips: The maximum efficiency of a single person making paper clips is 1 to 20 per day (depending on their proficiency), while a production chain of 10 people can produce 48,000 per day, an average of 4800 per person, with an efficiency increase of 240 to 4800 times. The improvement of efficiency is the result of the division of production, which is precisely based on the premise of agglomeration.

In other words, the possibility of division of labor can only be provided by clustering to a certain extent. In addition, if enterprises in a certain industry cluster in a region, it will also attract enterprises from other industries to engage in production and operation in the region [42]. At this time, the agglomeration economy broke through industrial boundaries and was called the "urbanization economy". From international experience, the size of a town is closely related to economic development. According to the World Bank report, more than half of the people in the high-income countries category live in big cities with populations of more than 1 million, and less than a quarter live in small towns with populations of less than 20,000. The opposite is true in low-income countries, where only about 1 in 10 people live in large cities with populations of more than 1 million and nearly three-quarters live in small towns with populations of less than 20,000 (Table 1). The agglomeration rule is universal, including China. Therefore, the allocation of land factors in production space should follow the law and emphasize the agglomeration effect, and the development of big cities should become the support for the construction of small cities.

Table 1. The proportion of city size in different development types of countries.

Size of Population	Low-Income Countries (%)	Middle-Income Countries (%)	High-Income Countries (%)
Small settlements: Under 20,000	73	55	22
Middle Settlement: 2 million to 1 million	16	25	26
The Big Settlement: More than 1 million	11	20	52

Source: World Development Report 2009.

From the above perspective, population agglomeration brings the scale effect of production exchange and promotes the development of urban innovation, production, and trade. However, on the negative side, the population agglomeration leads to pollution, crowding and other problems. When the positive externalities brought by the urban agglomeration effect cannot make up for the negative impacts brought by the urban problems, the social relations within the city will deteriorate. Therefore, while giving full play to the decisive role of the market in factors allocation, it is more important to rationally plan the regional economic layout, and earnestly do a good job in basic security work such as territorial and spatial planning, land property rights system and land legal system.

4.2. Allocation of Land Factors for Living Space

The living space is people oriented. The allocation of land factors needs planning and market to both guide a reasonable housing supply system. As mentioned in the report, Chinese modernization is characterized by a huge population, common prosperity for all the people, harmony between material and spiritual civilization, harmonious coexistence between man and nature, and the path of peaceful development. So, in this context, how to build China's housing system for 2035?

First, in the real estate market, we should focus on absorbing the rigid demand caused by the current population structure and improving the demand. In the face of such a huge population in China, it is impossible to rely on the government alone, so we need to rely on the market power and multi-subject supply. The housing demand for ordinary commodity housing can be realized through the distribution function of the free market, whose production, distribution, circulation, and consumption are regulated by the market mechanism. The operation of the real estate market with fierce competition and its supply structure (such as high-grade commodity apartments, villas, etc.) are basically within the scope of complete marketization. Besides maintaining the rules of fair competition, the government mainly decides the relationship between supply and demand according to market rules and market mechanism. Only in this way can we effectively increase supply, meet diversified demand, and improve the efficiency of housing resource allocation. Although the demand for ordinary commodity housing can be realized through the distribution function of the free market, ordinary commodity housing still needs to adhere to the "housing does not stir" requirement. A profit tax could be one option to curb property speculation. In addition, with the commercialization and liberalization of housing, the rate of home ownership has been greatly increased, and people have a higher pursuit of material and spiritual, and the demand for improving housing has become the main body of the real estate market, among which the ecological housing that realizes the harmonious modernization of human and nature can also be regarded as a kind of improving housing. Although there are no complete statistics, it is predicted in the relevant research report that there are many vacant houses, and many families own multiple homes. The "heavy transaction, light possession" housing tax system has no longer meet the needs of the current economic and social development. Levying resource occupancy tax on housing has become an important policy choice and the source of new land transfer fees in the future. Levying taxes and fees on the link of housing ownership and appropriately reducing the transaction tax burden can revitalize the stock of real estate, reduce the vacancy rate, and make full use of land and housing resources.

Second, under the market economy system, in order to realize the modernization of common prosperity for all the people and ensure that everyone has a house to live in, the government needs to implement some special policies and measures to help the floating population groups separating from their household registrations to solve the housing difficulties. The general term for this policy system is called the housing security system. However, the unbalanced development of housing security in the new era is mainly manifested in three aspects: the unbalanced distribution of supply and demand between cities, the unbalanced distribution of urban interior space, and the unbalanced construction and management of affordable housing. The construction of affordable housing ignores the internal demand difference between big cities and small and medium-sized cities, leading to short supply in big cities and oversupply in small and medium-sized cities. Public housing and low-rent housing are usually built far away from industrial urban centers, with poor transportation infrastructure, high commuting costs, and inadequate public services. Qualification audit and follow-up supervision of affordable housing are not in place. In view of the unbalanced development of housing security, the author believes that under the background of new urbanization, it is necessary to carry out planning allocation of land factors, formulate housing policies, and promote urban-rural integration. Through the planning and promotion of affordable housing, rail transit terminals in big cities should become an important choice of affordable housing. At the same time, only when the rural floating population has housing security in the city can the reform of rural homestead system be leveraged in a real sense to improve farmers' property income and achieve common prosperity.

4.3. Allocation of Land Factors for Ecological Space

During the 14th Five-Year Plan period, China's ecological civilization construction entered a critical period with carbon reduction as the key strategic direction, promoting the synergistic effect of carbon reduction and pollution reduction, promoting the comprehensive green transformation of economic and social development, and realizing the improvement of ecological environment quality from quantitative to qualitative change. Ecological space is guided by beauty, and the external requirements of transforming carbon to achieve carbon neutrality and peak carbon dioxide emissions are the internal driving force of ecological civilization construction. At present, the shortage of available land in China is becoming increasingly serious, while the demand for land use is constantly increasing, which requires us to effectively carry out territorial space planning and ecological environmental protection, by drawing various security bottom lines, implementing use control and ecological restoration.

First, the ecological pattern still needs to be planned according to the rules of territorial differentiation. Among them, the ecological protection red line is the lifeline to ensure ecological security and an important means for the state to control ecological space. It is necessary to use scientific methods to identify high-value carbon sink spaces, quantitatively assess the functional value of forest, grassland, wetland, ocean, and other ecological systems protection in carbon sinks, and incorporate their spatial location into the ecological protection red line of the national land control planning, strengthening the use control of national land space and strictly protecting high-value carbon sink spaces. At the same time, we should promote ecological restoration in the national territory and increase carbon sinks in ecosystems.

Second, urban development needs to respect nature and make good use of planning for top-level design. Among them, transport distance is the concentrated expression of the basic spatial characteristics of human and nature, as well as the interaction between humans and space. In particular, the geographical distance, density, segmentation, and heterogeneity have great influence on the carbon emission of cities. For example, Russia is much larger than Mexico, with a land area of 8.7 times greater. As a result, although Russia and Mexico have the same population and per capita GDP in 2021, Russia's per capita carbon emission of 12.04 tons is 3.2 times that of Mexico. According to the "Research on the Impact of Land Use Structure on Air Pollutants and carbon Emissions" project, Chinese urban and construction land accounts for 1% of the country's total land area, but carbon emissions account for nearly 90% of the country's total emissions. In addition, if the construction land scale doubled, the carbon emissions will increase by 1.7 times. Therefore, we need to conduct scale constraint and structural adjustment for all kinds of land development and construction based on geographical distance, density, segmentation, and heterogeneity. At the same time, we need to establish natural ethics, caring for the land, and guide residents to transform their behavior to the green and low-carbon direction.

Finally, ecology is a resource that can be transformed into assets, and its land factors allocation needs the assistance of the market. Through the market mechanism, ecological function can be transformed into ecological values and the modernization of harmonious coexistence between man and nature can be realized. Ecological environment and its functional diversity determine the different attributes of ecological value. Some ecological values take the products and services derived from the good ecological environment to meet certain needs of people as the carrier, such as ecological agricultural products, ecological tourism, etc., which are directly produced for peoples' consumption or use, so as to obtain certain monetary benefits and realize value transformation. In practice, if the economic value of natural resources cannot be fully tapped, the ideal of "lucid waters and lush mountains are invaluable assets" will not be realized. If we cannot benefit from ecological protection and ensure the simultaneous development of social benefits and corresponding economic benefits, ecological builders will lose their enthusiasm for ecological protection and construction, and ecological environmental construction will lose its power source. As far as we are concerned, ecological products and ecological industrialization are an important means to realize the ideal of "lucid waters and lush mountains are invaluable assets".

4.4. Interaction of Production-Living-Ecological Spaces: A Perspective from Livable City

The modernization of China's territorial space governance system and capacity looking forward to 2035 not only requires production, living, and ecological spaces to achieve their development goals respectively, but also requires an overall insight into the interactive relationship among production–living–ecological spaces to make allocation of land factors better serving for the optimization of territorial space layout at different scales. Cities are the crystallization of modern human civilization. Human yearning for "livable cities" has been reflected in Howard's "Garden City" concept as early as the end of the 19th century. In 1933, The Athens Charter, the representative of urban spatial planning theory, put forward the overall concept of the coordinated development of the city and its surrounding areas, and divided the urban functions into work, residence, and recreation. This classification perspective coincides with production–living–ecological spaces, where the work function corresponds to production space, the residential function corresponds to living space, and the recreational function corresponds to ecological space. China's development plan for 2035 also regards the construction of the "livable city" as an important goal. Therefore, we try to take the construction of the "livable city" as an example to specifically explain the interactive relationship between production–living–ecological spaces (Figure 2).

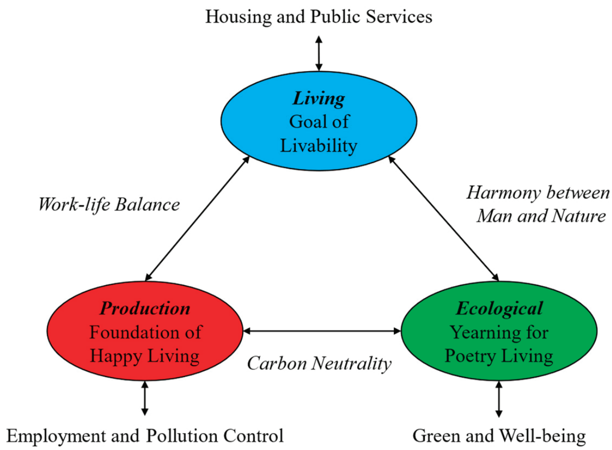


Figure 2. The interactive relationship of production–living–ecological spaces.

Livability is the primary goal of building a "livable city". In urban spaces, the need for intimate, continuous relationship comes first. Therefore, urban living spaces need to pay close attention to the basic needs of people including social and spiritual needs. This requires that urban planning must be primarily carried out at the human scale to provide the necessary housing and basic public services. Second, production and living are closely related, and the construction of a modern livable city cannot be separated from the drive of production, which provides the necessary material basis for human beings to live happily. On the one hand, innovative behavior in urban production space will continue to provide employment for its residents, but on the other hand, it is also necessary to control the pollution caused by agglomeration in production space. Furthermore, a livable city should try to achieve a work-life balance as much as possible, ensure that wages and rents match, and ensure that green spaces and fresh air are not sacrificed to earn wages [43]. Finally, the urban ecological space reflects humans' longing for poetic living. A beautiful ecological environment can not only directly promote human physical and mental health and realize "harmony between man and nature", but also provide nature-based habitat through ecological resource value conversion. In addition, ecological space can also promote the sustainable development of production space through carbon neutrality. As a result, production–living–ecological spaces of a livable city have achieved effective interaction and established a virtuous circle. The overall optimization of livable urban space that integrates production–living–ecological needs to systematically formulate land use policies, fully consider the interactive relationship between production-living-ecological spaces in the allocation of land factors. The integration of "truth-kindness-aesthetic" in urban space is crucial to improving the overall welfare of the city and achieving sustainable urban development.

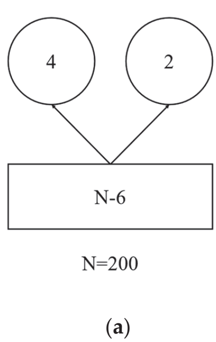
5. Findings

5.1. The Logics of Planning and Market Allocation of Land Factors

In the face of an increasingly complex global environment, the allocation of land factors shoulders the important task of coordinating development and security in the modernization of a country. Planning and market essentially represent two different logics of land factors allocation. The control and guidance functions of planning help build a security barrier for the development of national modernization, reflecting the "top-down" factors allocation logic, which is a manifestation of the modernization of the national governance system. The incentive and adjustment functions of market are the fundamental driving force to promote the country's development to a new level, reflecting the "bottom-up" factors allocation logic, which reflects the modernization of national governance capacity. On the one hand, the modernization of China's territorial space governance system and governance capacity, needs to follow the "top-down" logic, which starts from the continuity of the planning system and the overall coordination of the region, and realizes the allocation of land factors based on maximizing the overall social benefits. On the other hand, it also needs to follow the "bottom-up" land factors allocation logic to meet the interests of different individuals and stimulate the vitality and efficiency of market mechanism. Therefore, to realize the complementarity of public interests and personal interests in the development of national modernization requires a good connection between "top-down" and "bottom-up" logic in terms of allocation of land factors.

5.2. The Theoretical Mechanisms of Market and Planning Allocation of Land Factors

Individual rationality is the starting point of market allocations of land factors. To explain this argument, we introduce the "Centipede Paradox" model (Figure 3). It is a kind of paradox found in the study of game theory and game logic, and it is a kind of paradox of reasonable behavior choice. This game is called the "centipede game" because it spreads like a centipede. It means that two players have a square box with N gold coins and two round empty containers. First, you take two gold coins out of the box and put them both in one of the containers. Then every time after that, you take two gold coins out of the box and put one gold coin in each of the containers. The two players, A and B, take turns choosing strategies to either end the game, choose the container with the most coins, or let the game continue. Suppose A chooses first, then B, then A, and so on, and the number of games between A and B is a finite 100 times. The respective returns of this game are shown in Figure 1. For the first time, if A completes the decision, A and B get 2 and 0 gold coins, respectively. For the second time, if B's decision ends, A and B get 1 and 3 gold coins, respectively. For the third time, if A completes the decision, A and B get 4 and 2 gold coins, respectively, and so on. Based on the logic of the game, the rational person's assumption is that A is going to end the game on the second to last step. But the problem is that B is also smart, he anticipates A's motivation, and he ends the game on the third to last move. It is not hard to see that in the reasoning process of this game, backward induction is used. If the market pursues individual rationality too much, the composite whole may be irrational. Therefore, planning is needed to supplement and correct market failures in the allocation of land factors.



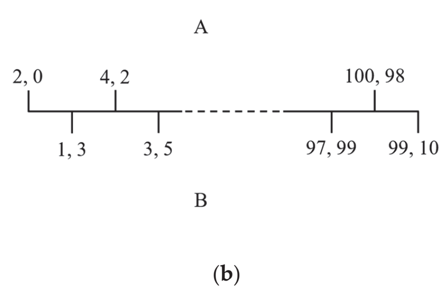


Figure 3. Centipede game model: (**a**) Description of game item: a square box with N − 6 gold coins and two round containers with 4 and 2 gold coins respectively; (**b**) Description of the game process. Before the comma is the return of A, after the comma is the return of B.

Overall rationality is the starting point of planning allocations of land factors. A social optimization model is introduced here to illustrate this point [44]. As shown in Figure 4, there are two ice cream stands A and B on the coastline that offer exactly the same goods and services. In order to gain a larger market, the positions of A and B spontaneously developed from the initial state I to the stable state III of the balanced match during the game. To reduce the overall transportation cost of residents along the coast, the layout of ice cream stand A and B should be planned for social optimization, and A and B should be placed in 1/4 and 3/4 places respectively. However, overall rationality also needs to incorporate individual rationality. Facing the ever-changing economic and social development environment, over-emphasis on the control and constraints of planning may be counterproductive. The basic conclusion is that light control is the most effective, while tight control can lead to overreaction and sometimes even the disintegration of the machine. The compilation of territorial space planning needs to consider its variability, adjustability, selectivity and reconfigurability.

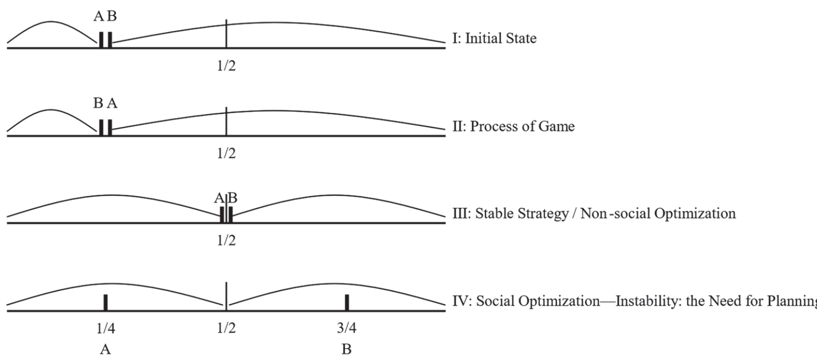


Figure 4. Social optimization model: A and B are two ice cream stands on the coastline that offer exactly the same goods and services.

5.3. Enlightenment of Middle-Around Theory

In China's reform to promote the modernization of territorial space governance system and capacity, we suggest that "middle-around" theory is a possible theoretical solution to effectively connect planning and market in the allocation of land factors. The western planning concept originates from city-state governance, with the city as the core and the bottom-up orientation as the starting point and the leading; however, the planning concept of China originated from irrigated agriculture. Since Yu controlled the flood, the core was rural areas, emphasizing top-down. In modern China, the influence of "Western learning to the east" and bottom-up Western planning concept influenced China. Especially after the reform and development in 1978, the western planning trend of thought had more and more profound influence on China. However, it conflicts with the deep-rooted top-down planning concept in China, so different plans have different ideas. It is under this background that "multi-planning integration" is proposed, and middle-around provides a new planning theory for the future "multi-planning integration".

Planning emphasizes goal orientation and usually starts from supply, so indicators are decomposed layer by layer from top to bottom. Market focuses on problem solving and tends to start from demand, which is a bottom-up demand orientation. "Middle-around", also known as theory of "Waist", is the intersection of "top-down" planning allocation theory and "bottom-up" market allocation theory (Figure 5), which is oriented by the balance between supply and demand, to achieve the synergy of achieving goals and solving problems. On the one hand, "middle-around" theory emphasizes that the rational allocation of land factors requires planning and market to be used together, neither cannot be neglected. On the other hand, it emphasizes that only by adaptively using government and market functions in face of specific problems in the allocation of land factors can avoid the logical conflict between "top-down" and "bottom-up", and truly release the power of territorial space governance systems and capacity when driving modernization reforms.

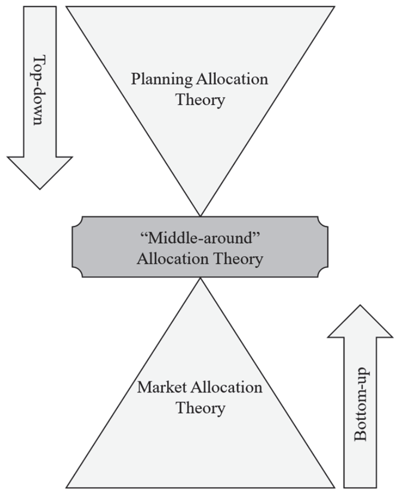


Figure 5. "Middle-around" theory in allocation of land factors.

From the perspective of production-living-ecological spaces, this study analyzes how China's land factors allocation in the modernization development towards 2035 should use the two methods of planning and market to achieve the overall requirement of "intensive and efficient production space, livable and moderate living space, and beautiful ecological space". Territorial space is extremely complex, but spatial scale is an entry point to understand the internal rules of it. Combining the guidance of "middle-around" theory and the starting point of spatial scales heterogeneity, we can better understand the differential mode of government-market collaborative allocation of land factors of production–living–ecological spaces. The first is global/country scale, which considers whether land resources can be used. In the case of available land, it can be divided into use/non-use. The theory needed here is sustainable development theory, including land ethics, global climate change and suitability assessment; the second is regional scale, considering the scale allocation of agricultural land and the utilization of non-agricultural construction land. The methods used here are demand forecasting and indicator decomposition. Demand forecasts must take into account the diversity of needs, including sustenance of food and housing, as well as agricultural and industrial productivity. Index decomposition involves structural adjustment; the third is local scale, considering the spatial layout, specifically the relationship between ecological land and construction land, as well as the internal relationship of construction land. The spatial layout should consider the social development stage, the influence of utilization and zoning planning, land use, location and transportation and other factors. To sum up, "middle-around" theory can provide helpful solutions to the practice of land factors allocation in developing countries, but the perfection of the theoretical solution always needs practice tests, timely feedback, and continuous improvement.

6. Conclusions

Planning and market are two means to allocate land factors, but there is a boundary between them. The territorial space is a complex system, current knowledge and cognition of human beings is limited, and the future is full of numerous variables and uncertainties. In this context, land factors allocation requires the synergistic allocation of planning and market to achieve both development and safety goals looking forward to 2035. Furthermore, land factors allocation should also consider the spatial scale differences [45]. To be specific, the adoptions to planning and market should follow the rule of "globally fuzzy to locally accurate" from top level to down level. The higher-level planning should be more macroscopic, more standardized, and more stylized. When it comes to detailed planning at lower level, the expression of spatial elements is more refined. For large-scale planning, it is necessary to do a good job of strategic guidance, coordinate the development goals and the bottom line of safety. For planning elements that must be implemented, such as urban development boundaries, permanent basic farmland red lines, and ecological protection red lines, planning should be strictly formulated, and relevant laws and regulations should be implemented. However, Technical standards can be in the form of guidelines, recommendations, etc., to provide flexible solutions to uncertainties, and leave enough room for market. For small-scale planning, due to the basic data information of clear research on market demand, the planning can be made clearer and more detailed. The layout of various spaces and facilities shall be coordinated to fully reflect the regional and cultural characteristics according to the local population and resource conditions, the stage of economic and social development, and the improvement requirements of the human settlements. Besides, it needs pay attention to the dynamic monitoring in the later period, so that the planning can be effectively implemented in the long run.

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References

1. Chen, J.H. The State Logic of Modernizing the Governance System. *Soc. Sci. China* **2022**, *43*, 37–52.
2. Wu, Y.Z.; Sun, X.F. The Review and Prospect of Land Use Policy in China after the 40 Years of Reform and Opening Up: An Urbanization Perspective. *China Land Sci.* **2018**, *32*, 7–14. (In Chinese)
3. Hopkins, L. *Urban Development: The Logic of Making Plans*; Island Press: London, UK, 2001.
4. Lai, S.-K. *Planning within Complex Urban Systems*; Routledge: New York, NY, USA, 2021.
5. Zhu, J.; Deng, M.L.; Pan, A. Three-Plan Integration: Exploring the Order and Regulation Capacity of Spatial Planning. *China City Plan. Rev.* **2015**, *24*, 31–40.
6. Chen, J.C.; Zhang, J.X.; Chen, H. The Bottom-Line Boundary, Analyses of the Governance Logic of Land Resource Allocation. *Urban Stud.* **2021**, *28*, 33–41.
7. Wang, W.M. The Nature of Planning and Multidimensional Thinking about Land Use Planning. *China Land Sci.* **2002**, *16*, 4–6. (In Chinese)
8. Wu, C.F.; Shao, X.Z. A Study on the Irrational, Uncertain and Flexible Theory of Land Use Planning. *J. Zhejiang Univ. (Hum. Soc. Sci.)* **2005**, *35*, 98–105. (In Chinese)
9. Qian, Z.H.; Mou, Y. Land Marketization Level of China: Measurement and Analysis. *Manag. World* **2012**, 67–75. (In Chinese) [CrossRef]
10. Chen, Y.Y. A Study of Government Intervention and Market Mechanism in the Allocation of Land Resources. *China Land Sci.* **2008**, *22*, 20–27. (In Chinese)
11. Samuelson, P.A. The Pure theory of public expenditure. *Rev. Econ. Stat.* **1954**, *36*, 387–389. [CrossRef]
12. Bailey, M.J. The Theory of Public Finance: A Study in Public Economy by Richard A. Musgrave. *J. Political Econ.* **1960**, *68*, 194. [CrossRef]

13. Sun, H. The Study on the Multiple Provision Modes of Public Goods in Chinese Countryside. In Proceedings of the 2009 International Conference on Public Administration (5th), Chengdu, China, 23 October 2009.
14. Celine, T. Private Investments, Public Goods: Regulating Markets for Sustainable Development. *Eur. Bus. Organ. Law Rev.* **2022**, *23*, 241–271.
15. Gebre, Y.K.; Demsis, B.A. Reasons for the Potential Implementation of Public-Private Partnerships in Ethiopian Road Infrastructure Provision. *Adv. Civ. Eng.* **2022**, *2022*, 4863210. [CrossRef]
16. Bagnoli, M.; Watts, S.G. Selling to socially responsible consumers: Competition and the private provision of public goods. *Econ. Manag. Strategy* **2003**, *12*, 419–445. [CrossRef]
17. Rohman, M.A. Assessment of the government's role performance in public-private partnership (PPP) toll road projects in Indonesia. *J. Financ. Manag. Prop. Constr.* **2022**, *27*, 239–258. [CrossRef]
18. Li, S.; Dong, C.; Yang, L.; Gao, X.; Wei, W.; Zhao, M.; Xia, W. Research on Evolutionary Game Strategy Selection and Simulation Research of Carbon Emission Reduction of Government and Enterprises under the "Dual Carbon" Goal. *Sustainability* **2022**, *14*, 12647. [CrossRef]
19. Colander, D. Keynes and Friedman on Laissez-Faire and Planning: Where to Draw the Line? *J. Histor. Econ. Thought* **2014**, *36*, 518–521. [CrossRef]
20. Thériault, M.; Le Berre, I.; Dubé, J.; Maulpoix, A.; Vandersmissen, M.H. The effects of land use planning on housing spread: A case study in the region of Brest, France. *Land Use Policy* **2020**, *92*, 104428. [CrossRef]
21. Finer, H. Planning and nationalization in Great Britain. *Int. Labour Rev.* **1948**, *57*, 157.
22. Sudoniene, V.; Matonien, D. Land Use Planning in Lithuania and in the United States. In Proceedings of the 4th International Scientific Conference on Rural Development, Lithuanian Univ Agr Akad, Noreikiskes, Lithuania, 15–17 October 2009.
23. Wu, L.Y. Habitat II and the Science of Human Settlements Environment. *City Plan. Rev.* **1997**, *3*, 4–9. (In Chinese)
24. Ayupova, Z.; Kussainov, D.; Bekbergenova, A.; Winston, N. Major ideas and main values of the universal un declaration on human rights: The 70-years experience. *Bull. Nat. Acad. Sci. Repub. Kazakhstan* **2019**, 68–74. [CrossRef]
25. Parnell, S. Defining a Global Urban Development Agenda. *World Dev.* **2016**, *78*, 529–540. [CrossRef]
26. Sabouri, S.; Dillon, A.; Proffitt, D.; Townsend, M.; Ewing, R. State-of-the-Practice in Connecting and Coordinating Transportation and Land Use Planning in the USA. *Transp. Res. Rec.* **2019**, *2673*, 240–253. [CrossRef]
27. Chai, Y.W.; Zhang, X.; Sun, D.S. A Study on Life Circle Planning Based on Space Time Behavioural Analysis: A Case Study of Beijing. *Urb. Plan. Forum* **2015**, 61–69. [CrossRef]
28. Willis, K. Viewpoint: International development planning and the Sustainable Development Goals (SDGs). *Int. Dev. Plan. Rev.* **2016**, *38*, 105–111. [CrossRef]
29. Stoker, P.; Albrecht, T.; Follingstad, G.; Carlson, E. Integrating Land Use Planning and Water Management in U.S. Cities: A Literature Review. *J. Am. Water Resour. Assoc.* **2022**, *58*, 321–335. [CrossRef]
30. Sadeghi, S.; Jalili, K.; Nikkami, D. Land use optimization in watershed scale. *Land Use Policy* **2009**, *26*, 186–193. [CrossRef]
31. Susan, K.; Van, B. Governance of Land Use Planning to Reduce Fire Risk to Homes Mediterranean France and California. *Land* **2017**, *6*, 24.
32. Tamiyo, K.; Shogo, T. Scenario Planning Approach to Pre-Event Planning for Post-Disaster Recovery: The Case of the Future Mega-Tsunami Striking Kushimoto, Japan. *JDR* **2022**, *17*, 541–545.
33. Dong, S.Q.; Han, Z.G. Study On Planning an "Eco-Sponge City" For Rainwater Utilization. *Urb. Dev. Stud.* **2011**, *18*, 37–41.
34. Rodrigues, J. Where to Draw the Line between the State and Markets? Institutionalist Elements in Hayek's Neoliberal Political Economy. *J. Econ. Issues* **2012**, *46*, 1007–1033. [CrossRef]
35. Beer, A.; Kearins, B.; Pieters, H. Housing Affordability and Planning in Australia: The Challenge of Policy Under Neo-liberalism. *Hous. Stud.* **2007**, *22*, 11–24. [CrossRef]
36. Nesslein, T.S. Housing: The Market Versus the Welfare State Model Revisited. *Urb. Stud.* **1988**, *25*, 95–108. [CrossRef]
37. Deegen, P.; Halbritter, A. The pure market allocation of land between forestry and agriculture. *For. Policy Econ.* **2018**, *97*, 122–131. [CrossRef]
38. Xu, S.Y.; Chen, J.; Zhao, G. How Does the Land Leasing Marketization Affect the Economic Growth? *China Ind. Econ.* **2018**, 44–61. (In Chinese) [CrossRef]
39. Coase, R.H. The Problem of Social Cost. *J. Law Econ.* **1960**, *3*, 1–44. [CrossRef]
40. Gyourko, J.; Shen, Y.; Wu, J.; Zhang, R. Land finance in China: Analysis and review. *China Econ. Rev.* **2022**, *76*, 101868. [CrossRef]
41. Wu, Y.Z.; Shan, J.M.; Choguill, C.L. Combining behavioral interventions with market forces in the implementation of land use planning in China: A theoretical framework embedded with nudge. *Land Use Policy* **2021**, *108*. [CrossRef]
42. Rosenthal, S.S.; Strange, W.C. Geography, Industrial Organizatin, and Agglomeration. *Rev. Econ. Stat.* **2003**, *85*, 377–393. [CrossRef]
43. Evans, P. *Livable Cities? Urban Struggles for Livelihood and Sustainability*; University of California Press: Berkeley, CA, USA, 2002.

44. Ding, C.R. *Theory and Methods in Urban Spatial Planning*; China Architecture & Building Press: Beijing, China, 2018.
45. Ke, S.Z.; He, M. Planning and Market: An Empirical Analysis of Determinants of Urban Land Scale in China. *China Land Sci.* **2008**, *22*, 12–18. (In Chinese) [CrossRef]

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Spatiotemporal of the Coupling Relationship between Ecosystem Services and Human Well-Being in Guanzhong Plain Urban Agglomeration

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Abstract: Understanding the complex relationship between ecosystem services and human well-being during the rapid development of urban agglomerations can promote the sustainable development of urban agglomerations. In this paper, the InVEST model and ArcGIS10.2 were used to analyze the spatial and temporal evolution characteristics of ecosystem services and human well-being in the Guanzhong Plain urban agglomeration. On this basis, the coupling coordination index is used to reveal the spatiotemporal coupling relationship between them. (1) From 2010 to 2018, the water conservation services, soil conservation services, and carbon sequestration services of the Guanzhong Plain urban agglomeration showed a fluctuating downward trend. The spatial differences of ecosystem services were significant. (2) From 2010 to 2018, human well-being in the Guanzhong Plain urban agglomeration showed a fluctuating downward trend, with a decrease of 17%, and regional differences tended to narrow. (3) The coupling coordination degree between ecosystem services and human well-being has slightly decreased while maintaining the basic coordination state. The results show that there was a significant relationship between the decline of ecosystem services and the rapid development of the Guanzhong Plain urban agglomeration, and policies should be classified according to the coupling coordination types of human well-being and ecosystem services to promote the sustainable development of urban agglomerations.

Keywords: Guanzhong Plain urban agglomeration; ecosystem services; human well-being; InVEST model; coupling coordination degree

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1. Introduction

Since the 21st century, along with the continuous expansion of global cities, growth in the intensity of human activities, and continuous increases in social demands and human demands for water, land, and energy have been increasing. These factors have intensified the exploitation of natural resources and severely damaged global ecosystem services [1]. Maintaining good ecosystem services in urban agglomerations and effectively improving local human well-being are hot topics for researchers. Therefore, the Millennium Ecosystem Assessment (MA), the Future Earth Program (GLP), and the 2030 Agenda for Sustainable Development, proposed by international organizations, have coordinated ecological and urbanization development as their goals. These international organizations have paid much attention to the relationship between ecosystem services and human well-being [2]. China's urban agglomerations are in a stage of rapid development. The high-quality development of urban agglomerations, in addition to the high-level protection of ecological environments, and ultimately the improvement of human well-being, are realistic issues that need to be faced in the construction of urban agglomerations [3].

Ecosystem services are defined as the various benefits humans derive from ecosystems [4] and are now recognized as provisioning services, regulating services, cultural services, and supporting services [5], which aim to improve human well-being [6]. Since the 1990s, many scholars have conducted studies around the theory, method and practical application of ecosystem service supply assessment. Extensive assessments of ecosystem services have been conducted in different regions, scales, and types [5–8]. There are a variety of quantitative assessment methods for ecosystem services. Cotatanza [4] et al. used the value equivalent scale to estimate the total capital structure value of ecosystem services. The InVEST model was used to visualize the value of ecosystem services, and the sustainable and dynamic evaluation methods. These two methods are the most widely used [9]. In contrast, human well-being has no standard definition and remains a contested concept [10]. Now, it is generally believed that human well-being is multi-dimensional, and the selected indicators are not the same under different research scales [11]. Easily accessible statistical indicators are used in large-scale studies [12], such as the Human Development index (HDI) [11] and National Well-Being Index (NWI) [13], and comprehensive well-being evaluations combining quality-of-life and material conditions [13,14].

2. Literature Review and Research Framework

2.1. Literature Review

The core issue of sustainable science is to extend the research on ecosystem services to human well-being, and to study the relationship between them [15]. Yang Xueting et al. [16], Liu Ziwen et al. [17], Willis C., and Kosanic et al. [18,19] explored the relationship between ecosystem services and human well-being from the perspectives of provisioning services, regulation services, and cultural services. Li [20] and Wei et al. [21] studied the impact of the supply–demand ratio of ecosystem services and different types of supply–demand mismatch on human well-being. Robinson B.E. et al. [22] proposed land management strategies based on the dependence of farmers' livelihoods on ecosystem services. Richard S. et al. [23] studied the impact of different decisions on human well-being from the community scale. Previous studies have shown that ecosystem services primarily play a bearing or constraint role in human well-being in terms of provisioning, regulation, culture, and support services [5], and the latter promotes or stresses ecosystem services as well as their functions through the differentiation of economic, social, and environmental well-being needs [24], thus forming a close bidirectional correlation between the two [25]. In the process of deepening geographical research into human–earth system coupling, ecosystem services and human well-being are increasingly closely interacting, and their correlation and coupling have gradually become the focus and frontier issues of current research [26].

In general, there are a lack of studies on the coupling relationship between ecosystem services and human well-being [26]. With the rapid development of urban agglomeration, many urban environmental problems have become increasingly prominent, and the ability of ecosystem to supply human well-being has been declining [27]. Assessing the coupling relationship between ecosystem service value and human well-being from the perspective of urban agglomerations can help cities maintain ecosystem service capacity and improve human well-being. This has important theoretical and practical significance for realizing the sustainable development of urban agglomerations.

2.2. Research Framework

The Guanzhong Plain urban agglomeration is an ecologically sensitive area, located in an important area of ecological function. The special geographical location and complex topography aggravate the vulnerability of the regional ecological environment; the environmental capacity is close to its limit. As a typical Western urban agglomeration with the prominent contradiction of "human–land", urban development and economic growth have intensified the waste of resources and resource constraints. At present, it is urgent to reveal the coupling relationship between human well-being and ecosystem services as well as to formulate a reasonable urban development strategy. Therefore, taking the Guanzhong Plain urban agglomeration as a research case, we used the InVEST model, coupling coordination degree, and other methods to analyze the coupling relationship and spatiotemporal evolution characteristics between ecosystem services and human well-being. In this way, the feedback of human well-being to ecosystem service changes and the well-being-driven effect of ecosystem service values were investigated. This provides a reference for the relationship between ecosystem services and well-being in the rapid urbanization of less developed regions around the world. The overall research framework is illustrated in Figure 1.

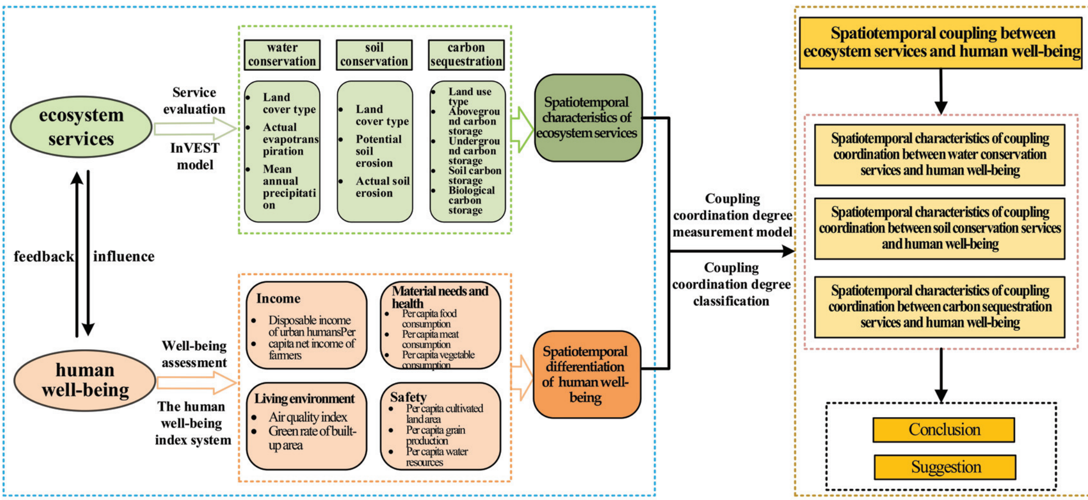

Figure 1. Research framework.

3. Materials and Methods

3.1. Study Area

As the second largest urban agglomeration in western China, the Guanzhong Plain urban agglomeration is an important growth pole, leading the development of the western region, and an important gateway facing the central and eastern regions. It includes the Guanzhong region of Shaanxi Province and some cities in Shanxi and Gansu Provinces, with a total of 90 counties (cities and districts). With an area of 10.71 × 10^4 km, and an average altitude of 400–3700 m (Figure 2), it possesses a temperate semi-humid monsoon climate. The rainfall decreases from west to east and from south to north. The regional geology and landforms are complex, with the mountains of the Southern Shaanxi and the Qinling Mountains to the south, the Loess Plateau to the north, and the Weihe River Lower Valley Plain in the middle, showing a basin topography with high surroundings and a low center. It is the core area of the middle reaches of the Yellow River Basin, and an important grain-producing area in China.

At the end of 2018, its permanent human population was 39.4853 million; its GDP was more than CNY 2 trillion, accounting for about 2.3% of the total GDP of China. However, the capacity of the natural ecological environment in this region is weak. Water resources are scarce, and groundwater overexploitation is prominent. The per capita water resources are less than one third that of the national average, and the spatial distribution of water resources is uneven. Water pollution in some sections of the Weihe River and Fenhe River Basin is serious. The massive mining of mineral resources has caused problems, such as soil erosion and soil pollution. It is necessary to strengthen the construction of ecological civilization and ecological environment protection in the future. The relationship between ecosystem services and human well-being is of great significance for solving the contradiction between ecological protection and economic construction in the Guanzhong Plain urban agglomeration.

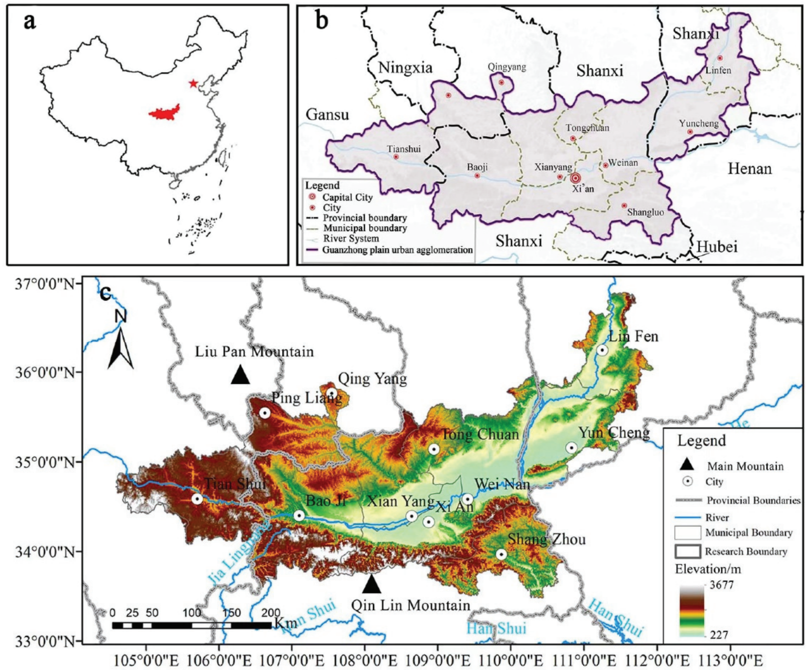

Figure 2. Overview of Guanzhong Plain urban agglomeration: (**a**) location in China; (**b**) administrative divisions; (**c**) elevation.

3.2. Data Sources

This paper mainly includes meteorological data, soil data, land use data, and statistical yearbook data. The meteorological data are from resources and environment data cloud platform (https://www.resdc.cn/Default.aspx (accessed on 6 December 2021)). The potential evapotranspiration data are from the Global Drought Index and Potential Evapotranspiration (ET0) Climate Database V2. Soil data are from the World Soil Database. The land use data of 2010, 2015, and 2018 were from China Land Use/Land Cover Remote Sensing Monitoring Database with a resolution of 100 × 100 m. DEM data are from geospatial data cloud (http://www.gscloud.cn/ (accessed on 8 December 2021)). All raster data were reclassified and transformed into projections in GIS, the resolution was uniformly transformed into 100 m × 100 m, and the projection was uniformly transformed into Albers projection. The data for the assessment of human well-being are mainly from the 2010, 2015, and 2018 China Urban Statistical Yearbook, China County Statistical Yearbook, and the statistical yearbooks of 90 counties (districts) in the Guanzhong Plain urban agglomeration.

3.3. Research Methods

3.3.1. Ecosystem Services

1. Water Yield model

As a typical water-scarce area, the Guanzhong area has rapidly increased the demand for water resources. The InVEST Water Yield model is used to calculate the water conservation services of the region, detailed in the following equations [28]:

$$Y_{xj} = \left(1 - \frac{AET_{xj}}{P_x}\right) \times P_x$$

$$\frac{AET_{xj}}{P_x} = \frac{1\ + \omega_x R_{xj}}{1 + \omega_x R_{xj} + \left(\frac{1}{R_{xj}}\right)}$$

$$\omega_x = Z\frac{AWC_x}{P_x}$$

$$R_{xj} = \frac{K_{xj} \times ET_x}{P_x}$$

where Y_{xj} is the annual water volume (mm) of the land cover type j in pixel x. AET_{xj} is the actual evapotranspiration (mm) of land cover type j in pixel x. P_x is precipitation (mm) of pixel x. ω_x is to correct the ratio of annual vegetation available water and precipitation. R_{xj} is the dry coefficient. Z is Zhang's coefficient, which is 30 [29] in this paper, according to previous studies. AWC_x is the effective soil water content (mm) of raster cell x. K_{xj} is the evapotranspiration coefficient of vegetation of land cover type j in pixel x. ET_x is the reference crop evapotranspiration.

2. Sediment Delivery Ratio (SDR) model

Soil erosion is a serious environmental problem faced by human beings that restricts the sustainable development of the global economy and society. Serious soil erosion can destroy land productivity, reduce biodiversity, threaten the regional ecological environment, and exacerbate poverty in mountainous areas. The Guanzhong Plain urban agglomeration is located in a fragile ecological environment. The soil erosion is very strong because of the combined action of natural and human factors. The Guanzhong Plain urban agglomeration is the key area of soil erosion research in the world. The soil retention in this area is calculated by the SDR Model in the InVEST model [30]:

$$SEDERT_x = RKLS_x - USLE_x$$

where $SEDERT_x$ denotes soil conservation (t) of pixel x. $RKLS_x$ and $USLE_x$ denote potential soil erosion (t) and actual soil erosion (t), respectively.

$$RKLS_x = R_x \times K_x \times LS_x$$

$$USLE_x = R_x \times K_x \times LS_x \times C_x \times P_x$$

where R_x is rainfall erosivity [MJ·mm/(hm·h·a)]. K_x is the soil erodibility. LS_x is the slope length and slope factor. C_x is the vegetation cover factor. P_x is the management factor.

3. Carbon Storage and Sequestration model

We calculated carbon Sequestration services of Guanzhong Plain urban agglomeration through the Carbon Storage and Sequestration in InVEST model. Carbon sequestration mainly includes aboveground carbon sequestration, underground carbon sequestration, soil carbon sequestration, and biological carbon sequestration. The carbon density data are from the literature [31].

$$G_C = G_{above} + G_{below} + G_{dead} + G_{soil}$$

where G_C is the total carbon sequestration of the ecosystem (t). G_{above} is the aboveground carbon sequestration (t). G_{below} is the underground partial carbon sequestration (t). G_{dead} is the carbon sequestration of dead organic matter (T). G_{soil} is the soil carbon sequestration (t).

3.3.2. Human Well-Being Level

1. The construction and evaluation of human well-being indicators

According to the Millennium Ecosystem Assessment Report, well-being mainly refers to the material, spiritual, and health needs of human beings, including basic living materials, safety, health, good social relations, and freedom of choice as well as action [32]. Generally, easy-to-obtain statistical indicators are selected for large-scale evaluation [13]. Based on the well-being connotations and related research in the Millennium Ecosystem Assessment Report, in addition to the availability of data, this paper constructed a well-being evaluation index body for humans in the Guanzhong Plain urban agglomeration from four dimensions: income, material needs and health, living environment, and safety (Table 1).

Table 1. The human well-being index system of humans in Guanzhong Plain urban agglomeration.

The Target Layer	Level Indicators	The Secondary Indicators	Weight
Human well-being	Income	Disposable income of urban humans	19.00%
		Per capita net income of farmers	17.00%
	Material needs and health	Per capita food consumption	13.00%
		Per capita meat consumption	7.00%
		Per capita vegetable consumption	9.00%
	Living environment	Air quality index	15.00%
		Green rate of built-up area	1.00%
	Safety	Per capita cultivated land area	5.00%
		Per capita grain production	3.00%
		Per capita water resources	11.00%

Among them, the need for a good life are not confined to the need for food and clothing; they include those necessary for pursuing a high quality of life, living environment beauty, and happiness of a better life. Basic substances for a good life include residents' income, purchasing power, and quality of life [32]. This paper will address residents' income and consumption of grain, meat, and vegetables to measure the material needs of residents to farmers, as well as their health. Living environments are an important source of residents' happiness. With the improvement of living standards, people pay more and more attention to the surrounding environment, and the degree of greenness and air quality are often the issues that are of most concern to urban residents [33]. Therefore, this paper includes an air quality index and the green rate of built-up areas in the evaluation indexes of human well-being [34]. In the arid region of northwest China, the ecological environment is fragile and the problems of soil erosion, desertification, and soil salinization are serious and threaten the livelihood and well-being of residents. Water resource security and food security are important factors affecting the well-being of residents [35,36]. Therefore, the per capita water resources, per capita cultivated land area, and per capita grain yield are used as the evaluation indexes of security.

In the evaluation, the entropy weight method was used to determine the weight of each index. The entropy weight method can determine the index weight according to the variation degree of the index value of each indicator. It is an objective weight method that avoids the deviations caused by human factors, gives full play to the advantages when determining the weights of many different indicators, and reflects the differences in the degree of fluctuation of different well-being dimensions [37]. Therefore, this paper first uses a range standardization method to standardize each index and determines the weight of each indicator via the entropy weight method. The well-being index of each county and district in the Guanzhong Plain urban agglomeration was then calculated via weighted summation. Finally, the overall well-being level of humans in the Guanzhong Plain urban agglomeration was evaluated through the average value of human well-being in each county.

2. Analysis of hot and cold spots

The spatial agglomeration degree of human well-being in Guanzhong Plain urban agglomeration was effectively identified by the cold–hot spot analysis.

$$G_i^*(d) = \frac{K_{xj} \times \sum_{i=1}^{n} W_{ij}(d) x_i}{\sum_{i=1}^{n} P_x}$$

where W_{ij} is weight. x_i is the sample value of i. $G_i^*(d)$ is the degree used to effectively identify the spatial agglomeration degree of human well-being. If the value is positive, the area is a high-value agglomeration area of human well-being. Otherwise, it is a low-value agglomeration area.

3.3.3. The Coupling Relationship between Ecosystem Services and Human Well-Being

In this paper, the coupling degree index was introduced to construct the coupling coordination degree [29–32] measurement model of urban ecosystem services and human well-being in the Guanzhong Plain. We studied the degree of interaction between ecosystem services and human well-being and characterized whether the functions are mutually promoting at high levels or constraining at low levels.

$$D = \sqrt{C \times T}$$

$$T_Y = \partial Y_i + \beta U_i,\ T_S = \partial S_i + \beta U_i,\ T_G = \partial G_i + \beta U_i$$

$$C_Y = 2 \times \left\{ \frac{Y_i \times U_i}{(Y_i + U_i)^2} \right\}^{1/2},\ C_S = 2 \times \left\{ \frac{S_i \times U_i}{(S_i + U_i)^2} \right\}^{1/2},\ C_G = 2 \times \left\{ \frac{G_i \times U_i}{(G_i + U_i)^2} \right\}^{1/2}$$

where D is the degree of coupling coordination. C represents the coupling value and characterizes the degree of interaction between ecosystem services and human well-being, $0 \leq C \leq 1$. T is a comprehensive evaluation index for the coordinated development of ecosystem services and human well-being, indicating the overall synergistic effect or the contribution of the two. Y_i, S_i, and G_i are water conservation service, soil conservation service, and carbon sequestration service, respectively. U_i is the human well-being index. ∂ and β are coefficients to be determined. Due to the coordinated development of ecosystem services and human well-being, both ∂ and β are set as 0.5.

Based on results of existing studies [12,38–40] and the actual situation of this study, the coupling coordination degree of "ecosystem services-human well-being" was classified into five types(Table 2).

Table 2. Types of coupling coordination degree between ecosystem services and human well-being.

Coupling Coordination Degree	Coupling Coordination Type	Characteristics
$D \in (0, 0.2]$	Serious imbalance	Ecosystem services and human well-being are mutually restricted. Excessive and disorderly development of urban agglomeration has seriously squeezed ecological space. This is contrary to human well-being.
$D \in (0.2, 0.4]$	Moderate imbalance	There are certain constraints on ecosystem services and human well-being. The ecological problems arising from the construction of urban agglomeration have become prominent, with a negative impact on human well-being.
$D \in (0.4, 0.6]$	Basic coordination	The relationship between ecosystem services and human well-being is basically harmonious. The construction of urban agglomeration can maintain healthy development.

Table 2. *Cont.*

Coupling Coordination Degree	Coupling Coordination Type	Characteristics
D ∈ (0.6, 0.8]	Moderate coordination	Ecosystem services and human well-being can promote each other at a high level, and the construction of urban agglomerations can healthy develop.
D ∈ (0.8, 1.0]	High coordination	Ecosystem services and human well-being mutually promote each other at a high level, and urban agglomeration construction is developing in an orderly manner.

4. Results

4.1. Spatial–Temporal Characteristics of Ecosystem Services

4.1.1. Spatial–Temporal Characteristics of Water Conservation Services

From 2010 to 2018, the water content of the Guanzhong Plain urban agglomeration showed an overall fluctuating decreasing trend, from 6.88×10^{11} mm in 2010 to 6.34×10^{11} mm in 2018, a decrease of 7.8%. From 2010 to 2015, the water conservation of the Guanzhong Plain urban agglomeration significantly decreased, from 6.88×10^{11} mm to 6.11×10^{11} mm, a decrease of 11.3%. From 2015 to 2018, the annual water conservation slightly increased, from 6.11×10^{11} mm to 6.34×10^{11} mm, an increase of 3.8% (Figure 3). From 2010 to 2018, the coefficient of variation of water conservation services in the Guanzhong Plain urban agglomeration showed an overall downward trend, with a decrease of 16% (Figure 3). The aforementioned information indicates that the regional differences in water conservation services in this region were gradually narrowed.

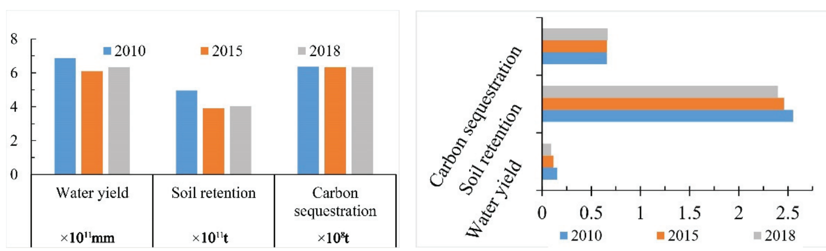

Figure 3. Total ecosystem services and coefficient of variation of ecosystem services.

Water conservation in the Guanzhong Plain urban agglomeration shows an overall distribution pattern of "high in the south and low in the north, decreasing from south to north". The high-value areas of water conservation were mainly distributed in the northern foothills of the Qinling Mountains. The second highest value areas of water conservation were mainly distributed in the upper reaches of the Weihe River, the northwest of the Guanzhong Basin, and the east of the Guanzhong Plain urban agglomeration. The low-value areas of water conservation were mainly distributed in the northwest of the Guanzhong Plain urban agglomeration and the Longdong region of the Gansu Province. This is consistent with the spatial distribution pattern of rainfall in the Guanzhong Plain urban agglomeration. From 2010 to 2018, the high-value areas of water conservation in the Guanzhong Plain urban agglomeration showed an expansion trend from east to west, whereas the low-value areas tended to shrink. From 2010 to 2015, the high-value areas were mainly distributed in the southeast and south of the Guanzhong Basin, with an expanding trend. From 2015 to 2018, the high-value area continued to expand westward, basically forming a distribution pattern consistent with the ecological barrier zone in the Qinba Mountains area in the south of the Guanzhong Plain urban agglomeration.

4.1.2. Spatial–Temporal Characteristics of Soil Conservation Services

From 2010 to 2018, the soil conservation in the Guanzhong Plain urban agglomeration showed a fluctuating downward trend from 4.96×10^{11} t to 4.05×10^{11} t, a decrease of 18.3%. From 2010 to 2015, the decreasing trend was significant, from 4.96×10^{11} t to 3.91×10^{11} t, a decrease of 21.2%. From 2015 to 2018, it slightly increased from 3.91×10^{11} t to 4.05×10^{11} t, an increase of 3.6%. The coefficient of variation of soil conservation services in the Guanzhong Plain urban agglomeration was decreased by 6.8% from 2010 to 2018. This indicates that the regional differences in soil conservation in the Guanzhong Plain urban agglomeration tended to narrow.

From 2010 to 2018, soil conservation in the the Guanzhong Plain urban agglomeration showed a spatial distribution of "high in the south and low in the north, high in the west and low in the east". The high-value areas were mainly distributed in the northern foothills of Qinling and the southeast of Longlong in the south of the Guanzhong Plain urban agglomeration. The low-value areas were mainly distributed in the Weihe River Valley and the Fenhe River Valley. From the perspective of interannual changes, the overall spatial distribution of soil conservation did not change much. The overall soil conservation in 2018 was less than that in 2010. However, the soil conservation in the Longdong area, especially Tianshui, was more than that in 2010.

4.1.3. Spatial–Temporal Characteristics of Carbon Sequestration Services

From 2010 to 2018, the carbon sequestration of Guanzhong Plain urban agglomeration was decreased from 6.36×10^8 t to 6.35×10^8 t, but the decrease was less than 1%. From 2010 to 2015, the carbon sequestration was decreased from 6.36×10^8 t to 6.34×10^8 t, a decrease of 0.3%. From 2015 to 2018, the carbon sequestration was increased from 6.34×10^8 t to 63.5×10^8 t. From 2010 to 2018, the coefficient of variation of carbon sequestration service in the Guanzhong Plain urban agglomeration showed an overall upward trend. This indicates that the regional difference in carbon sequestration service tended to increase, but the increase was small (0.92%). This indicates that the spatial variation of soil conservation was small during this period.

From 2010 to 2018, the spatial distribution of carbon sequestration in the Guanzhong Plain urban agglomeration was "high in southwest China and low in northeast China". The high-value areas were mainly distributed in the northern part of the Guanzhong Plain urban agglomeration, the northern part of Guanzhong Basin, the interlaced zone between the Liupan Mountains and the Guanzhong Basin, and the interlaced zone between the Taihang Mountains and the Jinshan Basin. The low-value areas were mainly distributed in the Weihe River Valley and the Fenhe River Valley. From the perspective of inter-annual variation, the overall spatial distribution of carbon sequestration did not change much. However, the carbon sequestration in 2018 was less than that in 2010 (Figure 4).

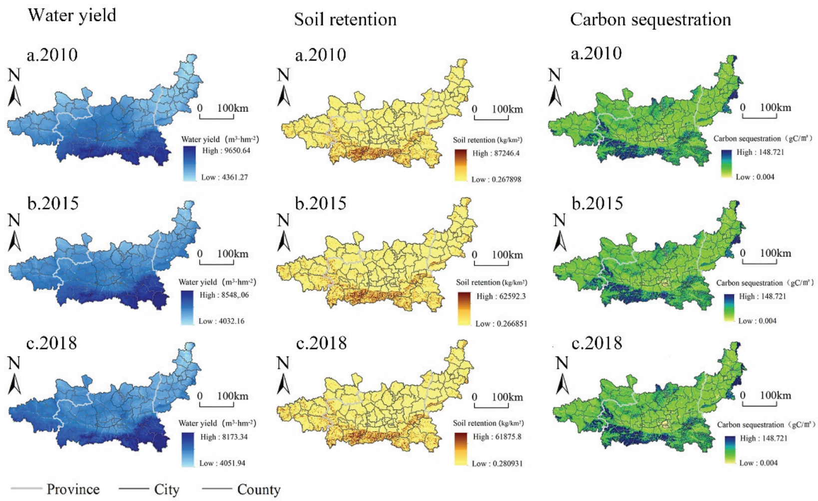

Figure 4. Spatial–temporal distribution of water conservation, soil conservation, and carbon sequestration in Guanzhong Plain urban agglomeration from 2010 to 2018.

4.2. Spatial-Temporal Differentiation of Human Well-Being

From 2010 to 2018, the comprehensive human well-being in the Guanzhong Plain urban agglomeration showed a fluctuating downward trend, from 0.53 in 2010 to 0.44 in 2018, a decrease of 17%. From 2010 to 2015, the human well-being showed a downward trend, from 0.53 to 0.42, a decrease of 21%. From 2015 to 2018, the human well-being showed a slow upward trend, from 0.42 to 0.44, an increase of 5%. The coefficient of variation of human well-being in the Guanzhong Plain urban agglomeration showed a downward trend, from 0.19 in 2010 to 0.14 in 2018, a decrease of 26% (Figure 5). This indicates that the regional differences in human well-being in the Guanzhong Plain urban agglomeration tended to narrow.

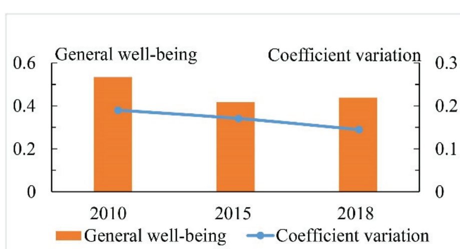

Figure 5. Changing trend of human well-being in Guanzhong Plain urban agglomeration from 2010 to 2018.

We classified the human well-being into five levels: high well-being, higher well-being, moderate well-being, lower well-being, and low well-being, by natural break point method (Figure 6). From 2010 to 2018, the overall human well-being in Guanzhong Plain urban agglomeration showed the spatial distribution of "high in the west and low in the east, high in the middle and low in the surrounding areas". In 2010, the high well-being areas were mainly concentrated in the urban functional developed areas of the Weihe River Valley and surrounding areas, with a stepped distribution from high to low from the center to surrounding areas. From 2010 to 2015, the urban functional developed areas and surrounding high well-being areas in the Weihe Valley expanded westward. A total of

10.5% of the counties and districts were transformed from medium- and low-level areas to high well-being areas, forming a stepped distribution of high-level districts with Xi'an and Baoji as the dual cores in the urban functional developed areas of the Wei River Valley. Therefore, high well-being generally shows an expansion trend. Low well-being areas expand eastward from Yuncheng City and Linfen City in the interlaced area of the Taihang Mountains and the Shanxi-Shaanxi Basin, but the overall change was not significant. From 2015 to 2018, 16.7% of counties and districts were transferred from low-level and high-level well-being areas to medium-level and high-level well-being areas. The regional difference in human well-being was further narrowed. In addition, high well-being areas expanded to the northwest on the basis of the previous stage. A total of 7.8% of the counties and districts were transferred to low-level areas. Xianyang City and Zhouzhi County in the central part of the study area, and Shangluo City in the southeast of Guanzhong Basin were transferred from moderate well-being areas and high well-being areas to low-level areas. There was a slight shrinking of high well-being areas, and the distribution was dispersed.

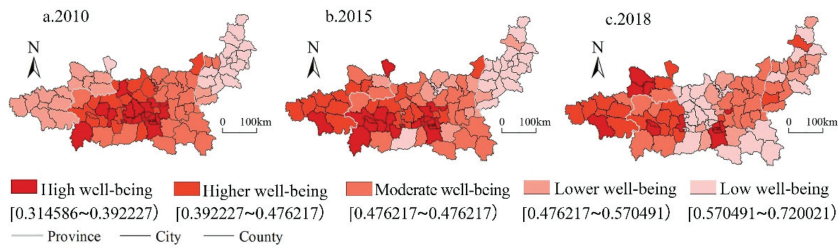

Figure 6. Spatial distribution of human well-being in Guanzhong Plain urban agglomeration from 2010 to 2018.

From 2010 to 2018, the spatial relationship of human well-being in the urban agglomeration in the Guanzhong area showed a "double contraction" trend, that is, the agglomeration of high-level and low-level areas of human well-being in the Guanzhong Plain urban agglomeration tended to weaken (Figure 7). From 2010 to 2015, the spatial relationship of human well-being showed a trend of "thermal contraction and cold expansion". The hot spots were mainly distributed in Xi'an, Xianyang, and eastern Baoji in the Weihe Valley. The cold spot area expanded from Linfen City and Yuncheng City in the intersection of the Taihang Mountains and the Shanxi-Shaanxi Basin to the Shanxi-Shaanxi junction area. From 2015 to 2018, the hot area and cold spot area both tended to shrink, and the hot area continued to shrink on the basis of the previous stage. Baoji City and Pingliang City at the border of Guanzhong Basin and the Longdong region were the core of the sub-hot area. The cold spot area turns from Linfen and Yuncheng in the Shanxi-Shaanxi border area to the northern part of the Guanzhong Basin.

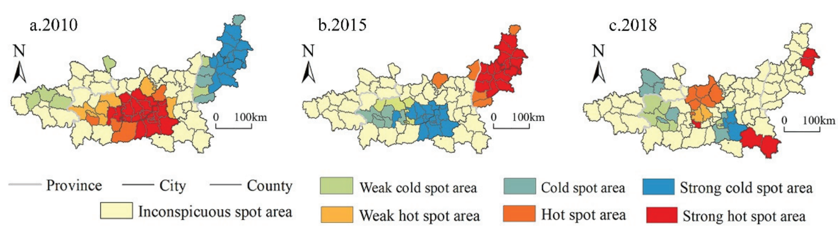

Figure 7. Spatial agglomeration characteristics of human well-being in Guanzhong Plain urban agglomeration from 2010 to 2018.

4.3. Spatiotemporal Coupling between Ecosystem Services and Human Well-Being

4.3.1. Spatial–Temporal Characteristics of Coupling Coordination between Water Conservation Services and Human Well-Being

The coupling coordination degree of "water conservation and human well-being" was significantly higher than that of "soil conservation services and human well-being" and "carbon sequestration services and human well-being" in the Guanzhong Plain urban agglomeration during the same period (Figure 8).

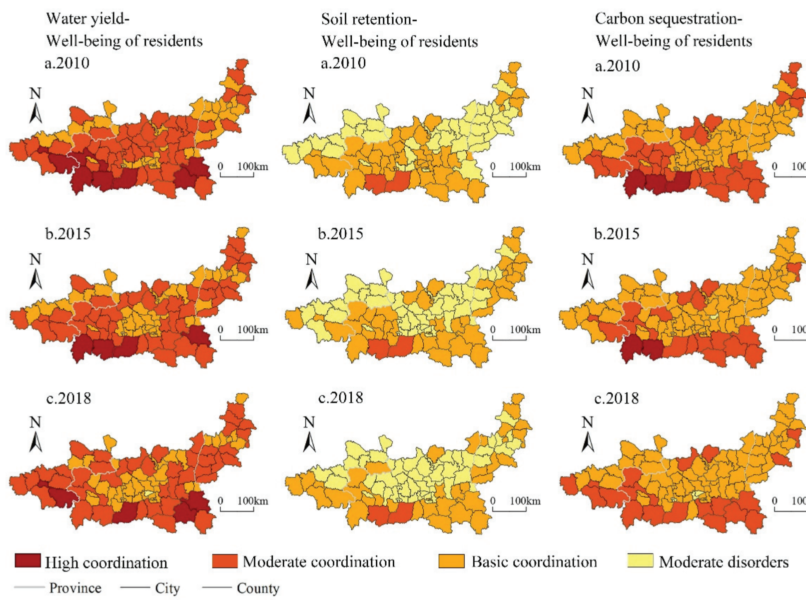

Figure 8. Spatiotemporal coupling patterns of water conservation, soil conservation, carbon sequestration, and human well-being in Guanzhong Plain urban agglomeration from 2010 to 2018.

In the spatial dimension, the coupling coordination degree of "water conservation and human well-being" gradually spread out from the core of urban functional developed areas of central cities, with a significant spatial distribution of "high around and low in the middle". The high-value areas were mainly distributed in the ecological protection areas with the Loess Plateau ecological barrier zone and the Qinba mountain ecological barrier zone, whereas the low-value areas were mainly concentrated in the central urban functional developed areas. The low-value areas were centered on the urban functional developed areas, and gradually expanded in the form of circle, and its influence scope was gradually enlarged.

In the temporal dimension, the overall coupling coordination degree of "water conservation and human well-being" was decreased from moderate coordination to basic coordination. The average level of coupling coordination degree was decreased from 0.64 to 0.60. In 2010, the coupling coordination degree was [0.46, 0.89], and the coupling coordination types mainly included basic coordination, moderate coordination, and high coordination, accounting for 41.11%, 51.11%, and 7.78%, respectively. The overall level was relatively high, and most of them were moderate coordination. In 2015, the coupling coordination degree was [0.42, 0.85]. In this period, the coupling coordination types of "water conservation and human well-being" were still basic coordination, moderate coordination, and high coordination, accounting for 48.9%, 46.6%, and 4.5%, respectively. The overall level was lower than that of 2005. In addition, the proportion of high coordination was lower than that of 2015. In 2018, the coupling coordination degree of "water conservation and human well-being" was between [0.39, 0.84]. The coupling coordination types in this period were moderate imbalance, basic coordination, moderate coordination, and high coordination, accounting for 1.1%, 47.8%, 46.7%, and 4.4%, respectively. The overall coordination level was moderate coordination.

The results show that the coupling coordination degree of "water conservation services and human well-being" of all districts and counties in the Guanzhong Plain urban agglomeration has a downward trend from moderate coordination to basic coordination.

4.3.2. Spatial–Temporal Characteristics of Coupling Coordination between Soil Conservation Services and Human Well-Being

The coupling coordination degree of "soil conservation services and human well-being" showed a fluctuation pattern of "increase first and then decrease", and the overall level was low.

In the spatial dimension, the low-value areas of coupling coordination degree of "soil conservation services and human well-being" in the Guanzhong Plain urban agglomeration were mainly distributed in the northern and central Guanzhong Plain urban functional developed areas, with the overall spatial distribution of "high in the south and low in the north". The high-value areas were concentrated in the northern Qinba mountain area, and the low-value areas were distributed in the northern Guanzhong Basin bounded by the Weihe River Valley.

In the temporal dimension, the coupling coordination degree of "soil conservation services and human well-being" in the Guanzhong Plain urban agglomeration showed a gradual decline from basic coordination to moderate imbalance. The average level of coupling coordination degree was decreased from 0.42 to 0.4. In 2010, the degree of coupling coordination was [0.30, 0.66]. The types of coupling coordination were mainly from basic coordination to moderate imbalance, basic coordination, and moderate coordination, accounting for 46.67%, 51.11%, and 2.22%, respectively. The overall level was relatively high and was in the state of basic coordination. In 2015, the coupling coordination degree was [0.32, 0.69]. The coupling coordination types of "soil conservation services and human well-being" were moderate imbalance, basic coordination, and moderate coordination, accounting for 51.11%, 46.67%, and 2.22%, respectively. The proportion of moderate coordination was decreased. The overall level was lower than that in 2010. In 2018, the coupling coordination degree of "soil conservation services-human well-being" in Guanzhong plain urban agglomeration was [0.28, 0.65]. The types of coupling coordination degree of "soil conservation services and human well-being" were moderate imbalance, basic coordination, and moderate coordination, accounting for 58.89%, 38.89%, and 2.22%, respectively. The overall level was moderate imbalance.

In general, the coupling coordination degree of "soil conservation services and human well-being" in the Guanzhong Plain urban agglomeration showed a fluctuating downward trend from basic coordination to moderate imbalance. The regional differentiation of coupling coordination degree did not change, but different regions showed different evolution trends. The overall coupling coordination degree in the northern Weihe River Valley continued to decline. However, the regional ecosystem services and human well-being in the southern Qinba Mountain and the southern Longdong Loess Plateau mutually promoted each other, orderly and benign high-level coupling coordination.

4.3.3. Spatial–Temporal Characteristics of Coupling Coordination between Carbon Sequestration Services and Human Well-Being

The coupling coordination degree of "carbon sequestration services and human well-being" in the Guanzhong Plain urban agglomeration was poor. The overall coupling coordination was at a low level. The carbon sequestration services were relatively weakened.

In the spatial dimension, the coupling coordination degree of "carbon sequestration services and human well-being" in the Guanzhong Plain urban agglomeration showed a significant spatial distribution of "high in the south and low in the north, and high in the west and low in the east". The high-value areas were concentrated in the northern Qinba

Mountains in the south. The low-value areas were mainly distributed in the areas with developed urban functions, such as Xi'an and Xianyang in the Guanzhong Plain, the Loess Plateau of Longdong, and the northeastern and western parts of the Guanzhong Plain.

In the temporal dimension, the coupling coordination degree of "carbon sequestration services and human well-being" in the Guanzhong Plain urban agglomeration showed a gradual declining trend from basic coordination to moderate imbalance. The average level of coupling coordination degree was decreased from 0.59 to 0.54. In 2010, the coupling coordination degree was [0.44, 0.86]. The coupling coordination types were basic coordination, moderate coordination, and high coordination, accounting for 67.78%, 28.89%, and 3.33%, respectively. The overall level was relatively high as basic coordination. In 2015, the coupling coordination degree was [0.39, 0.82]. The high-value areas in the southeast of the Guanzhong Plain urban agglomeration expanded to Fenhe Valley with Shangluo as the core, whereas the high-value areas in the west gradually shrunk with Tianshui in the southeast of the Longhe Plain as the core. The coupling coordination types of "carbon sequestration services and human well-being" were moderate imbalance, basic coordination, moderate coordination, and high coordination, accounting for 1.1%, 78.89%, 17.78%, and 2.22%, respectively. The overall level was lower than that in 2010. In 2018, the coupling coordination degree of "carbon sequestration services and human well-being" in the Guanzhong plain urban agglomeration was [0.36, 0.77]. The coupling coordination degree of "carbon sequestration services and human well-being" was promoted. The "Shangluo-Xi'an" cluster gradually shrunk, and the "Tianshui-Baoji" cluster shifted to the west while shrinking. The low-value area was gradually expanding outward with the urban functional developed areas in the Guanzhong Plain, especially the urban area of Xi'an as the core. There are three types in this period: moderate imbalance, basic coordination, and moderate coordination, accounting for 3.33%, 76.67%, and 20%, respectively. The overall level was basic coordination.

In general, the coupling coordination degree of "carbon sequestration services and human well-being" in districts and counties of the Guanzhong Plain urban agglomeration maintained the basic coordination state, whereas the overall level slightly decreased. The overall ordered and coordinated coupling coordination degree of "carbon sequestration services and human well-being" was degraded, and the number of high-value areas decreased (Figure 9).

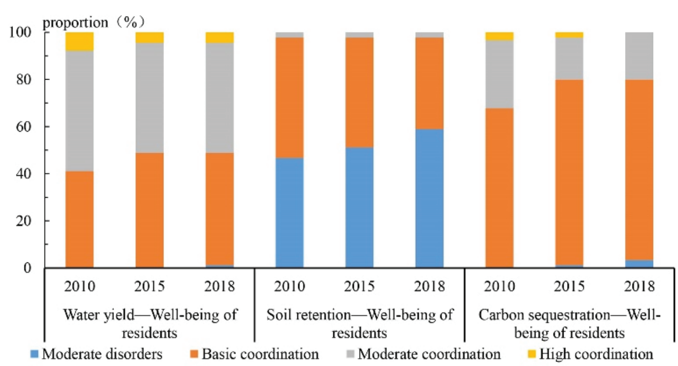

Figure 9. Changes of coupling coordination degree between ecosystem services and human well-being in Guanzhong Plain urban agglomeration from 2010 to 2018.

5. Discussion

As an ecologically sensitive area, the Guanzhong Plain urban agglomeration has a relatively fragile ecosystem. With the rapid development of urbanization, population density is increasing, industrial structures are changing, and construction land is expanding. These aspects lead to resource consumption and environmental pollution, which make the ecosystem face more severe pressure. This paper found that the three types of ecosystem services in the Guanzhong Plain urban agglomeration showed a downward trend from 2010 to 2018. This is closely related to the long-term human activities in the Guanzhong Plain. In the process of urban agglomeration construction, urban expansion encroaching on cultivated land space is serious. The vegetation coverage around the city has been severely damaged, resulting in serious pressure on the ecosystem. Wu Jiansheng et al. [41] found that the land carrying capacity in Guanzhong was decreasing, and that the land ecological deficit was increasing year by year. The sustainable development situation was not optimistic. Second, it is greatly influenced by geographical conditions and climatic factors. The most direct influencing factors are the interannual variation in precipitation and vegetation coverage. Severe soil and water loss as well as extreme water shortages in the Guanzhong Plain led to a reduction in vegetation. This greatly restricted the large-area coverage of vegetation. From 2010 to 2018, the area of forest land in the region decreased by 5.21%, the area of grassland decreased by 11.3%, and the annual rainfall decreased by 8.2%. These led to a decrease in the demand for ecosystem services. Bai Yujuan et al. [42] found that plants in the Loess Plateau mainly rely on precipitation for growth. However, there were serious water shortages in this region, and the vegetation coverage was low. Therefore, ecosystem services were declining.

From 2010 to 2018, human well-being in the Guanzhong Plain urban agglomeration showed a fluctuating downward trend, with a decrease of 17%. From 2010 to 2015, human well-being showed a downward trend. From 2015 to 2018, human well-being showed an upward trend, but did not return to the level seen in 2010. The human well-being indicators in this paper are mainly constructed from four dimensions: income, material needs and health, living environment, and safety. From 2010 to 2015, income as well as material needs and health in the Guanzhong Plain urban agglomeration increased, but living environment and safety significantly decreased. Air quality, urban area, the area of cultivated land per capita, green area, and per capita grain output all showed a downward trend. In the construction of the urban agglomeration the population increased, arable land was occupied, and per capita cultivated land decreased. In addition, many farmers began to work in cities, leaving their farmland abandoned. The air pollution in the urban development is relatively serious. Xi'an and Xianyang were the most concentrated areas of atmospheric pollution. As a result, human well-being is declining. The implementation of the national food security strategy and targeted poverty alleviation strategy proposed at the 2013 Central Rural Work Conference has greatly increased humans' income and improved farmland protection. In addition, Yang Ke et al. found that although the annual average PM2.5 concentration in the Guanzhong Plain urban agglomeration showed an overall downward trend from 2015 to 2019, it still exceeded China's air quality Level II (35 $\mu g/m^3$) [43]. Therefore, human well-being recovered from 2015 to 2018 but did not reach its initial level.

Human well-being is strongly dependent on the services provided by well-functioning ecosystems. Changes in the ecological functioning of systems can have direct or indirect effects on human well-being. The sustainable development of the Guanzhong Plain can only be ensured by realizing the coordinated development of human well-being and ecological environments. From 2010 to 2018, the level of coupling coordination between ecosystem services and human well-being in the Guanzhong Plain urban agglomeration showed a downward trend. Moreover, the spatial–temporal coupling relationship between ecosystem services and human well-being was lower in the developed urban areas and higher in the ecological protection areas dominated by the Loess Plateau ecological barrier zone and the Qinba Mountains ecological barrier zone. The results show that the disorderly expansion of the Guanzhong Plain urban agglomeration and the decrease in ecosystem services were significantly related to the rapid development of the Guanzhong Plain urban agglomeration. In the central region of urban functional developed areas, the economy has rapidly developed, and the land types dramatically changed in the urban agglomeration. The construction land occupied other types of land, especially in the urban fringe area where the ecological stress was the most serious. The main source of new construction land in urban expansion was cultivated land. Therefore, the coupling coordination degree between ecosystem services and human well-being was low. In the ecological protection areas dominated by the ecological barrier belt of the Loess Plateau and the Qinba Mountains, the quality requirements of the ecological environment are constantly improving, and the ecological environment is relatively good. The support of ecological compensation and poverty alleviation policies in the protection zones has significantly increased human well-being; human well-being was rapidly promoted in urban functionally developed areas. Therefore, the regional ecosystem services are highly coordinated with human well-being.

This paper studies the complex relationship between ecosystem services and human well-being during the rapid development of urban agglomerations, which provides a basis for the regional sustainable development of urban agglomerations in the arid region of northwest China. However, there are also some shortcomings. For example, in the process of assessing ecosystem services, some parameters in the InVEST model are based on the model user manual and the results of previous studies. In the future, field monitoring will be conducted to enhance the accuracy of the parameters in the study area, so as to improve the accuracy of ecosystem services' assessment results. This paper takes counties as the research units, and we focus on the macro level of ecosystem services as well as the welfare of the mutual influence between them; however, we found that the accessibility of medical facilities, the development of traffic, and a balanced diet are also important factors influencing human well-being. Due to these data, our paper positions itself within the research as a study on welfare into the future.

6. Conclusions and Suggestion

6.1. Conclusions

Understanding the complex relationship between ecosystem services and human well-being can promote the sustainable development of urban agglomerations. Taking the Guanzhong Plain urban agglomeration as a case area, we used the InVEST model and the coupling coordination model to analyze the spatial–temporal pattern and the coupling coordination degree of ecosystem services and human well-being, based on the water conservation, soil conservation, and carbon sequestration services of the Guanzhong Plain urban agglomeration in 2010, 2015, and 2018. We have the following conclusions:

(1) From 2010 to 2018, three types of ecosystem services in the Guanzhong Plain urban agglomeration showed a downward trend. The amount of water conservation services showed a fluctuating downward trend, with a decrease of 7.8%. It showed a spatial distribution of "high in the south and low in the north, decreasing from south to north". The amount of soil conservation services showed a fluctuating downward trend, with a decrease of 18.3%. It showed a spatial distribution of "higher in the south and lower in the north, higher in the west and lower in the east". The carbon sequestration services showed a fluctuating downward trend, with a decrease of less than 1%. It showed a spatial distribution of "high in the southwest and low in the northeast", and the regional differences tended to expand.

(2) From 2010 to 2018, human well-being in the Guanzhong Plain urban agglomeration showed a fluctuating downward trend, with a decrease of 17%. It showed a spatial distribution of "high in the middle and low around". Regional differences tended to narrow, and the agglomeration of high-level and low-level areas of human well-being tended to weaken.

(3) From 2010 to 2018, the coupling coordination degree between ecosystem services and human well-being in the Guanzhong Plain urban agglomeration showed a downward trend. The coupling coordination degree of "water conservation services and human well-being" showed a spatial distribution of "high around and low in the middle". The overall coordination decreased from moderate to basic coordination. The coupling coordination degree of "soil conservation services-human well-being" showed a distribution of "high in the south and low in the north". Different regions showed

different evolution trends. The overall trend decreased from basic coordination to moderate imbalance. The coupling coordination degree of "carbon sequestration services and human well-being" showed a significant distribution of "higher in the south and lower in the north, higher in the west and lower in the east". The overall level was slightly degraded while maintaining the basic coordination state.

6.2. Suggestion

Based on the above conclusions, we classified and implemented policies based on the coupling coordination types of human well-being and ecosystem services to promote the sustainable development of the Guanzhong Plain urban agglomeration.

The following are suggestions for areas with lagging water conservation services. In the construction of future urban agglomerations, we should give priority to water resource protection and water conservation, optimize the distribution pattern and efficiency of water resources, and optimize the urban spatial layout, industrial structure, and population size with the carrying capacity of water resources. The government should adhere to the bottom line for the sustainable development of the Guanzhong Plain, Qinling, and Wei River as well as Fenhe River basin ecologically sensitive areas, such as water conservation functions, and speed up the development and protection of ecological sources in the urban functionally developed areas of the Wei River valley. Improving the security of water supplies and water conservation can expand the space of city development and promote human well-being. For the areas with lagging soil conservation services, it is necessary to coordinate soil and water conservation with urban agglomeration construction and regional high-quality development in future urban agglomeration construction processes. We should implement the ecological red line and return sloping land above 25° to forest (grass), soil and water conservation, and the comprehensive treatment of soil and water loss to promote urban greening construction and improve urban livability. In addition, it should be noted that the conversion of farmland into forest is not suitable for all regions, especially the Loess Plateau region in the north, where water resources are limited. Therefore, ecological conversion should be arranged according to scientific laws. For areas with lagging carbon sequestration services, it is necessary to change the development ideas and the methods of economic growth, accelerate industrial structure optimization, reduce the degree of interference with ecological systems, strictly control energy-intensive and highly polluting industries of low benefit, set up green industry systems, strengthen the protection and construction of forest ecological systems, and promote the mutual promotion of urban agglomeration construction as well as ecosystem protection and restoration, thereby achieving the coordinated development of ecosystem services and human well-being. By regulating ecosystem services to improve air quality, we can improve the health of urban humans and the overall ecological environment. Ecological corridors are unevenly distributed in the urban agglomeration, and the main ecological sources and corridors are concentrated in the southern Qinling region of the urban agglomeration. In the future development planning of the urban agglomeration, we should pay more attention to the ecological construction of the Qinling National Park and accelerate the ecological corridor.

Ecosystem services and human well-being are important extensions of sustainable development theory. The carrying capacities of regional environments are important limiting factors for the coordinated development of urban agglomerations. The services provided by good ecosystems within urban agglomerations can effectively improve local human well-being. At present, China's urban agglomerations are in a stage of rapid development. To improve the spatial utilization efficiency of urban agglomerations, we should consider many factors, such as industries, spatial layouts, and ecological corridors, solve the environmental protection problems in the past single-city development mode stage, and coordinate the relationship between ecological protection and social as well as economic development. The coordination between the related goals of improving human well-being in urban agglomerations and the status quo of urban ecological protection is not only conducive to guiding the rational spatial layouts of urban agglomerations, but also crucial to improving internal ecological joint prevention and control ability in addition to the sustainable development of urban agglomerations. The construction of ecosystem security patterns is of great significance for the comprehensive management of hills, water, forests, fields, lakes, and grass, the formulation of multi-level ecological security policies, and the promotion of the resilience of urban agglomerations as well as the sustainable development goals of human well-being. In future research, it will be necessary to combine economic and social development factors, explore the internal source construction of urban agglomerations under the balance of the supply and demand of ecosystem services, strengthen the comprehensive management of urban agglomerations, and promote the regional integration in addition to high-quality development of urban agglomerations.

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References

1. Mendoza-González, G.; Martínez, M.; Lithgow, D.; Pérez-Maqueo, O.; Simonin, P. Land use change and its effects on the value of ecosystem services along the coast of the Gulf of Mexico. *Ecol. Econ.* **2012**, *82*, 23–32. [CrossRef]
2. Li, W.Q.; Zhang, X.Y.; Du, Y.X.; Ma, P.Y. Spatio-temporal changes of the coupling relationship between ecosystem services and human well-being in Qinba Mountains Area. *J. Nat. Resour.* **2021**, *36*, 2522–2540.
3. Fang, C.L.; Zhang, G.Y.; Xue, D.S. High-quality development of urban agglomerations in China and construction of science and technology collaborative innovation community. *Acta Geogr. Sin.* **2021**, *76*, 2898–2908.
4. Costanza, R.; d'Arge, R.; De Groot, R.; Farber, S.; Grasso, M.; Hannon, B.; Van Den Belt, M. The value of the world's ecosystem services and natural capital. *Nature* **1997**, *387*, 3–15. [CrossRef]
5. Board, M.E.A. Millenium Ecosystem Assessment-Ecosystems and human well-being: A framework for assessment. *Phys. Teach.* **2003**, *34*, 534.
6. Daily, G.C. *Nature's Services: Societal Dependence on Natural Ecosystems*; Island Press: Washington, DC, USA, 1997.
7. Ouyang, Z.Y.; Wang, R.S.; Zhao, J.Z. Ecosystem services and their economicvaluation. *Chin. J. Appl. Ecol.* **1999**, *10*, 635–640.
8. Li, W.H.; Zhang, B.; Xie, G.D. Research on ecosystem services in China: Progress and perspectives. *J. Nat. Resour.* **2009**, *24*, 1–10.
9. Mao, Q.Z.; Huang, G.L.; Wu, J.G. Urban ecosystem services: A review. *Ying Yong Sheng Tai Xue Bao* **2015**, *26*, 1023–1033.
10. Summers, J.K.; Smith, L.M.; Case, J.L.; Linthurst, R.A. A review of the elements of human well-being with an emphasis on the contribution of ecosystem services. *Ambio* **2012**, *41*, 327–340. [CrossRef]
11. Wang, B.J.; Tang, H.P. Human Well-Being and Its Applications and Prospects in Ecology. *J. Ecol. Rural. Environ.* **2016**, *32*, 697–702.
12. Li, Y.; Yang, Y.Y.; Shi, R.G.; Hu, S.W.; Mi, C.H. Research progress on human well-being and its relationship with ecosystem services. *J. Agric. Resour. Environ.* **2022**, *9*, 1–14.
13. Ma, L.; Jin, T.T.; Wen, Y.H. The Research Progress of InVEST Model. *Ecol. Econ.* **2015**, *31*, 126–131+179.
14. Wang, S.; Luo, Y.; Han, Y.; Li, J. Regional difference and determinants of human well-being in China: Based on the analysis of human development index. *Prog. Geogr.* **2018**, *37*, 1150–1158.
15. Otoiu, A.; Titan, E.; Dumitrescu, R. Are the variables used in building composite indicators of well-being relevant? Validating composite indexes of well-being. *Ecol. Indic.* **2014**, *46*, 575–585. [CrossRef]
16. Yang, X.T.; Qiu, X.P.; Xv, Y. Spatial heterogeneity and dynamic features of the ecosystem services influence on human well being in the West Sichuan Mountain Areas. *Acta Ecol. Sin.* **2021**, *41*, 7555–7567.
17. Liu, Z.W.; Yin, D.; Huang, Q.X.; He, C.Y.; Xue, F. Research and application progress of ecosystem services in land use planning: A bibliometric and textual analysis. *Prog. Geogr.* **2019**, *38*, 236–247.
18. Willis, C. The contribution of cultural ecosystem services to understanding the tourism–nature wellbeingnexus. *J. Outdoor Recreat. Tour.* **2015**, *10*, 38–43. [CrossRef]
19. Kosanic, A.; Petzold, J. A systematic review of cultural ecosystem services and human wellbeing. *Ecosyst. Serv.* **2020**, *45*, 101168. [CrossRef]
20. Li, J.; Jiang, H.; Bai, Y.; Alatalo, J.M.; Li, X.; Jiang, H.; Xu, J. Indicators for spatial–temporal comparisons of ecosystem service status between regions: A case study of the Taihu River Basin, China. *Ecol. Indic.* **2016**, *60*, 1008–1016. [CrossRef]

21. Wei, H.; Liu, H.; Xu, Z.; Ren, J.; Lu, N.; Fan, W.; Dong, X. Linking ecosystem services supply, social demand and human well-being in a typical mountain–oasis–desert area, Xinjiang, China. *Ecosyst. Serv.* **2018**, *31*, 44–57. [CrossRef]
22. Robinson, B.E.; Zheng, H.; Peng, W.J. Disaggregating liveli-hood dependence on ecosystem services to inform land management. *Ecosyst. Serv.* **2019**, *36*, 100902. [CrossRef]
23. Fulford, R.S.; Smith, L.M.; Harwell, M.; Dantin, D.; Russell, M.; Harvey, J. Human well-being differs by community type: Toward reference points in a human well-being indicator useful for decision support. *Ecol. Indic.* **2015**, *56*, 194–204. [CrossRef]
24. Wang, S.Y. Multidimensional turns and research frame reconstruction of well- being geography. *Prog. Geogr.* **2011**, *30*, 739–745.
25. Carpenter, S.R.; Mooney, H.A.; Agard, J.; Capistrano, D.; DeFries, R.S.; Díaz, S.; Whyte, A. Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 1305–1312. [CrossRef] [PubMed]
26. Qiu, J.J.; Liu, Y.H.; Yuan, L.; Chen, C.J.; Huang, Q.Y. Research progress and prospect of the interrelationship between ecosystem services and human well-being in the context of coupled human and natural system. *Prog. Geogr.* **2021**, *40*, 1060–1072. [CrossRef]
27. Li, Y.; Li, S.C.; Gao, Y.; Wang, Y. Ecosystem services and hierarchic human well-being: Concepts and service classification framework. *Acta Geogr. Sin.* **2013**, *68*, 1038–1047.
28. Bao, Y.B.; Li, T.; Liu, H.; Ma, T.; Wang, H.X.; Liu, K.; Liu, X.H. Spatial and temporal changes of water conservation of Loess Plateau in northern Shaanxi province by InVEST model. *Geogr. Res.* **2016**, *35*, 664–676.
29. Pan, X.; Wu, N.; Xu, Z. Coordination Difference Between Ecosystem Service and Multidimensional Poverty Under Precise Poverty Alleviation Standpoints: A Case Study of Gansu Qinba Mountain Poverty-stricken Core Areas. *J. Ecol. Rural. Environ.* **2020**, *36*, 879–889.
30. Chen, S.; Liu, K.; Li, T.; Yuan, J. Evaluation of Ecological Service Function of Soil Conservation in Shangluo City Based on InVEST Model. *Bull. Soil Sci. Soc. China* **2016**, *53*, 800–807.
31. Li, M.; Shang, G.Z.; Deng, L. Spatial distribution of carbon storages in the terrestrial ecosystems and its influencing factors on the loess plateau. *Acta Ecol. Since* **2021**, *41*, 6786–6799.
32. Huang, G.L.; Jiang, Y.Q.; Liu, Z.F.; Nie, M.; Liu, Y.; Li, J.W.; Wu, J. Advances in human well-being research: A sustainability science perspective. *Acta Ecol. Since* **2016**, *36*, 7519–7527.
33. Xu, Z.; Wei, H.; Fan, W.; Wang, X.; Zhang, P.; Ren, J.; Kong, W. Relationships between ecosystem services and human well-being changes based on carbon flow—A case study of the Manas River Basin, Xinjiang, China. *Ecosyst. Serv.* **2019**, *37*, 100934. [CrossRef]
34. Wei, H.L.; Wang, G.Y. Life satisfaction degrees of rural households in desertification-land control areas and the influential factors—Based on data collected from 12 counties of Gansu Province. *J. Arid. Land Resour. Environ.* **2017**, *31*, 1–8.
35. Cheng, L. A preliminary study on sustainable development ability of Jinhu County Agricultural ecological Demonstration Area in Jiangsu Province. *Chin. Rural. Econ.* **2004**, *6*, 54–60.
36. Ni, M.X.; An, Z.R.; Xia, J.X. Melting of mountain glacier and its risk to future water resources in Southern Xinjiang, China. *Mt. Res.* **2022**, *40*, 329–342.
37. Guan, S.Q.; Dong, R.T.; Tang, Z. Study on the Herders' Overgrazing Behavior-Based on the Perspective of Sustainable Livelihoods. *Chin. J. Grassl.* **2021**, *43*, 86–94.
38. Han, H.; Guo, L.; Zhang, J.; Zhang, K.; Cui, N. Spatiotemporal analysis of the coordination of economic development, resource utilization, and environmental quality in the Beijing-Tianjin-Hebei urban agglomeration. *Ecol. Indic.* **2021**, *127*, 107724. [CrossRef]
39. Li, W.; Wang, Y.; Xie, S.; Cheng, X. Coupling coordination analysis and spatiotemporal heterogeneity between urbanization and ecosystem health in Chongqing municipality, China. *Sci. Total Environ.* **2021**, *791*, 148311. [CrossRef]
40. Wang, X.; Yang, C.; Liu, T.; Chen, G.; Yue, H. Assessment spatio-temporal coupling coordination relationship between mountain rural ecosystem health and urbanization in Chongqing municipality, China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 48388–48410. [CrossRef]
41. Wu, J.; Li, K.; Zhao, Y. The use of land natural capital in the Guanzhong region based on a revised three-dimensional ecological footprint model. *Prog. Geogr.* **2020**, *39*, 1345–1355. [CrossRef]
42. Bai, Y.; Hong, Z.; Xue, X.; Shi, W. Coupling study of land intensive use and ecological civilization construction in Guanzhong Plain urban agglomeration. *Res. Soil Water Conserv.* **2021**, *28*, 272–280.
43. Yang, K.; Zhou, Z. Effect of landscape pattern index on PM2.5 simulation in Guanzhong Plain Urban Agglomeration. *J. Shanxi Norm. Univ. Nat. Sci. Ed.* **2022**, *50*, 115–124.

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Nudging Strategies for Arable Land Protection Behavior in China

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Abstract: Arable land protection is critical to the sustainable development of agriculture in China and acceleration of the realization of the trinity protection goal of the quantity, quality, and ecology of arable land. As a new program of behavioral science to promote social development, nudge has gradually gained the favor of researchers and policy makers due to its unique advantages of small cost and substantial effect. However, current research and practical exploration of arable land protection behavior intervention based on the idea of nudging are still lacking. Implicit nudging strategies directly target the heuristic and analytic systems of arable land protection behavior of each stakeholder and possess more advantages than traditional intervention strategies. Therefore, this article designs six arable land protection behavior nudging strategies from the perspectives of cognition and motivation to realize the theoretical discussion of "generating medium-scale returns with nano-level investment". The nudging strategies of the cognitive perspective include default options, framing effects, and descriptive norms, while those of the motivation perspective aim to stimulate home and country, and heritage and benefit motives to promote arable land protection behavior of various stakeholders. The utility of nudge to arable land protection behavior may be controversial in practice. Therefore, the implementation in China should be based on the division of farmers, the number of options should be appropriate, and the external environment of arable land protection behavior should be fully considered.

Keywords: arable land protection behavior; nudging strategies; behavioral intervention; theoretical discussion; China

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1. Introduction

Arable land is not only the most powerful guarantee for national food security but also determines the coordination and sustainability of socio-economic development and ecological environmental protection in a country or region to a large extent [1]. Food security is a national strategy in China, and arable land protection is especially important for such a country with a population of 1.4 billion [2,3]. Therefore, the No. 1 Document of the Central Committee of the Communist Party of China was proposed in 2019 to stabilize grain production, fully implement the special protection system for permanent basic farmland, and ensure the establishment of 800 million mu (mu, Chinese measurement that is commonly 666.7 square meters) of high-standard farmland by 2020. However, the contradiction between limited arable land resources and the construction land expansion has become increasingly serious with the acceleration of industrialization and urbanization, and the massive loss phenomenon of arable land resources has intensified [4,5]. Simultaneously, improper use of arable land and environmental pollution have degraded arable land quality, thus also becoming increasingly serious [6,7]. The survey shows that the degraded area of arable land accounts for more than 40% of the total arable land area at this stage, the productivity of arable land has declined, and the over-standard rate of soil heavy metals has reached 1.4% (data from the Ministry of Agriculture and Rural Affairs of China in 2018). Arable land users are the key stakeholders of the quantity, quality, and ecological investment of arable land [8,9]. A gap still exists between arable land protection behaviors and policy expectations despite the improvement of the micro-level arable land protection practices under the impetus of laws and regulations, No. 1 Central Documents, and various special plans [10,11]. Therefore, encouraging micro-stakeholders to adopt arable land protection measures actively is necessary to restore and improve the health level of arable land in China.

The central government is the maker of arable land protection policies and the ultimate regulator of arable land protection activities [12]. The central government focuses on long-term sustainability and stock in the management of arable land, hoping that different stakeholders (local governments and farmers) can use arable land in a balanced manner over time. Facing the strategic behavior of illegal occupation of arable land by local governments or farmers, the central government uses command-control and economic incentive tools to restrain and encourage the spontaneous arable land protection behaviors of various stakeholders [13,14]. Command-control tools are backed by national compulsory power [15] and directly stipulate the production behavior and utilization methods of arable land users through administrative orders or established regulations and standards. The economic incentive tool aims to use economic means or market forces to take subsidy measures or establish price mechanisms for arable land protection behaviors (such as soil fertilization behavior of farmers and transformation behavior of weak arable land) to realize the internalization of the negative externalities of arable land use [16]. These strategies for protecting arable land can be attributed to the two paths of carrot and stick, which belong to traditional social governance methods [17]. However, insurmountable difficulties are found in the design and implementation of simple paternalism management methods due to the differences in the interests of the main stakeholders of arable land protection. Therefore, a new low-cost and non-mandatory incentive strategy for arable land protection behavior should be formulated.

The essence of arable land protection is a management activity involving multiple subjects. However, due to the problems of inconsistent goals, non-equilibrium incentives, and differences in constraint pressures among various types of subjects in the process of arable land protection, it is easy for different subjects to take actions for their own interests in the process of arable land protection. The bad result is to gradually distort the original intention of arable land protection goal setting, and ultimately lead to the failure of the arable land protection policy. Therefore, the protection of arable land is inseparable from the joint efforts of multiple subjects. It is necessary for everyone to work together around the common goal of arable land protection, cooperate with each other, and finally form a joint force. Moreover, from the perspective of governance, how to promote the interaction of the participation of various subjects and mobilize the endogenous power of different subjects has become an important direction and path for the arable land protection in the future [18]. The main subjects of arable land protection include the central government, local governments, and farmers. The interest of central government is to ensure food security. In order to stimulate the endogenous motivation of local governments to protect arable land, while restraining their opportunistic behaviors, the central government implements a two-pronged management model of strict supervision and enhanced compensation to ensure the occurrence of arable land protection behaviors. The interests of local governments are the economic development and promotion trophies. Under the triple pressure of food security, economic performance and political promotion, local governments usually do not incorporate food security into the objective function, but are more inclined to the huge benefits brought by land finance. Therefore, local governments will adopt flexibility and collusion to deal with the goal of arable land protection, resulting in the dilemma of arable land management. The interests of farmers are to maximize their own interests. The comparative benefits of farmers operating arable land are low and the expected returns are unstable, which makes farmers gradually separated from the agricultural sector to the non-agricultural sector driven by economic interests, resulting in a serious shortage of labor force and a serious aging phenomenon in rural areas. Despite land attachment or limited non-agricultural skills, there are still some farmers who continue to engage in agricultural production by transferring, taking over, or renting the arable land of the remaining farmers. However, in view of the harsh natural environment, the serious marginalization of arable land, and the psychological gap brought about by low agricultural returns, agriculture has weakened and arable land has become "non-food", "non-agricultural", "abandoned" and other phenomena. Therefore, arable land protection is essentially a behavioral planning issue of stakeholders from the perspective of behavioral science, and behavior is the result of individual decision-making choices [19]. Influencing individuals to make correct decisions is an effective way to intervene individual arable land protection behaviors to increase the scale of arable land, improve arable land quality, and enhance the arable land structure. Behavioral economists Richard H. Thaler and Cass R. Sunstein first proposed the concept of nudge in 2008; that is, a nudge is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives [20]. The boost strategy integrates psychology and behavioral economics into public policy making, avoiding the shortcomings of pure paternalism or libertarian. This strategy is neither carrot nor stick; thus, it is called the fifth way of social governance (the four remaining roads are hierarchy, markets, networks, and persuasion) [21]. The multiple advantages of the nudging strategies have received extensive attention from the academic community and the government. At present, applied research has been conducted in various fields, such as health (including a healthy diet, medical treatment and health, and weight loss), environmental protection, social security, education, and charity, and has shown good application value [22–25]. Nudging is also applicable in the field of arable land protection behavior. For example, the central government can establish an assessment mechanism linking arable land protection goals with political performance, thereby enhancing the role of arable land protection in the performance assessment of local governments and mobilizing the inherent incentives for arable land protection. In addition, the central government can also strengthen dissemination on the effectiveness of arable land protection through publicity and guidance tools, so that more farmers can truly recognize and understand the market value and non-market value brought by arable land protection. The publicity and guidance tools are to disseminate the arable land protection policy by means of media, so as to reduce the cost of arable land protection, reduce the pressure of policy implementation, strengthen the consensus of various subjects on the applicability of the policy, and then consolidate the behavior of farmers to participate in arable land protection. Effective policy dissemination can not only reduce farmers' indifference or resistance to arable land protection, but also enable the government to obtain timely feedback from public opinion to improve the policy content. There are still many typical nudging tools. In reality, different nudging strategies should be adopted according to different arable land resource endowments and different social scenarios, and in many situations, it is even a comprehensive application of many nudging strategies. Thus, this article aims to provide a simple and low-cost architecture choice through nudge. Therefore, arable land protection behavior will change in the expected direction, and an attempt to generate medium-scale returns with nano-level investment can be realized.

2. Nudge Theory

2.1. What Is Nudge?

Behavioral economics has three basic assumptions concerning human nature: limited rationality, willpower, and self-interest. The decision-making rationality of humans is limited, not only restricted by the limitation of knowledge but also by the decision-making environment. The limitations of human cognitive abilities, such as greed, impulsivity, inertia, and other weaknesses, lead to various cognitive biases, such as selective perception, proximity effect, correlation fallacy, and overconfidence in the judgment of decision-making [26]. The decision-making choices demonstrate abnormal phenomena, such as loss aversion, contention with the status quo, and short-term preferences. In addition, human behavior is often affected by social factors and cannot be truly autonomous. Thus, people often encounter difficulties when facing complex and major decision-making issues, failing to make correct decisions that conform to their wishes and well-being.

Therefore, how should government managers deal with the systematic biases of human behavior? The paternalism management method advocates that individuals lack rationality and self-control and supports mandatory restraints on individual behavior [27]. Meanwhile, the liberalism management method advocates that the individual's right to choose is inalienable and does not approve of mandatory intervention in individual behavior [28]. The nudge management method advocates the concept of libertarian paternalism, which finds the factors that are ignored by traditional economists in the selection environment to influence individual decision-making choices while ensuring that free choice of individual decision makers is not reduced, and objective payment and remuneration remain unchanged. Thus, individual decision-making will develop in the direction of improving personal and social welfare. [29]. The typical nudge is the change in choice architecture. The core of choice architecture is that policy makers create specific situations and change specific conditions by grasping the psychology of policy executors; thus, the latter can make decisions according to the hope of the former. Moreover, this process is low cost and highly rewarding, which is similar to "nudging with an elbow or other parts of the body", making it easy for people to do what they want [30].

Nudge attempts to influence and change the decision-making behavior of the public with small non-mandatory measures by understanding the psychological mechanism of behavior. Thus, on the basis of maximizing resource saving, nudge plays an important role in reducing impulsive behavior and improving rational behavior. Intervention on individual behavior through the nudge method reveals the small entry point but grasps the nature of the problem from the behavior, and the behavior stems from the choice. Therefore, the rational use of nudging strategies can promote social development.

2.2. Why Do We Need Nudge for Arable Land Protection Behavior?

Currently, the nudging theory has been widely used by different scholars in different fields around the world. For example, Zhang et al. [31] argue that effective diffusion of electric vehicles could help China achieve carbon neutrality by 2060. Moreover, the paper points out that the combination of nudging policies and charging infrastructure can have a greater publicity effect than subsidies for car purchases. In other words, the role of nudging policies in information promotion helps Chinese people to accept electric vehicles more easily. Wang [32] believed that humans are often unable to make optimal behavioral decisions due to their limited attention span and limited computing power. With the development of behavioral economics, nudge has become an important tool to improve human irrational behavior and ultimately achieve happiness. Among them, commitment devices and default options can help people stick to their decisions; social comparison and incentives can encourage people to realize their behavioral intentions; message framing and simplifying complex information can lead to increased service usage. The flexible use of nudging strategies by social workers can facilitate policy formulation and practice design. Chen et al. [33] proposed that ozone pollution poses serious health risks and premature death. Additionally, gas stations are a significant source of organic compounds released by cities. The government's call on car owners to refuel at night is one of the important strategies for green nudging. The results of its research show that the preferential policy of refueling at night will contribute to the reduction of ozone concentration and bring great benefits to human health. It can be seen that the nudging strategies consider both the motivation and control of human behavior, and can effectively change people's behavior through the ingenious design of some mechanisms. In turn, it promotes people to make certain behaviors that meet specific goals, but at the same time does not compromise people's freedom of choice. Moreover, the core of nudging is to influence and change the behavioral decision-making of the public with non-coercive measures by understanding the mechanism of psychology. On the basis of saving resources to the greatest extent, it can help reduce impulsiveness and improve rational behavior [34–36]. Therefore, this paper tries to propose nudging strategies based on behavioral economics by analyzing the status quo of arable land protection behaviors of various subjects in China.

Different from daily life decision-making, people have relatively little knowledge in the field of arable land protection. For example, people mistakenly believe that soil pollution can quickly disappear with the reduction in the large-scale use of fertilizers and pesticides. However, unlike mobile pollution, such as water and gas, soil environmental degradation, pollution, and hazards have the characteristics of accumulation, concealment, and inhomogeneity. Unless it is removed and repaired by manual measures, it will remain for a long time and cause various hazards along with the arable land use [37,38]. In addition, people generally blindly believe that the arable land ecosystem can be restored through governance measures. However, the destruction of arable land due to natural disasters, arable land abandonment, and extensive use of arable land has become an irreversible process of land degradation [39,40].

Psychologists believe that human judgment and decision-making usually involve two major cognitive systems: a heuristic system based on intuition (system 1) and an analytical system based on reason (system 2) [41] (Figure 1). System 2 is characterized by its consciousness, energy consumption, and control. This system needs to mobilize attention to analyze and solve problems. Moreover, this system is not prone to errors despite its slow operation [42]. The formulation of traditional intervention strategies for arable land protection is mostly based on the assumption that individuals are rational people, that is, individuals are believed to be able to use system 2 to conduct rational analysis and take the behavior of sustainable use of arable land [43]. However, numerous studies in behavioral economics show that the process of individual judgment and decision-making is not completely rational [44]. Especially in the case of relatively limited knowledge in the field of arable land protection, using the information processing mode of system 2 to make decisions becomes fairly difficult, and people are inclined to implement rapid automated decision-making based on system 1. Compared with system 2, system 1 is a conscious and automated system, which runs fast and is full of emotions. However, people often focus on the short-term benefits of arable land use and neglect long-term considerations, leading to phenomena, such as arable land pollution, arable land desertification, and soil erosion [45]. Moreover, people have substantially limited experience and are prone to decision-making errors due to the deterioration of the arable land ecological environment and the long and complex dynamic change process of arable land spatial patterns [46]. Thus, nudge is a necessary strategy for decision-making and behavioral intervention.

In addition, the result of the trade-off between the input cost and the expected benefits of arable land protection determines the behavioral decisions of various stakeholders despite the sufficient knowledge of people in the field of arable land protection. Arable land protection costs mainly include direct input, non-agricultural opportunity, and policy implementation costs; the benefit is to guarantee the space for the future social economy and sustainable development of the region [47]. The behavioral cost of arable land protection is currently certain, but its benefits will be full of uncertainty in the future. This asymmetry between costs and benefits easily lowers the motivation of people to protect arable land [48]. In addition, this asymmetry is reflected in that the cost belongs to the stakeholders of arable land protection, while the benefit belongs to the society. As a special ecosystem, arable land has the attributes of public goods. The ecological (such as water conservation, soil and water conservation, climate adjustment, and environmental purification) and social (such as ensuring food security and maintaining social stability) benefits produced by arable land have not been included in the benefits of arable land use due to the characteristics of universal supply, non-exclusion, and non-competitiveness of public goods. This imperfect arable land use mechanism reduces the enthusiasm of stakeholders to protect arable land, which makes it impossible to realize the non-market value of arable lands, and contributes to the lack of public welfare existing in the externality of arable land [49,50]. A variety of specific measures can be formulated for the objectives of arable land protection based on the flexibility of nudging. These measures can circumvent the lack of motivation of the stakeholders of arable land protection and promote their effective decision-making.

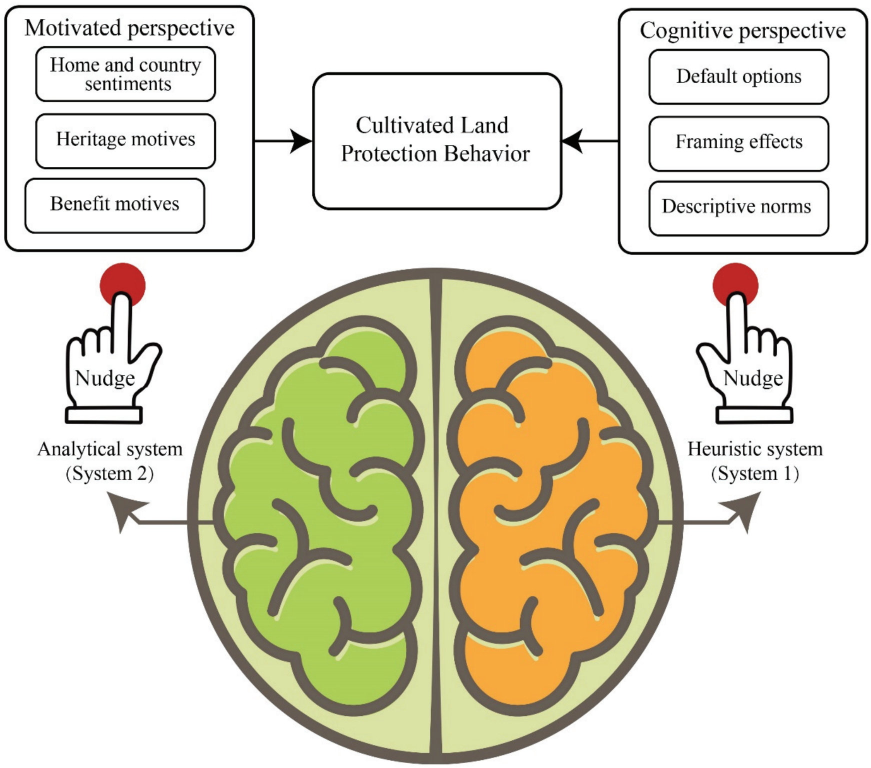

Figure 1. Nudging Strategies for Arable Land Protection Behavior in China.

People have relatively minimal knowledge and experience in the field of arable land protection, thus relying on system 1 for decision-making. However, the decision path that relies on system 1 has the characteristics of modular closed operation, automatic response, and susceptibility to stereotyped impression, and this path is prone to unreasonable behavior. By contrast, the costs and benefits of arable land protection are asymmetrical at the two levels of present–future and internality–externality, which lead to insufficient micro-motivation and enthusiasm of relevant stakeholders of arable land protection. Therefore, arable land protection behavior can be nudged from the following four perspectives. (1) Cognition is the prerequisite for various stakeholders to participate in the arable land protection. The improvement of cognition level plays a decisive role in its willingness to pay for participating in arable land protection. The increase in the various values of arable land can introduce benefits and welfare improvements to the stakeholders of arable land protection. Therefore, the psychological source of unreasonable arable land protection behaviors is emphasized and nudging measures are used to avoid cognitive biases and abnormal choices of decision makers, thus achieving the purpose of changing behaviors of stakeholders. (2) The policy design of arable land protection should conform to the psychological laws of decision-making of various stakeholders. Moreover, the choice architecture should be reasonably designed to guide the stakeholders to change their arable land protection behaviors to conform to individual interests and social well-being. (3) From the perspective of psychological cognition, the individual's perception of arable land protection behavior is accompanied by the cognitive process comprising elements, such as feeling, perception, memory, thinking, and imagination. Introducing the analytical framework of behavioral economics into the field of arable land protection behavior has theoretical consistency and necessity. (4) "Very cherish, rational use, and effective protection of arable land" has become the basic national policy in China, and improving the quality and efficiency of arable land use has become an important theme of the policy formulation of the Chinese government. However, behavior-based intervention mechanisms in the existing arable land protection policy toolbox are still lacking. Therefore, one of the most appropriate reasons for introducing the nudging mechanism in the field of arable land protection behavior is to incorporate the psychology, motivation, and cognition of each stakeholder into the policy action framework and establish arable land protection as a solid foundation for the continued prosperity of rural areas and the happy lives of farmers.

In addition, the current restraint mechanism of arable land protection mainly relies on the top-down management mode. The reason is that the conventional public governance model usually fails when intractable public crises and public problems arise. At that time, it is necessary to force the decree through the administrative force, and then decompose and manage the pressure-oriented goals and tasks from the top to the bottom in the bureaucratic structure. As a public resource, arable land has the general attributes of a public resource. Taking a top-down approach in the management process can effectively reduce ambiguity and randomness, thereby ensuring the implementation of policy goals. However, in the top-down arable land protection management mode, there are two obvious defects. First, for a bureaucratic organization with complex and super-large scales, long information dissemination channels and multiple principal-agent mechanisms responsible for each level can easily lead to the absence of arable land protection supervision. Second, this approach to arable land protection pays too much attention to the compulsory control of the government, and tends to ignore the initiatives, demands and actual conditions of other subjects. This easily leads to the diversity, deviation and uncertainty of the actual action results, which has been widely criticized by the academic circles. As a bottom-up management method, nudging tends to pay more attention to the arable land protection process of each subject at the micro-scale. The most important feature of nudging is: nudging can pay attention to the practical problem of the inconsistency between the overall system design of arable land protection and the micro-behavior level. Arable land protection can produce windfall gains or wipe-out losses, resulting in uneven interests of land users. Agricultural production on arable land is not only inefficient in terms of economic benefits, but its non-market value has certain attributes of public goods. To a certain extent, the protection of arable land sacrifices the opportunities and space for local governments and farmers to develop non-agricultural construction, and gives up the greatest opportunity cost that can be obtained by converting arable land into construction land. Therefore, although traditional administrative intervention strategies can improve the target population's awareness of the risk of arable land destruction or their willingness to protect arable land in a short period of time, they may not actually lead to effective behavior changes. Moreover, even if the arable land protection behavior can be effectively improved, the time and economic costs required for administrative intervention, economic intervention and continuous monitoring are huge. Therefore, perhaps we can learn from the nudge theory to carry out empirical, unconscious, and automatically triggerable arable land protection behaviors, and then turn them into habits to help people overcome the gap between arable land protection intentions and arable land protection behaviors. Drawing on the toolkits used in past nudging, this study divides nudging mechanisms into six categories: default option, framing effects, descriptive norms, home and country sentiments, heritage motives, and benefit motives. The default option refers to re-examining the existing default options and taking arable land protection as a default option with potential economic, social, and ecological benefits, so as to improve the possibility of each subject taking arable land protection behaviors. The framing effect refers to the phenomenon that different representations of the same information lead to different decision-making effects. The framing effect in arable land protection refers to the phenomenon that the decision-making behavior of each subject is affected by the media or leaders' frame representation of cultivated land protection issues, and shows different decision-making preferences. The descriptive norm refers to the obvious role model effect and group effect among various subjects in the process of arable land protection. It reflects that the attitude and participation enthusiasm of a subject towards arable land protection will have a significant impact on whether other subjects continue to participate in arable land protection. For example, inter-neighborhood exchanges and demonstrations can increase farmers' willingness to apply environmentally friendly technologies more than government policy interventions. The home and country sentiment refers to the moral rationality that emphasizes the value and meaning of individual life must rely on the value and meaning of the country, and also refers to the individual's psychological, emotional attachment and satisfaction to family, hometown, and patriotic feelings. The Chinese people have a strong sense of home and country, as well as patriotic cultural values and corresponding behavior patterns. Moreover, the arable land protection is also a major support for China's national security strategy. Therefore, there is a high social consensus on the arable land protection and the guarantee of food security. The heritage motive refers to the economic behavior of older generations to pass on a portion of their income and wealth to the next generation. Arable land has important social security value and social stability value. The elderly farmers pass the arable land to the next generation, in fact, they hope that the income of young farmers will be more diversified. For them, arable land is the last guarantee for the survival of family members and an asset that may greatly appreciate in the future. Benefit motives means that each subject is an independent operating subject pursuing the maximization of their own profits. In view of this, only when each subject believes that arable land protection is profitable, will the supply behavior of arable land protection be increased.

Therefore, nudges can influence people's choices, but they don't force people to change their choices, nor do they make choices for people, but help people make better choices at insignificant increased costs. However, due to the constraints of information acquisition, cognitive ability, and self-control, people's daily decision-making usually shows the characteristics of bounded rationality. People often rely on empirical judgments of various heuristics, and thus often make inefficient decisions that are inconsistent with their own well-being. The nudging strategies is aimed at improving this situation. It is unique in that it does not need to resort to executive orders or economic leverage, but to change people's behavior in the desired direction by providing an appropriate choice framework. Of course, nudging cannot solve all the problems arising in the process of arable land protection. In practice, it still needs to be managed through tough measures such as arable land occupation tax, arable land dynamic monitoring, and arable land use control. However, nudge is a new insight from behavioral economists based on psychology, and provides a new perspective for understanding and predicting economic behavior. The purpose of this study is to try to use nudge (this low-cost and high-efficiency regulatory method) to intervene in the micro-level arable land protection behavior more finely, so that each subject can make decisions in a more optimized way, thereby improving the arable land environment.

3. Cognitive Perspective of the Nudging Strategies of Arable Land Protection Behavior

The cognitive perspective of the nudging strategies of arable land protection behavior aims to avoid the cognitive bias and abnormal selection of decision makers by designing a reasonable choice architecture to promote their rational arable land protection behaviors. This article focuses on the application of default options, framing effects, and descriptive norms in the field of arable land protection behavior. Default options and framing effects can encourage the arable land protection behavior by cleverly presenting decision-making information, while the descriptive norms promote arable land protection behavior through customized information.

3.1. Default Options Nudge Arable Land Protection Behavior

The default option refers to the option to be accepted when the individual has not yet made a decision [51]. The decision will be affected by the framework in the absence of a formed value or preference of an individual, and the default option is then used as a reference point [52,53]. Therefore, people tend to keep the default options without making any changes during decision-making. This phenomenon is the default option effect. In the application and research of public policies, the nudging strategies of default options are widely used in environmental protection [54], consumer food choices (Just et al., 2018), and public health [55]. Policy designers should focus on the use of default options to make minor adjustments in the design of arable land protection policy to cause significant changes in the arable land protection behavior of each stakeholder and then achieve the goal of arable land protection. For example, land-use change caused by the increase in various types of construction land is one of the most significant features of urbanization. The essence of urbanization is the transformation process of land use function. Population agglomeration, industrial structure agglomeration, and infrastructure construction must be realized through the reconfiguration of land [56,57]. However, urban expansion invaded and occupied a large amount of arable and ecological lands, which directly led to a sharp decline in the amount of arable land and the occurrence of ecological and environmental problems, posing a serious threat to food security and ecological protection in China [58]. Therefore, optimizing the allocation of limited land resources and realizing the coordinated development of urban expansion, arable land protection, and ecological conservation is a serious challenge facing sustainable land use in China.

At present, delimiting urban growth boundaries, establishing arable land occupation tax, restricting basic arable land zoning, and setting up land regulatory agencies have become important means to control urban expansion and protect arable land. The central government has paid huge administrative costs and financial investment, and has been improving the governance efforts of illegal activities on arable land yearly. However, illegal cases of arable land became increasingly concealed and challenging to investigate when local officials conspired to participate in such illegal use. In response to this problem, Wu [59] believes that high-, medium-, and low-gradient quota systems can be set in the construction land quota application system according to the development of each region and resource endowments. In the high-gradient quota application system, local governments will face problems, such as a large number of application materials, complicated approval procedures, and long waiting times for approval. The procedure is simplified and the application is easy in the medium- and low-gradient quota application systems, and this option is set as the default. Local governments have the political task of ensuring regional economic development and fiscal balance and reducing unemployment and social stability. Thus, they may not choose the low-gradient option. However, the local government may choose the default option because the high-gradient option has the characteristics of complexity, rigorous approval process, and prohibitive length of approval time.

Cases in real life, wherein the absolute superiority option (that is, a better option than others in all dimensions) is among the choices that people face, are relatively few. Most decision-making tasks involve the comparison of alternatives with default options and objectively equivalent losses and gains. People tend to regard the default option as a reference point during decision-making. Judgments of people regarding losses and gains are prone to change due to reference point dependence. People argue that the loss of abandoning the default option is larger than the benefit of choosing an alternative option (loss aversion) [60]. The individual subjective susceptibility caused by the loss is substantial; thus, people usually keep the default option and are unwilling to make changes to avoid the psychological loss caused by abandoning the default option, leading to the generation of the default effect (settle for the status quo) [61]. The above-mentioned characteristics of human habitual thinking provide a practical idea for nudging arable land protection behavior. That is, replacing traditional options with arable land protection ones as the default, thereby guiding people to make arable land protection behaviors.

3.2. Framing Effects Nudge Arable Land Protection Behavior

The framing effects can also effectively avoid the cognitive bias in decision-making caused by human loss aversion, thereby nudging arable land protection behavior. The framing effects mean that attitudes and preferences of people toward the event will change or even be reversed when presented with essentially the same events only because of the modified way of presentation. That is to say, different ways of expressing the same problem may cause individuals to make different decision-making results. Researchers generally believe that intuitive experience and emotional preference, which are crucial for the decision-making system, are the underlying causes of framing effects [62]. This section mainly discusses the influence of delay–advance and goal framing effects on the behavioral decisions of various stakeholders in the arable land protection.

The delay–advance framing effects indicate that people have different perceptions of waiting time under delayed and advanced conditions due to the reference point. Therefore, delays and advances are often regarded as losses and gains, respectively [63,64]. The agricultural subsidy policy, which aims to protect and develop agriculture, is an important program of strengthening and benefiting farmers in China [65]. At present, adjusting the agricultural subsidy policy and linking the issuance of various agricultural subsidies with the effect of arable land protection, which forms an agricultural subsidy system with arable land protection as the core, plays an important role in increasing the income of farmers and ensuring national food security. However, the issuance time of agricultural subsidies in China significantly varies in different regions. Some regions can be issued before the end of March, while others have to be delayed until the end of April or even later. At present, in the face of continuously increasing agricultural production materials, the government needs to issue agricultural subsidies promptly to ensure the enthusiasm of farmers for arable land protection. Therefore, governments at various levels should adjust the timing of the issuance of agricultural subsidies to the beginning of the year to mobilize the enthusiasm of farmers for growing grain effectively and prevent the increasing phenomenon of non-grainization.

The goal framing effects refer to the changes in the willingness of individuals to implement the behavior when describing the relationship between the implementation or non-implementation of certain behavior and the realization of the goal [66]. For example, the value of arable land mainly includes economic production, social security, ecological conservation, and cultural inheritance [67,68]. Among these values, economic production value can provide farmers with agricultural economic income and agricultural products; social security value can provide farmers with employment opportunities and reduce the risk of farmers going out to work; ecological conservation value can consolidate the foundation of agricultural reproduction and reduce the loss of agricultural output and production costs; and cultural inheritance value can increase the recognition and respect of farming culture by future generations. Therefore, the arable land protection behavior can be described as follows: "if you protect arable land, you will increase family income, increase employment security, reduce reinvestment in agricultural production, and be praised by future generations" or "if you do not protect arable land, then you will significantly reduce the level of agricultural income, lose the most basic social security, increase the cost of agricultural production, and is not conducive to ensuring the livelihood of future generations". Therefore, the information expression of the goal framing can significantly affect the willingness of farmers to protect arable land.

Different delay–advance and goal framing will generally affect individual arable land protection decisions. In practice, rational use of the framing effects and finding the key variables in these effects can promote the arable land protection behavior of individuals.

3.3. Descriptive Norms Nudge Arable Land Protection Behavior

The default options and framing effects nudge the arable land protection behavior of people by masterly presenting decision-making information, while the descriptive norms nudge such behavior by directly providing customized information. When arable land protection behavior becomes a descriptive norm, which is a typical practice of most people in a certain situation, the possibility of individuals taking arable land protection behavior will remarkably increase. Descriptive norms convey information to individuals regarding the behavior of most people in a specific situation. This information is equivalent to telling the individual what to do in a specific situation and is most likely to be effective and suitable, providing a basis for the decision-making of an individual; thus, people can behave in accordance with the behavior of most individuals [69,70].

Conservation tillage refers to a technical system with surface mulch, straw return, and no-tillage as the core technology using comprehensively supporting measures, such as reduced tillage, no-tillage, surface micro-topography modification technology, surface cover, and rational planting [71,72]. Most farmers are subjectively cautious due to their education level and smallholder management restrictions, which is not conducive to the promotion and application of conservation tillage. The producer, who is the first to adopt a new mode of production, faces the largest uncertainty, while the followers encounter a relatively small amount of uncertainty [73]. Therefore, a demonstration is the best way to reduce the uncertainty faced by farmers in adopting conservation tillage. In addition, farmers often make choices based on the adoption of conservation tillage by influential farmers or individuals (such as large-scale growers, cooperative leaders, village officials, and rural elites) in the village. The adoption behavior of this part of farmers has descriptive and silent dissemination effects. Therefore, the government should explore the establishment of a conservation tillage training and promotion mechanism for rural elites while guiding them to play a positive role. Thus, farmers can subtly learn new knowledge of conservation tillage during the communication process to accelerate the adoption and diffusion improvement of new technologies in the social network of farmers.

Therefore, the government should actively build experimental demonstration bases for conservation tillage in various regions and use them as carriers to conduct conservation tillage promotion and new-type professional farmer training and actively cultivate application entities that support conservation tillage. In addition, technology demonstrations can reduce the risk expectations of farmers and increase their enthusiasm for applying conservation tillage technologies.

4. Motivated Perspective of the Nudging Strategies of Arable Land Protection Behavior

Two asymmetries are observed in the costs and benefits of arable land protection behavior: “present–future” and “individual–society”. Moreover, under the incentive of the substantial benefits of non-agriculturalization of arable land, each stakeholder lacks the exogenous implementation power of arable land protection behavior due to the imperfection or absence of the incentive mechanism for arable land protection behavior. On the one hand, the home and country sentiments and heritage motives can be stimulated to raise the attention of people to the future food security, the inheritance of farming culture, and the preservation of arable land resources for future generations. Consequently, the “present–future” asymmetry between the costs and benefits of arable land protection behavior can be alleviated. On the other hand, it can stimulate the benefit motives of each stakeholder to enhance their recognition of the multi-functional value of arable land and the arable land development rights. Consequently, the “present–future” asymmetry between the costs and benefits of arable land protection behavior can be alleviated. Therefore, home and country sentiments and heritage and benefit motives can nudge the occurrence of arable land protection behavior.

4.1. Home and Country Sentiments Nudge Arable Land Protection Behavior

Adopting arable land protection behavior is the result of weighing the current costs and future benefits of each stakeholder. The stakeholders often act unfavorably to the ecological environment of arable land mainly because they are short-sighted and cannot see the value of sustainable use of arable land. Therefore, they lack the motivation to invest in arable land protection. For example, the behavioral decisions of local governments regarding arable land protection are often inconsistent with their social goals. This inconsistency is mainly due to the inherent requirements of regional economic development goals, which drive local governments to choose to provide land at a low price in the process of attracting investments. Local governments provide excessive attention to the transfer of arable land to achieve the practical needs of fiscal revenue increase [74]. Therefore, a nudging design that allows various stakeholders to see the future value of arable land will encourage their participation in arable land protection behavior. Considering the country, people intuitively perceive a long future for the country when its history is long. This intuitive feeling easily stimulates the sense of responsibility of people for the future of the country [75,76] to allow effective consideration of such future and conduct additional arable land protection behaviors. The feelings of home and country are the quintessence of the traditional culture of the Chinese nation. Awakening home and country sentiments and raising awareness of arable land protection are crucial in the current situation.

The development of rural slogans in rural areas of China is crucial due to the scattered geographical distribution of villages, weak cultural environment, and single access to information. Rural slogans are highly praised by the vast rural areas because of their short, concise, easy-to-remember, easy-to-recognize, and catchy features. Slogans are not only an important and direct teaching material for farmers to learn and understand various policies and guidelines but are also effective in guiding and educating farmers to form correct values. Rural slogans play an irreplaceable role to a large extent [77]. Therefore, the rural slogan can elicit home and country sentiments of people regarding arable land protection (for example, "the land is connected to thousands of families, and the supervision depends on you, me, and him".). This slogan also makes easily recognizable arable land protection-related policies and choice architecture of people, thereby increasing the selection chance. In addition, rural slogans are an important tool and carrier for "policy to the countryside". Rural slogans have the characteristics of wide coverage, conformity to audience awareness, and low economic costs, which are particularly suitable for arable land protection policy dissemination in rural communities. Basic-level administrative organizations have transformed arable land protection policies and regulations into an easily understandable language to facilitate comprehension and acceptance of the broad masses of farmers.

4.2. Heritage Motives Nudge Arable Land Protection Behavior

Stimulating home and country sentiments solves the short-sighted problem of people. However, the long period and excessively far away return on investment from future generations is also another psychological obstacle that affects the arable land protection behavior. People focus more on the current self-interest than on the future social interests (future generations), thus generally showing low willingness to protect arable land. Heritage motives theory is an economic concept that studies intergenerational exchange and wealth transfer within a family. The wealth accumulation of the micro family is through family savings, consumption, and asset allocation decisions, macro investment, and public policy choices [78]. Therefore, raising the attention of people to the interests of future generations may nudge their arable land protection behavior.

The heritage value of arable land is the allocation question of arable land resources between generations. That is to say, contemporary farmers are willing to pay a certain amount of fees to protect the arable land resources considering the arable land resources usufruct for future generations. Thus, future generations can also enjoy the effects of arable land resources. However, the main focus of agricultural policy in China has long been on the pure or narrow economic value of arable land resources. The unsustainability of arable land protection policies and the decline of arable land ecosystem service functions are easily induced due to the lack of consideration of the heritage value of arable land resources in agricultural policies. Therefore, the government should open up the useful life of arable land and provide strong guarantees for stable investments and operations of farmers by continuously extending the contracting period of arable land. In the past, capitalist landowners tended to shorten the lease term to capture the excess profits generated by the additional investment of operators in the land. Consequently, arable land operators often choose to exploit the land fertility as much as possible during the lease term. The long-term unchanging arable land contracting period guarantees the actual operating stakeholders to gain the usufruct right to the excess profits of the arable land for an extended period [79,80]. In addition, the old generation of farmers can pass on their accumulated land capital to the next generations, thus fully stimulating the enthusiasm of farmers to protect arable land. Governments at all levels can consider including elements of heritage motives when promoting the concept of arable land ecological environment to enhance awareness and behavioral level of people considering arable land protection.

4.3. Benefit Motives Nudge Arable Land Protection Behavior

Home and country sentiments and heritage motives aim to nudge the arable land protection behavior through the attention of people to the future of the country and future generations. In addition, rationally designing the choice architecture to realize consistent arable land protection decision-making with the interests of different stakeholders can stimulate the benefit motives of each stakeholder and then nudge the occurrence of arable land protection behavior. For example, the intensive application of chemical fertilizers and pesticides meets the need to increase food production under the guidance of production targets to a certain extent but also causes serious resource and environmental problems, such as soil compaction, soil acidification, water pollution, and excessive emission of greenhouse gases [81]. Therefore, the No. 1 Central Document in 2019 once again proposed the green agricultural development goal of achieving a negative growth in the use of chemical fertilizers. From the perspective of the efficient use of agricultural waste and the maintenance of arable land capital, organic fertilizer substitution technology, which can also promote sustainable agricultural development, is necessary to realize green agriculture [82]. However, the price of organic fertilizers on the market is generally higher than that of chemical fertilizers, and the application of organic fertilizers often requires additional capital investment. Thus, these requirements generally decrease the willingness and behavioral level of farmers to buy organic fertilizers.

In reality, farmers often simplistically divide the products on the market into "green and environmentally friendly but expensive" and "not environmentally friendly but relatively cheap". However, this division is only the result of the excessive attention of farmers on the initial purchase cost of the product and is not the real case. Compared with traditional chemical fertilizers, many new organic fertilizers have complete nutrients and long-lasting fertilizer effects despite their high initial purchase cost. The total cost of new organic fertilizer is low due to its advantages in improving soil quality, enhancing crop quality, and reducing agricultural non-point source pollution. Life cycle cost refers to the sum of all costs related to the life cycle of the product system, including initial and operating costs [83]. If life cycle cost information can be indicated for new organic and traditional chemical fertilizers, then the preference of farmers for new organic fertilizers can be nudged, and the proportion of organic fertilizers usage can be gradually increased. Therefore, stimulating individual benefit motives can effectively resolve the "individual-society" asymmetry between the cost and benefit of arable land protection behavior.

5. Discussion: Controversies That May Exist in the Practice of Nudge in Arable Land Protection Behavior

The six nudge-based intervention strategies for arable land protection behavior proposed in this article reveal that nudge not only ensures the free choice of each stakeholder but also reflects the policy intentions of quantity control and quality and ecological management of arable land. Therefore, nudge is a new tool for smooth and effective policy intervention. In addition, the growth rate of fiscal revenue has slowed down while fiscal expenditure has rapidly grown after the entrance of economic development in China into the economic new normal, and cost constraints of arable land protection policy interventions have continued to increase. However, unlike traditional interventions that change arable land protection behavior of people by modifying the cost–benefit structure of decision-making at a considerable economic cost, the nudging strategies trigger only the intuition, feelings, and automatic decision-making process of individuals. Nudge can also achieve the goal of arable land protection through simple clues and small changes in the selection environment. Moreover, nudge is a low-cost intervention that can be widely used. The advantages of nudge have achieved convincing results in different countries and research fields and have shown remarkable application value. However, questions and disputes regarding the validity, reliability, and ethics of nudge frequently arise due to its novelty [84,85]. The following disputes may emerge upon the implementation of the nudging strategies of arable land protection behavior.

5.1. Nudge May Be Evil?

The most direct objection to nudge theory comes from "evil nudge", which is a certain form of despotism or control threat theory. That is, people with ulterior motives use cognitive biases and other psychological laws to guide the behavior of decision makers to realize beneficial resulting behaviors to specific interest groups. For example, some local governments are accustomed to adopting "transactional", "bribery", and "buying-out" methods to increase the non-agricultural income of farmers. Therefore, the rights-safeguarding mechanism is not sound when its channel is rough. Moreover, farmers will feel pessimistic regarding rights protection and are inclined to assist the local government in implementing CLPP flexibly when the cost of rights-safeguarding is relatively high. However, as a method and technology, nudge has no moral and ethical issues. Any method can be abused, but such abuse is not a problem of the method itself; instead, the problem mainly lies in the purpose of the person using such a method. Restraining possible abusive behavior in the practice of nudging is necessary. Simultaneously, the positive effect of nudging methods on arable land protection behavior should be affirmed.

5.2. Nudge Leads to Childization?

The implementation of the nudging strategies compensates for the defects of thinking systems of people and relies on system 1 for decision-making to guide them and produce choices close to the goal of arable land protection. However, this guidance method does not transfer knowledge to the stakeholders and does not improve their decision-making skills, which hinders the accumulation of knowledge of arable land protection and the ability of independent selection of the stakeholders to a certain extent. This kind of operation will cause people to become dependent and threaten them to think naively. People who have the above doubts often overestimate the role of autonomy. In the absence of nudges, local governments also have strong political and economic demands, and their consideration focuses on developing the local economy, achieving rapid growth in fiscal revenue, and maximizing political performance during the term of office. Driven by comparative interests, an increasing number of rural laborers choose to abandon traditional agriculture and enter non-agricultural industries, and the proportion of non-agricultural income is gradually increasing [86]. Therefore, under the condition of cost–benefit, a considerable amount of critical reflection that people invest in the process of autonomous formation and adjustment does not necessarily guide individuals to make the most correct response. Thus, verifying whether nudge will lead to childization will take a long time.

5.3. Can Nudge Be Effective in the Long Term?

Simultaneously, some scholars argue that the role of nudging strategies has been exaggerated. In a real environment, nudging strategies may not be able to solve complex social problems [87]. The various nudging strategies of arable land protection behavior in this article are still a preliminary discussion on the theoretical level despite their capability to provide strong evidence for their effectiveness. These measures require further experiments and research by the government to evaluate their feasibility, cost, and effectiveness. Subsequent research should also further integrate the institutional design and decision-making mechanism of arable land protection policies in China, observe the cognitive behavior patterns of farmers in different regions, explain the differences in the nudging strategies formulated by local governments at different levels and regions, and then propose practical and feasible nudging strategies.

6. Policy Implications: Effective Use of Nudge to Promote Arable Land Protection Behavior in China

As a country with the largest population, the top priority of China is to protect arable land for national well-being and the livelihood of people. Such a priority is not only essential to achieving sustainable social and economic developments in China but is also of considerable strategic significance for ensuring world food security and stabilizing international food prices. As a rational method of behavioral science that attempts to change the psychology and behavior of people to promote social development, nudge will play a unique and irreplaceable role in this process. Considering national conditions in China when the nudging strategies are implemented is necessary to achieve the intervention goal.

6.1. Selection of Nudging Strategies Based on the Subdivision of Farmer Groups

Similar to traditional intervention strategies, the choice of nudging strategies should be based on the subdivision of farmer groups. Facing farmers with different characteristics, the same nudging strategies may have different effects for various intervention contents. Therefore, the policy makers of the nudging strategies should first clarify the characteristics of the target farmers. The existing literature classifies the types of farmers in a variety of ways: the types of farmers based on their employment and economic status, their decision-making behavior goals, and age as an intergenerational difference [88,89]. Under the internal and external stimuli of four new modernizations and the reform of the rural economic system in China, farmers have rapidly differentiated and transformed along various paths and methods. Significant differences are also found in the willingness and behavioral response of different types of farmers to arable land protection. For example, Xie et al. [90] divides farmers into young farmers, middle-aged farmers and old farmers according to the intergenerational differences. In addition, Xie believes that the need for livelihood security for elderly farmers makes them more dependent on arable land. Middle-aged farmers tend to achieve a state of moderate-scale operation through arable land transfer. In addition, the scale of arable land has a significant positive impact on the occurrence of arable land protection behavior, and these farmers are more inclined to adopt environmentally friendly technologies to use and manage arable land; due to fact that young farmers have more opportunities to obtain non-agricultural income and employment opportunities, they are prone to abandoning arable land. Based on the rice planting data of 537 Chinese farmers, Cai et al. [91] analyzes how the differentiation of farmers' livelihoods affects the pesticide use status of Chinese farmers. The results of the study found that, compared with pure farmers, part-time farmers were more inclined to reduce the use of pesticides to maintain the quality of cultivated land resources. The reason is that arable land plays an important role in social security for part-time farmers, and maintaining the quality of arable land can increase the diversity of their income. Therefore, formulating different nudging strategies according to different types of farmers, mobilizing the enthusiasm and initiative of various types of farmers in arable land protection, and focusing on their subjective functions is an important guarantee for improving the effectiveness and promoting the orderly development of arable land protection.

6.2. Number of Options for the Nudging Strategies Should Be Appropriate

Four to five are appropriate considering the options provided by the choice architecture [92–94]. Providing additional options can help cater to the needs of farmers. However, the burden of decision-making on the stakeholders of arable land protection will increase with the number of options. Therefore, the designer of the choice architecture needs to balance the two above-mentioned factors according to the characteristics of farmers in practice. For example, providing an excessive number of options at once when promoting environmentally friendly technologies or green agricultural products to elderly farmers is inappropriate. This inappropriate behavior is due to the preference of elderly farmers with poor information processing capabilities to choose from fewer options than young farmers. For example, Zhao et al. [95] conducted a random sampling survey of farmers who grow grain in Jiangsu Province, China, and analyzed the differences in farmers' willingness to choose arable land protection technologies based on micro-data. The research results show that from the perspective of individual characteristics of farmers, the age of farmers and the health of farmers have hindering effects on arable land protection technology, which is also due to the fact that arable land protection requires a certain amount of physical strength and energy. The health status, physical strength and energy of farmers have a significant impact on arable land protection behavior. Therefore, it is impossible to require elderly farmers to understand and master a certain number of arable land protection technologies in a short period of time. Xie et al. [96] used the meta-analysis method to conduct a comprehensive analysis of 77 empirical studies to reveal the influencing factors, sources of heterogeneity and influence effects of farmers on the adoption of pro-environmental technologies. The results of the study show that the gender, age, and education level of farmers are regarded by many literatures as the decisive factors for farmers to adopt pro-environmental technologies. Therefore, age has a significant negative impact on farmers' adoption of pro-environmental technologies, suggesting that as farmers age, they are less likely to adopt these technologies. The number of options matching different characteristics of farmers is not the same. Thus, providing four to five options can be used as a general guideline without the restriction of additional factors.

6.3. Clarification of the External Environment That Nudges the Arable Land Protection Behavior

Arable land protection is not only a personal behavior problem but also a social problem. This phenomenon is the result of the joint influence of internal psychological resources and the external environment. If policy makers do not consider external environmental factors and blindly rely on nudge to achieve the goal of arable land protection, then its effectiveness will be severely limited. The external environment of nudge can be divided into underutilized and unprepared environments [97]. Underutilized environments mean that the central government has introduced the most stringent arable land protection system and is fully equipped with corresponding agricultural infrastructure. However, problems regarding the pessimistic effect of arable land protection and the biased implementation of arable land protection policies remain. These problems emerge due to the imperfect psychological system of the public, often making decisions that are not conducive to the arable land environment. The use of social governance methods of nudge can effectively circumvent the cognitive and motivational limitations of people at this time and guide them to act in the direction of arable land protection.

Unprepared environments refer to locations that lack agricultural supporting infrastructure. Only the nudging strategies designed for choice architecture fail in such environments. For example, agricultural infrastructure is an important material condition and core element to support the development of agricultural modernization in China and is also a crucial investment that takes advantage of cost-saving measures, such as agricultural scale operation and technological progress [98]. However, agricultural infrastructure in China is still facing problems and challenges, such as insufficient total supply, low satisfaction rate of farmers, and failure to meet the construction needs of new forms of agricultural operations effectively. Therefore, improving the efficiency of investment and financing of agricultural infrastructure, as well as the benefits of construction and use, has become the top priority for promoting arable land protection behavior. Further improvement of arable land protection policies and the construction of agricultural supporting infrastructure will help the formation of the external environment and improve its effects. Thus, policy makers can effectively evaluate the external environment of nudges to design reasonable and effective intervention programs to protect the ecological environment of arable land.

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References

1. Zhou, Y.; Li, X.; Liu, Y. Arable land protection and rational use in China. *Land Use Policy* **2021**, *106*, 105454. [CrossRef]
2. Liu, H.; Hao, H.; Hu, X.; Du, L.; Zhang, Z.; Li, Y. Livelihood Diversification of Farm Households and Its Impact on Arable Land Utilization in Agro-pastoral Ecologically-vulnerable Areas in the Northern China. *Chin. Geogr. Sci.* **2020**, *30*, 279–293. [CrossRef]
3. Tian, Z.; Ji, Y.; Xu, H.; Qiu, H.; Sun, L.; Zhong, H.; Liu, J. The potential contribution of growing rapeseed in winter fallow fields across Yangtze River Basin to energy and food security in China. Resources. *Conserv. Recycl.* **2021**, *164*, 105159. [CrossRef]
4. Li, W.; Wang, D.; Liu, S.; Zhu, Y. Measuring urbanization-occupation and internal conversion of peri-urban arable land to determine changes in the peri-urban agriculture of the black soil region. *Ecol. Indic.* **2019**, *102*, 328–337. [CrossRef]
5. Hou, X.; Liu, J.; Zhang, D.; Zhao, M.; Xia, C. Impact of urbanization on the eco-efficiency of arable land utilization: A case study on the Yangtze River Economic Belt, China. *J. Clean. Prod.* **2019**, *238*, 117916. [CrossRef]
6. Li, W.; Wang, D.; Li, Y.; Zhu, Y.; Wang, J.; Ma, J. A multi-faceted, location-specific assessment of land degradation threats to peri-urban agriculture at a traditional grain base in northeastern China. *J. Environ. Manag.* **2020**, *271*, 111000. [CrossRef]
7. Ding, J.; Chen, Y.; Wang, X.; Cao, M. Land degradation sensitivity assessment and convergence analysis in Korla of Xinjiang, China. *J. Arid. Land* **2020**, *12*, 594–608. [CrossRef]
8. Wang, Y.; Li, X.; He, H.; Xin, L.; Tan, M. How reliable are arable land assets as social security for Chinese farmers? *Land Use Policy* **2019**, *90*, 104318. [CrossRef]
9. Xie, H.; Wang, W.; Zhang, X. Evolutionary game and simulation of management strategies of fallow arable land: A case study in Hunan province, China. *Land Use Policy* **2018**, *71*, 86–97. [CrossRef]
10. Xie, H.; Jin, S. Evolutionary Game Analysis of Fallow Farmland Behaviors of Different Types of Farmers and Local governments. *Land Use Policy* **2019**, *88*, 104122. [CrossRef]
11. Liu, R.; Yu, C.; Jiang, J.; Huang, Z.; Jiang, Y. Farmer differentiation, generational differences and farmers' behaviors to withdraw from rural homesteads: Evidence from chengdu, China. *Habitat Int.* **2020**, *103*, 102231. [CrossRef]
12. Zhong, T.; Huang, X.; Zhang, X.; Scott, S.; Wang, K. The effects of basic arable land protection planning in Fuyang County, Zhejiang Province, China. *Appl. Geogr.* **2012**, *35*, 422–438. [CrossRef]
13. Kuang, B.; Han, J.; Lu, X.; Zhang, X.; Fan, X. Quantitative evaluation of China's arable land protection policies based on the PMC-Index model. *Land Use Policy* **2020**, *99*, 105062. [CrossRef]
14. Yang, B. Performance Evaluation Model of Economic Compensation Policy for Arable Land Protection in Coastal Areas Based on Propensity Value Matching Method. *J. Coast. Res.* **2020**, *103*, 19–23. [CrossRef]

15. Xie, H.; Wen, J.; Choi, Y. How the SDGs are implemented in China-A comparative study based on the perspective of policy instruments. *J. Clean. Prod.* **2021**, *291*, 125937. [CrossRef]
16. Wang, G.; Liu, Y.; Li, Y.; Chen, Y. Dynamic trends and driving forces of land use intensification of arable land in China. *J. Geogr. Sci.* **2015**, *25*, 45–57. [CrossRef]
17. Heffernan, T.; Daly, M.; Heffernan, E.; Reynolds, N. The carrot and the stick: Policy pathways to an environmentally sustainable rental housing sector. *Energy Policy* **2021**, *148*, 111939. [CrossRef]
18. Huang, C. Estimating the environmental effects and recreational benefits of arable flower land for environmental quality improvement in Taiwan. *Agric. Econ.* **2016**, *48*, 29–39. [CrossRef]
19. Zhang, C.; Robinson, D.; Wang, J.; Liu, J.; Liu, X.; Tong, L. Factors Influencing Farmers' Willingness to Participate in the Conversion of Arable Land to Wetland Program in Sanjiang National Nature Reserve, China. *Environ. Manag.* **2011**, *47*, 107–120. [CrossRef]
20. Thaler, R.; Sunstein, C.R. *Nudge: Improving Decisions about Health, Wealth, and Happiness*; Yale University Press: New Haven, CT, USA, 2008.
21. Mols, F.; Haslam, S.A.; Jetten, J.; Steffens, N.K. Why a nudge is not enough: A social identity critique of governance by stealth. *Eur. J. Political Res.* **2015**, *54*, 81–98. [CrossRef]
22. Bimonte, S.; Bosco, L.; Stabile, A. Nudging pro-environmental behavior: Evidence from a web experiment on priming and WTP. *J. Environ. Plan. Manag.* **2019**, *63*, 651–668. [CrossRef]
23. Mikkelsen, B.; Sudzina, F.; Ornbo, L.; Tvedebrink, T. Does visibility matter?-A simple nudge reduces the purchase of sugar sweetened beverages in canteen drink coolers. *Food Qual. Prefer.* **2021**, *92*, 104190. [CrossRef]
24. von Kameke, C.; Fischer, D. Preventing household food waste via nudging: An exploration of consumer perceptions. *J. Clean. Prod.* **2018**, *184*, 32–40. [CrossRef]
25. Grady, A.; Barnes, C.; Lum, M.; Jones, J.; Yoong, S. Impact of Nudge Strategies on Nutrition Education Participation in Child Care: Randomized Controlled Trial. *J. Nutr. Educ. Behav.* **2021**, *53*, 151–156. [CrossRef]
26. Lu, H.; Hu, L.; Zheng, W.; Yao, S.; Qian, L. Impact of household land endowment and environmental cognition on the willingness to implement straw incorporation in China. *J. Clean. Prod.* **2020**, *262*, 121479. [CrossRef]
27. Morrison, T.; Wilson, C.; Bell, M. The role of private corporations in regional planning and development: Opportunities and challenges for the governance of housing and land use. *J. Rural. Stud.* **2012**, *28*, 478–489. [CrossRef]
28. Siskind, P. "Enlightened System" or "Regulatory Nightmare"?: New York's Adirondack Mountains and the Conflicted Politics of Environmental Land-Use Reform During the 1970s. *J. Policy Hist.* **2019**, *31*, 406–430. [CrossRef]
29. Thaler, R. Nudge, not sludge. *Science* **2018**, *361*, 431. [CrossRef]
30. Thaler, R.; Sunstein, C.; Balz, J. Choice architecture. *SSRN Electron. J.* **2014**. [CrossRef]
31. Zhang, Q.; Liu, J.; Yang, K.; Liu, B.; Wang, G. Market adoption simulation of electric vehicle based on social network model considering nudge policies. *Energy* **2022**, *259*, 124984. [CrossRef]
32. Wang, J. Nudging for Social Change: Promises and Cautions for Social Workers to Apply Behavioural Economic Tools. *Br. J. Soc. Work* **2022**, bcac153. [CrossRef]
33. Chen, B.; Liu, M.; Ye, W.; Zhang, B. Assessing the impact of green nudges on ozone concentration: Evidence from China's night refueling policy. *J. Environ. Manag.* **2022**, *312*, 114899. [CrossRef] [PubMed]
34. Duflo, E.; Kremer, M.; Robinson, J. Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. *Am. Econ. Rev.* **2011**, *101*, 2350–2390. [CrossRef]
35. Hausman, D.; Welch, B. Debate: To Nudge or Not to Nudge. *J. Political Philos.* **2010**, *18*, 123–136. [CrossRef]
36. Hertwig, R.; Grune-Yanoff, T. Nudging and Boosting: Steering or Empowering Good Decisions. *Perspect. Psychol. Sci.* **2017**, *12*, 973–986. [CrossRef]
37. Romaniw, J.; Sa, J.; Lal, R.; Ferreira, A.; Inagaki, T.; Briedis, C.; Goncalves, D.; Canalli, L.; Padilha, A.; Bressan, P. C-offset and crop energy efficiency increase due industrial poultry waste use in long-term no-till soil minimizing environmental pollution. *Environ. Pollut.* **2021**, *275*, 116565. [CrossRef]
38. Xu, W.; Jin, X.; Liu, J.; Zhou, Y. Analysis of influencing factors of arable land fragmentation based on hierarchical linear model: A case study of Jiangsu Province, China. *Land Use Policy* **2021**, *101*, 105119. [CrossRef]
39. Shang, Z.; Cao, J.; Degen, A.; Zhang, D.; Long, R. A four year study in a desert land area on the effect of irrigated, arable land and abandoned cropland on soil biological, chemical and physical properties. *Catena* **2019**, *175*, 1–8. [CrossRef]
40. Belayneh, M.; Yirgu, T.; Tsegaye, D. Runoff and soil loss responses of arable land managed with graded soil bunds of different ages in the Upper Blue Nile basin, Ethiopia. *Ecol. Process.* **2020**, *9*, 66. [CrossRef]
41. Kahneman, D. *Thinking, Fast and Slow*; Macmillan: New York, NY, USA, 2011.
42. Evans, J.; Stanovich, K. Dual-process theories of higher cognition: Advancing the debate. *Perspect. Psychol. Sci.* **2013**, *8*, 223–241. [CrossRef]
43. Li, W.; Feng, T.; Hao, J. The evolving concepts of land administration in China: Arable land protection perspective. *Land Use Policy* **2009**, *26*, 262–272. [CrossRef]
44. Thaler, R.H. *Misbehaving: The Making of Behavioral Economics*; W. W. Norton & Company: New York, NY, USA; London, UK, 2015.
45. Fan, J.; Wang, L.; Qin, J.; Zhang, F.; Xu, Y. Evaluating arable land stability during the growing season based on precipitation in the Horqin Sandy Land, China. *J. Environ. Manag.* **2020**, *276*, 111269. [CrossRef] [PubMed]

46. Xu, D.; Fu, R.; Liu, H.; Guo, X. Current knowledge from heavy metal pollution in Chinese smelter contaminated soils, health risk implications and associated remediation progress in recent decades: A critical review. *J. Clean. Prod.* **2021**, *286*, 124989. [CrossRef]
47. Su, M.; Guo, R.; Hong, W. Institutional transition and implementation path for arable land protection in highly urbanized regions: A case study of Shenzhen, China. *Land Use Policy* **2019**, *81*, 493–501. [CrossRef]
48. Zhang, S.; Hu, W.; Huang, L.; Du, H. Exploring the Effectiveness of Multifunctional Arable Land Protection Linking Supply to Demand in Value Engineering Theory: Evidence from Wuhan Metropolitan Area. *Sustainability* **2019**, *11*, 6229. [CrossRef]
49. Zhang, J.; Zhang, A.; Song, M. Ecological Benefit Spillover and Ecological Financial Transfer of Arable Land Protection in River Basins: A Case Study of the Yangtze River Economic Belt, China. *Sustainability* **2020**, *12*, 7085. [CrossRef]
50. Jiang, G.; Wang, M.; Qu, Y.; Zhou, D.; Ma, W. Towards arable land multifunction assessment in China: Applying the "influencing factors-functions-products-demands" integrated framework. *Land Use Policy* **2020**, *99*, 104982. [CrossRef]
51. Gajewski, J.; Heimann, M.; Meunier, L. Nudges in SRI: The Power of the Default Option. *J. Bus. Ethics* **2021**, *177*, 547–566. [CrossRef]
52. Jones, R.; Pykett, J.; Whitehead, M. The geographies of policy translation: How nudge became the default policy option. *Environ. Plan. C Gov. Policy* **2014**, *32*, 54–69. [CrossRef]
53. Dolan, P.; Hallsworth, M.; Halpern, D.; King, D.; Metcalfe, R.; Vlaev, I. Influencing behaviour: The mindspace way. *J. Econ. Psychol.* **2012**, *33*, 264–277. [CrossRef]
54. Becchetti, L.; Salustri, F.; Scaramozzino, P. Nudging and corporate environmental responsibility: A natural field experiment. *Food Policy* **2020**, *97*, 101951. [CrossRef]
55. Ledderer, L.; Kjaer, M.; Madsen, E.; Busch, J.; Fage-Butler, A. Nudging in Public Health Lifestyle Interventions: A Systematic Literature Review and Metasynthesis. *Health Educ. Behav.* **2020**, *47*, 749–764. [CrossRef] [PubMed]
56. Wei, Y.; Li, H.; Yue, W. Urban land expansion and regional inequality in transitional China. *Landsc. Urban Plan.* **2017**, *163*, 17–31. [CrossRef]
57. Wei, Y.; Ye, X. Urbanization, urban land expansion and environmental change in China. *Stoch. Environ. Res. Risk Assess.* **2014**, *28*, 757–765. [CrossRef]
58. Chau, N.; Zhang, W. Harnessing the Forces of Urban Expansion: The Public Economics of Farmland Development Allowances. *Land Econ.* **2011**, *87*, 488–507. [CrossRef]
59. Wu, Y.; Shan, J.; Choguill, C. Combining behavioral interventions with market forces in the implementation of land use planning in China: A theoretical framework embedded with nudge. *Land Use Policy* **2021**, *108*, 105569. [CrossRef]
60. Inesi, M. Power and loss aversion. *Organ. Behav. Hum. Decis. Process.* **2010**, *112*, 58–69. [CrossRef]
61. Nicolle, A.; Fleming, S.M.; Bach, D.R.; Driver, J.; Dolan, R.J. A Regret-Induced Status Quo Bias. *J. Neurosci.* **2011**, *31*, 3320–3327. [CrossRef]
62. Druckman, J. Evaluating framing effects. *J. Econ. Psychol.* **2001**, *22*, 91–101. [CrossRef]
63. Loewenstein, G.F. Frames of mind in intertemporal choice. *Manag. Sci.* **1988**, *34*, 200–214. [CrossRef]
64. Breuer, W.; Soypak, K. Framing effects in intertemporal choice tasks and financial implications. *J. Econ. Psychol.* **2015**, *51*, 152–167. [CrossRef]
65. Lopez, R.; He, X.; De Falcis, E. What Drives China's New Agricultural Subsidies? *World Dev.* **2017**, *93*, 279–292. [CrossRef]
66. Krishnamurthy, P.; Carter, P.; Blair, E. Attribute framing and goal framing effects in health decisions. *Organ. Behav. Hum. Decis. Process.* **2001**, *85*, 382–399. [CrossRef] [PubMed]
67. Jin, J.; He, R.; Wang, W.; Gong, H. Valuing arable land protection: A contingent valuation and choice experiment study in China. *Land Use Policy* **2018**, *74*, 214–219. [CrossRef]
68. Li, H.; Zhang, X.; Zhang, X.; Wu, Y. Utilization benefit of arable land and land institution reforms: Economy, society and ecology. *Habitat Int.* **2017**, *77*, 64–70. [CrossRef]
69. Rivis, A.; Sheeran, P. Descriptive norms as an additional predictor in the theory of planned behaviour: A meta-analysis. *Curr. Psychol.* **2003**, *22*, 218–233. [CrossRef]
70. Cialdini, R. Descriptive social norms as underappreciated sources of social control. *Psychometrika* **2007**, *72*, 263–268. [CrossRef]
71. Si, R.; Lu, Q.; Aziz, N. Does the stability of farmland rental contract & conservation tillage adoption improve family welfare? Empirical insights from Zhangye, China. *Land Use Policy* **2021**, *107*, 105486.
72. Wang, W.; Yuan, J.; Gao, S.; Li, T.; Li, Y.; Vinay, N.; Mo, F.; Liao, Y.; Wen, X. Conservation tillage enhances crop productivity and decreases soil nitrogen losses in a rainfed agroecosystem of the Loess Plateau, China. *J. Clean. Prod.* **2020**, *274*, 122854. [CrossRef]
73. Han, Q.; Siddique, K.; Li, F. Adoption of Conservation Tillage on the Semi-Arid Loess Plateau of Northwest China. *Sustainability* **2018**, *10*, 2621. [CrossRef]
74. Xu, N. What gave rise to China's land finance? *Land Use Policy* **2019**, *87*, 104015. [CrossRef]
75. Gott, J.R., III. Implications of the Copernican principle for our future prospects. *Nature* **1993**, *363*, 315–319. [CrossRef]
76. Gott, J.R., III. Future prospects discussed. *Nature* **1994**, *368*, 108. [CrossRef]
77. Wang, G. Wall Slogans: The Communication of China's Family Planning Policy in Rural Areas. *Rural Hist.* **2018**, *29*, 99–112. [CrossRef]
78. Wang, P.; Han, W. Decision analysis of the elderly participating in the housing reverse mortgage: Based on bequest motivation constraint. *J. Intell. Fuzzy Syst.* **2021**, *40*, 8569–8586. [CrossRef]

79. Gao, L.; Huang, J.; Rozelle, S. Rental markets for arable land and agricultural investments in China. *Agric. Econ.* **2012**, *43*, 391–403. [CrossRef]
80. Hong, Z.; Sun, Y. Power, capital, and the poverty of farmers' land rights in China. *Land Use Policy* **2020**, *92*, 104471. [CrossRef]
81. Wu, H.; MacDonald, G.; Galloway, J.; Zhang, L.; Gao, L.; Yang, L.; Yang, J.; Li, X.; Li, H.; Yang, T. The influence of crop and chemical fertilizer combinations on greenhouse gas emissions: A partial life-cycle assessment of fertilizer production and use in China. Resources. *Conserv. Recycl.* **2020**, *168*, 105303. [CrossRef]
82. Xu, F.; Liu, Y.; Du, W.; Li, C.; Xu, M.; Xie, T.; Yin, Y.; Guo, H. Response of soil bacterial communities, antibiotic residuals, and crop yields to organic fertilizer substitution in North China under wheat- maize rotation. *Sci. Total Environ.* **2021**, *785*, 147248. [CrossRef]
83. Ilyas, M.; Kassa, F.; Darun, M.; Klemes, J. Life cycle cost analysis of wastewater treatment: A systematic review of literature. *J. Clean. Prod.* **2021**, *310*, 127549. [CrossRef]
84. Sunstein, C. The Ethics of Nudging. *Yale J. Regul.* **2015**, *32*, 413–450. [CrossRef]
85. Blumenthal-Barby, J.; Burroughs, H. Seeking Better Health Care Outcomes: The Ethics of Using the "Nudge". *Am. J. Bioeth.* **2012**, *12*, 1–10. [CrossRef] [PubMed]
86. Zhang, Y.; Li, X.; Song, W.; Zhai, L. Land abandonment under rural restructuring in China explained from a cost-benefit perspective. *J. Rural. Stud.* **2016**, *47*, 524–532. [CrossRef]
87. Ploug, T.; Holm, S.; Brodersen, J. To nudge or not to nudge: Cancer screening programmes and the limits of libertarian paternalism. *J. Epidemiol. Community Health* **2012**, *66*, 1193–1196. [CrossRef]
88. Yang, L.; Liu, M.C.; Lun, F.; Min, Q.; Li, W. The impacts of farmers' livelihood capitals on planting decisions: A case study of Zhagana Agriculture-Forestry-Animal Husbandry Composite System. *Land Use Policy* **2019**, *86*, 208–217. [CrossRef]
89. Solano, C.; Leon, H.; Perez, E.; Herrero, M. Characterising objective profiles of Costa Rican dairy farmers. *Agric. Syst.* **2001**, *67*, 153–179. [CrossRef]
90. Xie, H.; Huang, Y. Study on Farmland Abandonment Behavior of Farmers from Intergenerational Differences Perspectives: Based on 293 Farmer Questionnaires in Xingguo County, Jiangxi Province. *China Land Sci.* **2021**, *35*, 20–30.
91. Cai, L.; Wang, L.; Ning, M. Farmers' Livelihood Differentiation and Pesticide Application: Empirical Evidence from a Causal Mediation Analysis. *Sustainability* **2022**, *14*, 8502. [CrossRef]
92. Iyengar, S.; Lepper, M. When choice is demotivating: Can one desire too much of a good thing? *J. Personal. Soc. Psychol.* **2000**, *79*, 995–1006. [CrossRef]
93. Glimcher, P. Efficiently irrational: Deciphering the riddle of human choice. *Trends Cogn. Sci.* **2022**, *26*, 669–687. [CrossRef]
94. Luan, M.; Liu, Z.; Li, H. Taking Decisions Too Seriously: Why Maximizers Often Get Mired in Choices. *Front. Psychol.* **2022**, *13*, 878552. [CrossRef] [PubMed]
95. Zhao, D.; Zhou, H.; Gao, F. Differentiation of farmers, technical constraints and the differences of cultivated land protection technology selection: A theoretical analysis framework of farmer households' technological adoption based on different constraints. *J. Nat. Resour.* **2020**, *35*, 2956–2967. [CrossRef]
96. Xie, H.; Huang, Y. Influencing factors of farmers' adoption of pro-environmental agricultural technologies in China: Meta-analysis. *Land Use Policy* **2021**, *109*, 105622. [CrossRef]
97. Meder, B.; Fleischhut, N.; Osman, M. Beyond the confines of choice architecture: A critical analysis. *J. Econ. Psychol.* **2018**, *68*, 36–44. [CrossRef]
98. Zhang, Q.; Xiao, H.; Duan, M.; Zhang, X.; Yu, Z. Farmers' attitudes towards the introduction of agri-environmental measures in agricultural infrastructure projects in China: Evidence from Beijing and Changsha. *Land Use Policy* **2015**, *49*, 92–103. [CrossRef]

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Maximize Eco-Economic Benefits with Minimum Land Resources Input: Evaluation and Evolution of Land Use Eco-Efficiency of Agglomerations in Middle Reaches of Yangtze River, China

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Abstract: Increasing land-use eco-efficiency can alleviate human-land conflict in urban areas as well as improve regional urbanization quality to achieve sustainable development. As the central urban agglomeration in China, the Middle Reaches of Yangtze River (MRYR) has experienced rapid urbanization and huge land-use change during 2000 to 2020, which poses great threats to its ecological environment. This study adopted the Super-Slack-Based Data Envelopment Analysis (Super SBM-DEA) model to evaluate the eco-efficiency of land use in MRYR. The result shows that the average eco-efficiency value of land use is above 0.77 for each year, indicating that the general efficiency is at a middle level. The trend of the evolution of the eco-efficiency can be summarized as a "U-shape" style curve. The variance between the four urban agglomerations of the MRYR changed over time. Not all capital cities or cities with higher GDP per capita obtain higher eco-efficiency in this study. Policy intervention, population and land use, technique, and environmental pollution are influencing factors of land-use eco-efficiency. Based on slacks analysis, this study proposed the optimization of the land-use structure to improve eco-efficiency from four aspects of land-use structure, investment and labor, ecosystem services value (ESV) and environment pollution, and industry structure.

Keywords: eco-efficiency of land use; the middle reaches of Yangtze River; Super SBM-DEA model; ecosystem services value; slacks analysis

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1. Introduction

Sustainable development promotes economic growth while also taking into account the need to maintain the environment for future generations [1]. Ecological civilization is an inevitable requirement for the harmonious development of man and nature, and the construction of ecological civilization is fundamental for the sustainable development of China. According to the European Environmental Agency (EEA), eco-efficiency is the ability to maximize the benefits of fewer natural resources [2].

This can be used to gauge how resource utilization, pollution emissions, and economic growth are related [3,4]. The fact that eco-efficiency connects the environment and the economy makes it a crucial instrument for assessing sustainable development [5]. Meanwhile, regulations that encourage efficiency are more likely to be implemented than those that limit economic activity, particularly in developing countries such as China [6]. Thus, eco-efficiency research has become a hot issue in sustainable development research [7–9]. Urbanization has had a significant impact on the world. Large-scale land conversion is a significant issue in China, where growing urbanization has also created major land-use problems [10]. Land resources play a vital role in the ecological environment, and should be used sparingly and efficiently. The sustainable and efficient use of land resources is intimately tied to the eco-efficiency of land use. Eco-efficiency of land use can be defined as the reduction in inputs from land resources, in order to attain sustainable development goals and to achieve a mutually beneficial situation for the economy, resources, and environment. Eco-efficiency of land use cannot be quantified in absolute terms, but it does depend on the socioeconomic activities carried out on it [11]. Research on the eco-efficiency of land use in China is extremely valuable, in order to preserve land resources, safeguard the environment, and advance sustainable development.

Urban agglomeration is the area where land-use change and production activities are most concentrated. The land of urban agglomeration is a gathering place for social and economic activities, and its utilization process causes a certain degree of impact on the environment and ecosystem [7]. In East Asia, urban agglomerations have grown in Japan and South Korea since the 1950s. From the 1960s through the 1980s, South Korea relied on traditional heavy chemical industries, processing, and export industries to achieve rapid economic growth. Since the 1990s, with the disappearance of the demographic dividend and the establishment of the WTO, the domestic and foreign environments that supported South Korea's continued rapid economic growth have undergone major changes. This has forced South Korea to achieve industrial transformation and upgrade through reform, and embark on an efficient, intensive, and environmentally friendly high-quality development path. Japan's Tokyo Metropolitan Area and the Tokyo Bay Area, as a world-class mega city group, have brought considerable agglomeration economic effects to Japan. Compared with China, Japan's economic center is more concentrated. The polarization of the metropolitan area is so severe that it differs too much from other cities. This enlightens China to establish a multi-dimensional urban agglomeration, to cooperate with each other and complement each other, and to form a coordinated urban agglomeration development model with coordinated industrial land use. In China, urban agglomerations mainly began to develop in the 1990s. Since the beginning of the revolution, the Yangtze River Delta (YRD) urban agglomeration, the Pearl River Delta (PRD) urban agglomeration, and the Beijing-Tianjin-Hebei (BTH) metropolitan area have been recognized as the three major growth poles of China's economic development. The middle reaches of the Yangtze River, by building a new urbanization frontier zone in the central and western regions, can be built into a green growth pole of China. Although the socioeconomic development of urban agglomerations has achieved remarkable achievements, there are also increasing ecological and environmental threats. An extensive economy has been promoted in China for a long time [2]. In the context of this, the threat that urban agglomerations' economic expansion poses to ecosystems has increased, making it a highly concentrated and intensifying highly sensitive area of a series of ecological and environmental problems.

In terms of research scales, most studies related to the eco-efficiency of land use have been assessed from the perspective of national and provincial levels [12,13]. However, few studies have integrated the analysis of ecosystems and socioeconomic elements at the regional scale in the context of sustainable development. Due to this, there is a lack of theoretical foundation for developing strategies and policies for urban agglomerations. In terms of research methods, at the moment, the most widely used modeling methods are stochastic frontier analysis (SFA), slack-based measurement (SBM), and data envelopment analysis (DEA). Traditional DEA methods do not account for the influence of slack variables and do not exhibit the characteristics of non-parametric statistics [14]. Traditional SFA requires the definition of a specific function of the error term consisting of a null term and a random error term, which has specification and estimation problems [15]. Because the influences of environmental and stochastic factors are not taken into consideration, traditional SBM has the disadvantage of not being able to compute the efficiency values of all decision units, and traditional SBM-DEA has the issue of bias in arithmetic efficiency [16]. In terms of research contents, previously, the studies of land-use efficiency mainly discussed the land-use efficiency of built-up land in urban areas [17–20]. In recent years, scholars have combined the study of land-use-cover change study with eco-efficiency; how to measure land-use efficiency in the context of environmentally friendly developments [21–23]. Eco-efficiency is not prioritized by scholars. Instead, they concentrate on either pure economic efficiency or holistic efficiency. At the same time, scholars have focused more on the eco-efficiency of a certain type of land, such as industrial land and cultivated land, or land of a certain function, for example, mining land. In fact, the land-use adjustment should consider all kinds of land-use types. This enables the analysis of the eco-efficiency of land use in light of the structural composition of the land. In terms of environmental policy, spatial planning, and other regulations, environmental impact assessment can significantly lessen the harmful effects of initiatives on the environment and contribute significantly to sustainable development [24]. The weak points of the environmental impact assessment process are frequently noted as the lack of sufficient scientific evidence in impact assessment studies and the minimal engagement of experts in policy and decision-making [25]. A crucial instrument for determining environmental sustainability in the context of assuring economic growth is the ex-ante environmental evaluation [24]. In fact, the eco-efficiency of land use is analyzed, helping to design pertinent regulations specifically in the context of pre-assessment. The need for expert knowledge and citizen participation in fostering innovation and broad adoption of strategic plans for spatial planning [26]. Starting with land-use type research on the eco-efficiency of land use can help regulate the structure of land use and offer some theoretical groundwork for the creation of pertinent spatial planning.

In this paper, we introduce ecosystem services value (ESV) as the ecological output in the process of land use and utilize the Super-SBM model. By reclassifying all types of land data into three categories-farming land, construction land, and other land-we employ all types of land data acquired from remote sensing images as the input for land resources. It can raise the value of the results, provide precise and targeted land-use adjustment targets, and help with the creation of pertinent policies.

As shown in Figure 1, this paper builds an evaluation system with the eco-efficiency of land use as the core. The eco-efficiency of land use in urban agglomerations is centered on the input of land resources and the output of ecological and economic value. It obtains the economic value and ecological service value and the negative impact on the environment in the land-use process, and the comprehensive ability to achieve the goal of using the land resource efficiently. Improving the eco-efficiency of land use requires the coordinated development of the socioeconomic subsystem and the ecological environment subsystem.

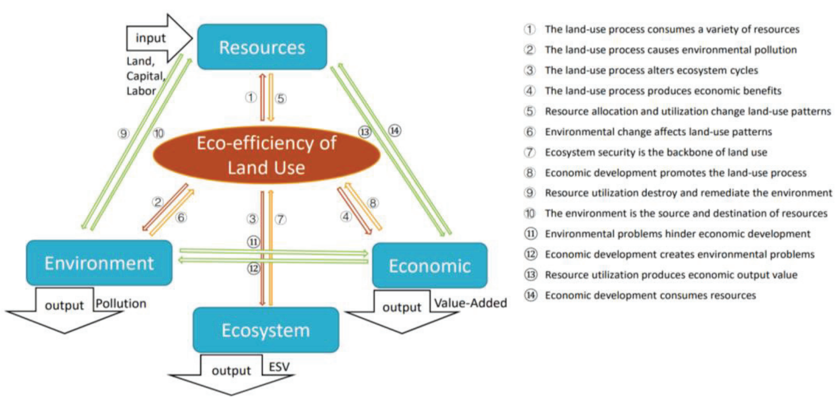

Figure 1. Framework of the input and output factors in the assessment of the ecological efficiency of land use. Source: own elaboration.

The evaluation of land-use eco-efficiency takes three basic production factors, land, capital, and labor as the input, and environmental pollution, ecosystem service value, and economic output value as the output. Focusing on the core of land-use eco-efficiency, it first expounds the impact and interaction mechanism of the land-use process on resources, environment, ecology, and economy. Secondly, the interaction between input and output factors is analyzed. Let us take the example of a city called S. In the process of the utilization of farming land, construction land, and other natural ecological land, S city in the urban agglomeration invests labor resources and capital, and finally produces ecosystem service value and economic output value, accompanied by certain environmental pollution. The environmental pollution caused by the process changes the land-use pattern, limiting economic development and industrial upgrading.

2. Methodology and Data Sources

2.1. Study Area

The Yangtze River is the largest river in China and the third largest river in the world, and "The Yangtze River Economic Belt Strategy" is one of China's national strategies. In the Yangtze River Basin, the connection between cities is relatively close, and the natural "golden waterway" can greatly reduce transportation costs (http://www.gov.cn/xinwen (accessed on 10 September 2014)). As an important part of it, the Middle Reaches of Yangtze River (MRYR) is identified as the new growth pole by the State Council of China. In the national "14th Five-Year Plan" outline, the positioning of the MRYR urban agglomeration has been upgraded to the same echelon as the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta (http://www.gov.cn/zhengce (accessed on 15 February 2022)). It has experienced dramatic urbanization during the study period, and land for future development has become a scarce commodity. Studying the eco-efficiency of land use is crucial for the sustainable development of the study area as well as the entire nation. As can be seen from Figure 2, this paper takes the four city groups of the MRYR urban agglomerations, which contains 31 prefecture-level cities as the study area. In the year 2020, the study area contributes about 9.3% of GDP ("Bulletin of Statistics for national economic and social development (2020)"). With a total land area of 326,000 square kilometers, accounting for 3.4% of the country, it is the largest urban agglomeration in China, 1.5 times that of the Yangtze River Delta and 6 times that of the Pearl River Delta (China Urban Statistical Yearbook 2018). The permanent population is about 130 million people, accounting for 9.1% (http://www.gov.cn/zhengce (accessed on 15 February 2022)) of the country, only lower than the Yangtze River Delta.

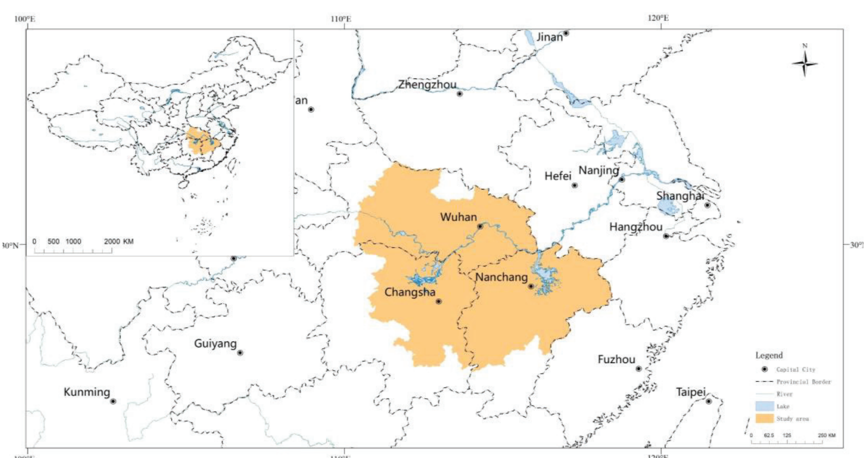

Figure 2. Geographical location and main cities of the middle reaches of the Yangtze River. Source: National Foundation Geographic Information Center and own elaboration.

(1) Wuhan City Circle and Xiang-Jing-Yi City Belt

The Wuhan city circle includes "1 + 8" cities, which are Wuhan and Huangshi, Ezhou, Huanggang, Xiaogan, Xianning, Xiantao, Qianjiang, and Tianmen around it. The natural environment of the land in the Wuhan city circle is diverse and the land resources are distributed in a multi-level circle. Same in the Hubei province. The Xiang-Jing-Yi City Belt includes Xiangyang, Jingmen, Jingzhou, and Yichang. It is an urban economic development belt in western Hubei formed by the Jiaoliu Railway, E'guang Expressway, and Hanjiang River. The two city groups use 64.6% land area contributing up to 90.9% GDP of Hubei province in 2020 in Table 1.

Table 1. List of cities of MRYR.

City Circle	City	Area (km^2)	GDP (CNY 100 Million)	City Circle	City	Area (km^2)	GDP (CNY 100 Million)
Poyang Lake City Circle	Fuzhou	18,799	1573	Wuhan City Circle	Ezhou	1594	1005
	Ji'an	25,373	2169		Huanggang	17,457	2170
	Jingdezhen	5261	957		Huangshi	4583	1641
	Jiujiang	19,798	3241		Qianjiang	558	765
	Nanchang	7402	5746		Tianmen	440	617
	Pingxiang	3831	964		Wuhan	8494	15,616
	Shangrao	22,791	2624		Xiantao	598	828
	Xinyu	3178	1001		Xianning	10,033	1525
	Yichun	18,669	2790		Xiaogan	8910	2194
	Yingtan	3560	983				
Chang-Zhu-Tan City Circle	Changde	18,910	3749	Xiang-Jing-Yi City Belt	Jingmen	12,404	1906
	Hengyang	15,303	3509		Jingzhou	14,067	2369
	Loudi	8119	1680		Xiangyang	19,728	4602
	Xiangtan	5008	2343		Yichang	21,230	4261
	Yiyang	12,320	1853				
	Yueyang	14,858	4002				
	Changsha	11,816	12,143				
	Zhuzhou	11,272	3106				

Data sources: "Bulletin of Statistics for national economic and social development (2020)" of cities in China; *Hubei Statistical Yearbook (2020); Hunan Statistical Yearbook (2020); Jiangxi Statistical Yearbook (2020).*

(2) Poyang Lake City Circle

The city cluster around Poyang Lake covers 10 cities including Nanchang, Jingdezhen, Yingtan, Jiujiang, Xinyu, Pingxiang, Fuzhou, Yichun, Shangrao, and Ji'an. The land area is 128,662 square kilometers, which occupies 77.1% of the land area of Jiangxi Province. The GDP accounts for 85.8% of Jiangxi Province. The infrastructure construction of the Poyang Lake city circle has been continuously improved, and the urban layout structure has basically formed.

(3) Chang-Zhu-Tan City Circle

The Chang-Zhu-Tan City Circle consists of 8 cities of Changsha, Zhuzhou, and Xiangtan, and the surrounding Changde, Yiyang, Yueyang, Hengyang, and Luodi. The distances between Changsha and Zhuzhou are 49 km away, Xiangtan and Zhuzhou are 37 km away, and Changsha and Xiangtan are 51 km away. The layout of the three medium-sized cities is compact, and the transportation between the cities is very convenient. The total land area of the Chang-Zhu-Tan City Circle is about 97,606 square kilometers, accounting for 46% of the province's land area.

2.2. Data Sources

The research data of this paper come from "Geospatial Information Platform of Chinese Academy of Sciences", "China Urban Statistical Yearbook 2001–2020", "China Urban Construction Statistical Yearbook 2001–2020", "The Middle Reaches of Yangtze River Development Plan 2015", and other provinces and cities' statistical yearbooks and various annual reports from the government websites. The spatial dataset is from Geospatial Information Platform of Chinese Academy of Sciences. The original remote sensing image with 30 m accuracy of Landsat TM is from the United States Geological Survey (USGS) of Jiangxi Province, Hunan Province, Hubei Province. Remote sensing interpretation derived from the National Fundamental Geographic Information Systems in China.

2.3. Super SBM-DEA Model

At present, DEA models are the primary methods to measure land-use efficiency; the evaluation methods mainly focus on DEA models, and SFA [21,23,27–30]. They are a non-parametric efficiency estimation method that does not need the specific form of production frontier and are easier to deal with when using multiple outputs. DEA provided by Charnes et al. in 1978 [31] was based on the relative efficiency of similar decision unit multi-index evaluation of the concept of input and output efficiency of a linear programming model, known as the "Charnes-Cooper-Rhodes (CCR)" model [31]. After updating the model for variable returns to scale the "Banker-Charnes-Cooper (BCC)" model [32]. The two measures with the efficiency of the unit are based on the radial and angular dimensions, when non-zero slack calculation results will be large. Tone (2001) [33] proposed the non-radial slack-based measure (SBM) model, which can deal with the redundancy problem of unexpected output. Effectively handle the input factors "crowded" or "relaxation" phenomenon. The efficiency of the SBM model calculated the maximum value to be 1; when there are a number of cities at the efficiency of 1, it will not be able to further determine which cities are more efficient. Tone (2002) [34] solved the problem with the Super Efficiency SBM model. The model can be described as follows:

$$\begin{gathered} \rho = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{k}\sum_{r=1}^{k}\frac{s_r^+}{y_{r0}}} \\ \text{s.t. } x \geq X\lambda + s^-,\ y0 \leq Y\lambda - s^+, \\ \lambda \geq 0,\ s^- \geq 0,\ s^+ \geq 0 \end{gathered} \tag{1}$$

where ρ means efficiency value evaluation of standard; input vector x_0 has m kind of input elements, its elements, respectively, for $x_{i0} = (i = 1, 2, \ldots, m)$; output vector y0 has k kind of output elements, its elements, respectively, for $y_{r0} = (i = 1, 2, \ldots, k)$; X and Y, respectively, for input elements matrix and output elements matrix; s^- stands for input redundant, its elements for $s_i^- = (i = 1, 2, \ldots, m)$, s^+ stands for output shortage, its elements $s_r^+ = (r = 1, 2, \ldots, k)$. When $\rho \geq 1$, the production unit is fully effective. When $\rho < 1$, there is loss in the DMU, which can be improved by optimizing the input and output factors.

To consider the undesirable output factors, scholars have extended the above model to divide the output vector into desired output a and undesired output b, the input vector $x \in R^m$, the desired output $y^a \in R^a$, the undesired output $y^b \in R^b$; the input element matrix, the desired output matrix, and the undesired output matrix are $X = [x_1, \ldots, x_n] \in R^{m\times n}$, $Y^a = [y_1^a, \ldots, y_n^a] \in R^{a\times n}$, $Y^b = [y_1^b, \ldots, y_n^b] \in R^{b\times n}$, assuming that X, Y^a, and Y^b are greater than zero, and the production possibility set is defined under CRS as: $P = \left\{(x, y^a, y^b) \mid x \geq X\lambda,\ y^a \leq Y^a\lambda,\ y^b \geq Y^b\lambda,\ \lambda \geq 0\right\}$, the SBM-undesirable model:

$$\left\{ \begin{gathered} \rho^* = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{a+b}\left[\sum_{r=1}^{a}\frac{s_r^a}{y_{r0}^a}+\sum_{r=1}^{b}\frac{s_r^b}{y_{r0}^b}\right]} \\ \text{s.t. } x0 = X\lambda + s^-,\ y_{r0}^a = Y^a\lambda - s^a,\ y_{r0}^b = Y^b\lambda + s^b, \\ \lambda \geq 0,\ s^- \geq 0,\ s^a \geq 0,\ s^b \geq 0 \end{gathered} \right.$$

where ρ^* denotes the efficiency value evaluation criterion; the input vector x0 has m input elements, whose elements are $x_{i0} = (i = 1, 2, \ldots, m)$; the desired output vector y_0^a has a few kinds of output elements, whose elements are $y_{r0}^a = (r = 1, 2, \ldots, a)$; the undesired output vector y_0^b has b kinds of output elements, whose elements are $y_{r0}^b = (r = 1, 2, \ldots, b)$;

s^- denotes input redundancy, whose elements are $s_i^- = (i = 1, 2, \ldots, m)$, s^a denotes desired output deficiency, whose elements are $s_r^a = (r = 1, 2, \ldots, a)$, s^b denotes non-desired output redundancy with elements $s_r^b = (r = 1, 2, \ldots, b)$. Similarly, when $\rho^* \geq 1$, then we have $s^- = 0$, $s^a = 0$, $s^b = 0$, indicating that there is no input and non-expected output redundancy and expected output deficiency, i.e., the decision unit is valid. When $0 < \rho^* < 1$, then, the decision unit is inefficient and can be improved by optimizing inputs and outputs.

2.4. Calculate the ESV

In 1997, Costanza et al. [35] divided ecosystem service functions into 9 items, and calculated the total value and each sub value of ecosystem services worldwide. Their study focuses can be summed up as follows: Firstly, classify the ecosystems according to certain classification standards, such as different environment and land type of the study area. Secondly, calculate the ecosystem service value of each ecosystem according to various standards and methods. Finally, summarize the ecosystem service value of the study area. Obtain the general structure table in the area. The specific model is as follows:

$$V_t = \sum_{i=1}^{n}\sum_{j=1}^{n} S_i \times M_{ij} \tag{2}$$

where V_t represents the total value of ecosystem services in the region in year t (CNY); S_i represents the area of i land use type (hm^2); M_{ij} stands for coefficient of class j ecosystem service function of class j ecosystem (CNY/hm^2); i represents the numbers of land-use types; j stands for numbers of ecosystem services.

In 2008, Xie Gaodi et al. [36] formulated the research results of Costanza et al. and updated the calculation table combined with the geographical characters of China to make it more suitable for the country. They conducted a questionnaire survey of 700 professionals with ecological backgrounds in China in 2002 and 2006 to derive a new ecosystem service valuation system. The comparison showed that the expert knowledge-based ecosystem service unit price system obtained from the survey was more comparable with the quality-based ecosystem service value. This expert knowledge-based ecosystem service valuation system can be used for known land-use areas, and can obtain more accurate results in a shorter period of time.

The model they worked out is the initial model, according to the regional actual and time-scale grain unit price; the total value of regional ecosystem services is calculated.

The model was based on research conducted nationwide. However, there are variations in the geographical environment and vegetation growth in different regions. In this study, we use the net primary productivity (NPP) of vegetation to make regional adjustments. The adjustment process is as follows:

$$P_{ij} = \frac{B_{ij}}{B_{average}} \tag{3}$$

where P_{ij} is NPP space-time regulators, B_{ij} refers to NPP of the j month of the i region of this type of ecosystem, and $B_{average}$ refers to NPP of the annual average of this ecosystem nationwide.

2.5. Index Selection

The input and output indicators of economic, social, and ecological aspects related to land utilization are selected in Table 2 in order to construct a comprehensive and objective evaluation of the land-use eco-efficiency of the urban agglomerations in the middle reaches of the Yangtze River. There are 3 aspects of input: (1) Land resources, which are divided into 3 types: farming land (FAR), construction land (CON), and other land (OTH). (2) Capital resources (CAP), we choose the investment in fixed assets to measure the capital input on the land. (3) Labor resources (LAB), we choose the number of people employed in the whole society to measure the labor input on the land. At the same time, the paper chooses 3 aspects of output: (1) Ecological value (ESV), the paper calculates the Ecosystem Service Value using a certain estimate method, using it to describe the output of the land use. (2) Economic value, the added value of the first (FIR), secondary (SEC), and tertiary (TER) industries are selected. (3) Environmental pollution, the paper selects industrial sulfur-dioxide emissions (SO_2) and industrial wastewater discharge (WAS) according to the principles of data availability and precision.

Table 2. Index selection of input and output.

Indicators	Units	Mean	Max	Min	Std. dev.
Input indicators					
Land resources [23,28]					
Farming land	hm^2	417,021.27	991,976.67	76,749.21	241,549.89
Construction land [7]	hm^2	39,760.90	118,698.03	7330.41	23,151.40
Other land	hm^2	671,166.13	1,815,773.94	21,200.49	510,568.82
Capital resource [28]					
Investment in fixed assets [7,19,29,37]	CNY 10 thousand	11,456,262.07	95,856,748.59	49,835.00	16,168,281.28
Labor resource [28,38]					
Number of people employed [7]	10 thousand persons	233.03	603.79	47.20	127.93
Output indicators					
Ecological value [39]					
ESV	CNY 10 thousand	1,558,322.27	4,033,055.02	128,802.86	1,109,511.41
Economic value [23,28,38]					
First industry	CNY 100 million	146.38	513.01	10.85	121.54
Secondary industry	CNY 100 million	642.72	5557.47	21.30	890.34
Tertiary industry	CNY 100 million	615.14	9656.40	20.80	1149.71
Environmental pollution [23,28]					
Industrial sulfur dioxide emission	ton	35,338.50	133,442.00	408.00	29,130.17
Industrial wastewater discharge	10 thousand ton	6278.34	40,661.00	229.07	6139.99

Data sources: *Urban Statistical Yearbook of China* (2001–2021); *China Statistical Yearbook* (2001–2021); *Hubei Statistical Yearbook* (2001–2021); Land cover data of 3 central provinces from "Geospatial Information Platform of Chinese Academy of Sciences".

3. Results

3.1. Isotonicity Analysis

Before using DEA models, it is necessary to test whether the data meet the assumptions of the models. First, the number of units should be at least twice the number of inputs and outputs. The number of DMUs in this study was much larger than the number of inputs and outputs, which met the quantity conditions. In addition, the input-output indicators must satisfy the isotonicity assumption that an increase in any input should not result in a decrease in any output. In this study, the Pearson correlation coefficient was used for testing (Figure 3). The correlation coefficient table shows that all input-output indicators passed the isotonicity test. Thus, the constructed indicator system can be analyzed using DEA models.

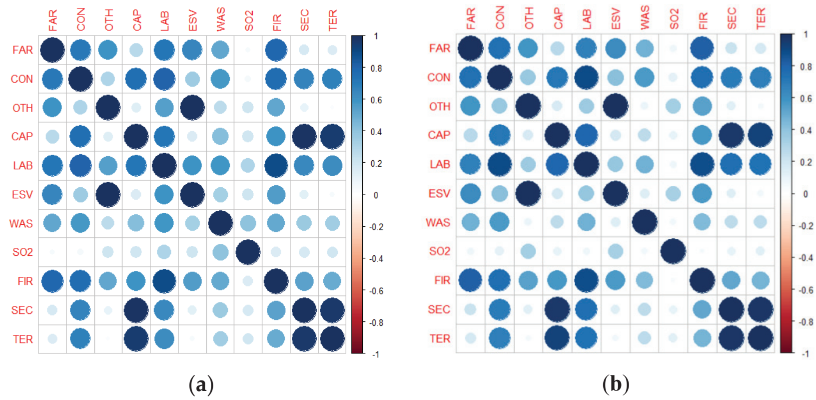

Figure 3. Correlation of inputs and outputs of 2015 (**a**) and 2020 (**b**).

3.2. Temporal-Spatial Trends of Land-Use Eco-Efficiency

3.2.1. Land-Use Eco-Efficiency of four City Groups

- Wuhan City Circle and Xiang-Jing-Yi City Belt

Wuhan City Circle and the Xiang-Jing-Yi City Belt are both located in Hubei Province, which is the geographically central province of China. Wuhan, the capital city of the province, is known as the "thoroughfare of nine provinces". From Figure 4, it can be seen that Wuhan's eco-efficiency of land-use level improved after 2010, when it was lower due to the excessive pollution emissions and insufficient agricultural production values. Wuhan's eco-efficiency of the land-use level was at the middle level in the province in 2000, 2005, and 2015, especially, in 2020 when it reached a higher level among all cities in the study area. Huangshi's eco-efficiency of land use has the lowest value of eco-efficiency of land use in Hubei province, and the large input of labor and land resources without the corresponding economic output made its value of eco-efficiency of land use at the lowest level in most years. Qianjiang, Tianmen, and Xiantao, as the three county-level cities under the province's administration, maintained high-efficiency levels from 2000 to 2020, mainly due to various land-use policies and the development of green industries. Tianmen City, with its ecological environment and other advantages, was at a high level of efficiency value except for 2010, and reached the maximum provincial efficiency value in 2020. The efficiency values of Huanggang and Xianning show a "W-shaped" trend. From 2000 to 2005, the eco-efficiency of land use in Huanggang and Xianning showed a sharp downward trend, as the area of construction land increased dramatically while the ecological and economic output remained constant. From 2015 to 2020, the efficiency values showed an upward trend attributable to the industrial reorganization from high-polluting industries to tourism. Ezhou city showed an upward trend in eco-efficiency of land use during the study period, which indicates that the city's land-use is developing toward rationalization and high-efficiency with high-quality.

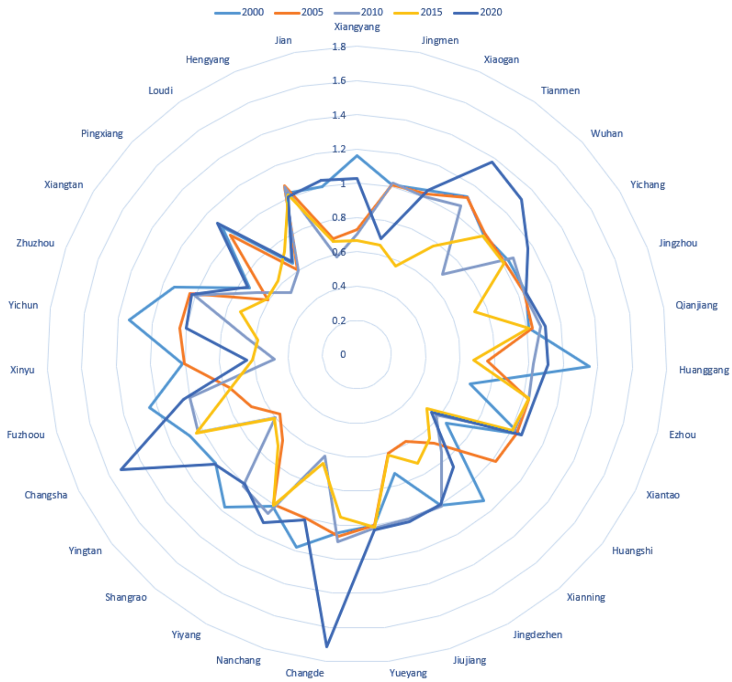

Figure 4. The results of the Ecological Efficiency of land use.

In the Xiang-Jing-Yi urban belt, Xiangyang city has a low level of eco-efficiency of land use and shows a "U-shaped" trend of first rising and then falling, which is due to the fact that Xiangyang's production factor inputs are at a medium level while its economic output is at a low level. Jingmen City shows a decreasing trend in general, whereas Jingzhou City and Yichang City show a medium level overall; this is because these cities have more land input than other cities in the province, but insufficient economic output.

- Poyang Lake City Circle

In Poyang Lake City Circle, Nanchang, the capital of Jiangxi Province, had a higher value of eco-efficiency of land use in 2000 and a lower value of eco-efficiency of land use ranking afterward, which may be due to the waste of land caused by the blind expansion of the city and the environmental pollution caused by the unreasonable industrial structure since 2000, which has further exacerbated the decrease in land-use eco-efficiency until 2020. Fuzhou, Shangrao, and Yichun converge with Nanchang. The eco-efficiency of land use in Jingdezhen, Ji'an, Yingtan, and Pingxiang first decreases and then increases steadily in a "U-shaped" trend, which may be explained by the region's low economic growth. The eco-efficiency of land use in Xinyu city declined and remained at a low level during the study period. The eco-efficiency of land use in Jiujiang City showed a general upward trend and decreased in some years, mainly owing to the same problem of insufficient economic output, which led to the lack of obvious economic benefits of land inputs.

- Chang-Zhu-Tan City Circle

In the Chang-Zhu-Tan City Circle, Changsha, as the capital of Hunan province, is the national "two-type society" comprehensive supporting reform pilot area. From Figure 4, we can see that the value of eco-efficiency of land use in Changsha City has been on the rise since 2005 during the study period, until 2020, when Changsha City's value of eco-efficiency of land use was second only to Changde City, reaching an efficiency value of 1.52. This is closely related to the fact that Changsha and Changde do not blindly pursue urban expansion and have a friendly development policy orientation. Zhuzhou City, Hengyang City, Yiyang City, and Yueyang City all maintain high levels of land-use eco-efficiency. Loudi and Xiangtan cities have been at a low level of land-use eco-efficiency value, and according to statistical data, their economic output value is insufficient as the main reason.

3.2.2. Trends of the Eco-Efficiency of Land Use

From Figure 5, the middle reaches of the Yangtze River urban agglomeration have average annual land-use eco-efficiency values over 0.77, which indicates that the overall efficiency is in the middle to upper range. The eco-efficiency of land use in MRYR shows a decreasing and then increasing trend, which we summarize as a "U-shaped" curve. From the perspective of urban clusters, the average eco-efficiency of four urban clusters in MRYR is ranked as WH (average 0.95) > XJY (average 0.94) > PYL (average 0.93) > CZT (average 0.87). In 2000, XJY had the highest average efficiency value and WH had the lowest; in 2005, WH had the highest value and PYL Circle had the lowest. PYL and XJY show "W-shaped" curves from 2000 to 2020, twice experiencing a rise and fall. WH and CZT show "U-shaped" curves, with higher eco-efficiency of land use in 2000 and 2020, and lower eco-efficiency of land use in 2005, 2010, and 2015.

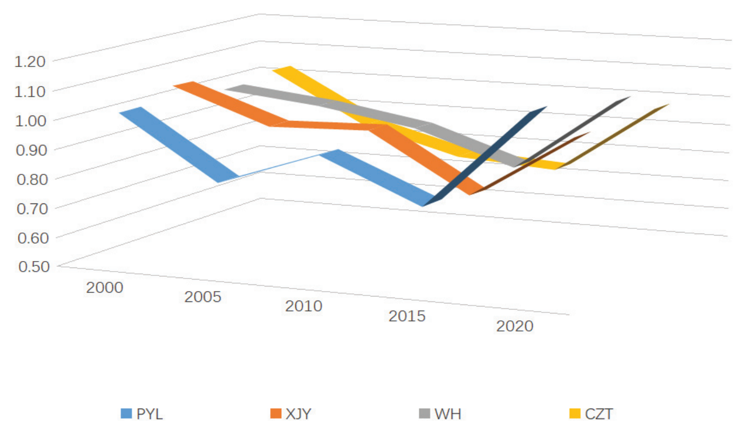

Figure 5. Average eco-efficiency of 4 urban agglomerations.

3.2.3. Focused Cities' Eco-Efficiency of Land Use

From the perspective of cities in Figure 6, the cities with the highest eco-efficiency of land use are, in order, Huanggang (2000), Tianmen (2005), Changde (2010), Changsha (2015), and Changde (2020), and the cities with the lowest eco-efficiency of land use are Loudi (2000), Yingtan (2005), Xinyu (2010) Huangshi (2015, 2020). During 2000-2005, most cities showed a decreasing trend, and the eco-efficiency of land use of Ezhou City increased the most from 0.67 to 1.03; the eco-efficiency of land use of Huanggang City decreased the most from 1.35 to 0.76. During 2005-2010, most cities showed an increasing trend, and the eco-efficiency of land use of Jingdezhen City increased the most from 0.57 to 1.01; the eco-efficiency of land use of Xinyu City decreased the most, from 1.00 to 0.47. From 2010 to 2015, most cities show a decreasing trend, with Wuhan City's eco-efficiency of land use increasing the most from 0.68 to 1.00, and Xiaogan City's eco-efficiency of land use decreasing the most from 1.00 to 0.56. From 2015 to 2020, most cities show an increasing trend. The eco-efficiency of land use in Changde City increased the most from 0.95 to 1.71, and the eco-efficiency of land use in Loudi City decreased the most from 0.73 to 0.66. Among the provincial capital cities, Changsha has a "U-shaped" trend with the highest mean value; Wuhan has a "V-shaped" trend with the second highest mean value; and Nanchang has a "W-shaped" trend with the lowest mean value. The provincial capital cities have bottlenecks regarding the problem of how to use land resources efficiently and ecologically, which will be improved to some extent in 2020 under a series of policy interventions and other influencing factors.

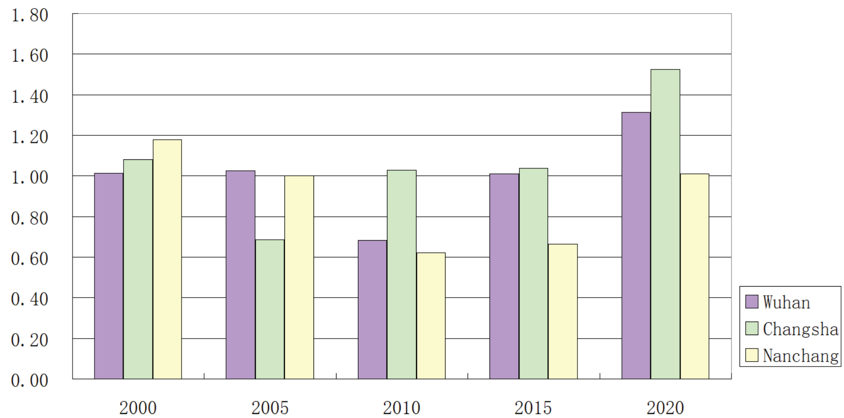

Figure 6. Capital cities' eco-efficiency of land use.

3.3. Influencing Factors

3.3.1. Policy Summary

China pursues comprehensive and coordinated sustainable development, and ecological safety in the Yangtze River basin is of increasing concern. From 2000 to 2005, efficiency values dropped significantly. The rapid growth of GDP at this stage relied on the high consumption of resources, resulting in high environmental pollution. At the same time, all kinds of environmental problems broke out intensively, and environmental protection became an important trigger point for social conflicts of interest.

In 2002, the report of the 16th National Congress of the Communist Party of China put forward the goal of building a well-off society in an all-around way, requiring the continuous enhancement of sustainable development capabilities, the improvement of the ecological environment, and the significant increase in resource utilization efficiency. In 2017, the 19th National Congress of the Communist Party of China proposed high-quality economic development and other environmental regulating measures, China's economy is progressively transitioning to high-quality intense development. Among these policies, the ecological compensation policy is an important one, aiming at protecting the ecological environment and using economic instruments to coordinate the interests of stakeholders in favor of sustainable development. Ecological compensation will be implemented in terms of environmental pollution, economic status, and ecosystem values, which are closely linked to the measurement of eco-efficiency of land use. In the context of China's ecological compensation policy, Dong [15] measured the eco-efficiency of land use in small watersheds, and the results showed that the efficiency gradually improved under the first round of ecological compensation policy implementation.

3.3.2. Population and Land Use

With the rapid advancement of the urbanization process, urban development has attracted more and more attention from society. Most local governments equate "urbanization" with "urban construction", placing too much emphasis on the growth of built-up areas at the expense of urban population clustering and social security implementation after clustering. From 2000 to 2011, the area of urban built-up areas increased by 76.4%, which was much higher than the growth rate of the urban population of 50.5%, and "land urbanization" was significantly faster than "population urbanization". Continuous urbanization has brought about a number of issues, including deteriorating environmental quality, a lack of cultivated land, and deterioration of ecosystem processes, which have altered the structure and operation of regional ecosystems [40]. The results of Shan's [41] research show that large population living in cities, increasing urban population density, and the demand for resources from city dwellers all harm the environment and lower efficiency levels.

The urban-rural dualist system, economic growth, and land-use regulations are all connected with land-use concerns in China, which have distinctively Chinese characteristics. Large-scale land conversion due to rapid urbanization has led to major issues with land use, including the loss of cultivated land, the abandonment of cultivated land, and the formation of hollow villages, which pose a threat to China's resources and food security. As the carrier of urban social, economic, political, and cultural activities, urban land is the spatial basis for the realization of the overall function of the city. In the process of urban development, the fact that the scale of land use has expanded too fast, the extensive use of construction land, and the continuous erosion of cultivated land and ecological land have brought serious consequences to urban construction and social and economic development, making the already scarce land resources suffer. With large-scale enclosures such as "new districts", "new towns", and "development zones", the contradiction between land-use supply and demand has become more prominent, the demand for new construction land is large, and the situation of cultivated land protection is severe. Land-use conditions can have different effects on the eco-efficiency of different areas [11]. In our study, land resources were divided into three categories of farming land, construction land, and other land, and different land-use types were used as input factors to explore the eco-efficiency of land use. According to Lu [42], cultivated land resources are both a source of agricultural products and a significant source of carbon emissions, which can have an impact on the stability of regional ecosystems. This shows that the ecological efficiency of land use is significantly influenced by land use.

3.3.3. Techniques and Social Factors

In China, energy savings and emission reductions have gained considerable attention due to environmental pollution and excessive resource consumption caused by rapid economic growth and urban expansion. Since entering the 21st century, China's clean energy has developed rapidly. The installed capacity of hydropower, solar thermal utilization, wind power, and solar power generation have successively become the first in the world. As of the end of 2018, the proportion of hydropower in China's installed capacity of clean energy had dropped from 100% in 1949 to 45.52%, while the installed capacity of wind power had reached 23.81%, the installed capacity of photovoltaic power generation had reached 22.57%, the installed capacity of nuclear power had reached 5.77%, and the installed capacity of biomass power generation had reached 2.3%. The development and expansion of terminal applications have also led to the comprehensive development of China's clean energy industry chain. According to Yang [43], higher levels of research and development can help facilitate innovation in cleaner production methods, accomplish cleaner production at the source, lower the intensity of resource consumption, and produce more of the desired output while decreasing more of the undesirable output. This shows that improvements in land-use eco-efficiency are facilitated by developments in science and technology.

Environmental pollution is a major challenge to the sustainable development of human societies and natural ecosystems. Carbon emissions have gained a lot of attention from people all over the world. Agricultural carbon sources, such as the generation of agricultural waste, rice cultivation, and the burning of biological tissues, are directly related to land-use activities [44]. Kuang [13] explores the efficiency of provincial cultivated land use in China, using carbon emissions as an undesirable output. Dong [15] measures the efficiency of chemical elements such as lead, total phosphorus, fluoride, and selenium while taking into account pollution from home sewage and fertilizers. Environmental pollution is an important factor affecting the eco-efficiency of land use.

3.4. Slacks Analysis and Optimization Adjustment

The paper calculated the eco-efficiency of land use of the study area and briefly analyzed the previously reported potential influence factors. Based on that, this paper summarizes the slacks of the inputs and outputs of the model, to figure out the targeted constraints to the eco-efficiency of land use of the city groups. The Super-SBM model is used in the evaluation of the eco-efficiency of land use. When measuring efficiency, the DEA model is evaluated according to the input and output levels of each decision-making unit. The efficiency value that is measured is relative efficiency; the level of efficiency in comparison to the most efficient decision unit [45]. Therefore, cities not found to be DEA effective may have constraints from inputs, outputs, or both inputs and outputs. Those are factors that limit efficiency improvement. The variables that constrain efficiency gains in the data envelopment model are referred to as slacks, including "input redundancy" and "output insufficient". "Input redundancy" means the quantity of inputs that can be saved from the associated resources in order to attain efficiency; "output insufficient" means the number of outputs that must be increased in order to achieve efficiency; in this article, we found that the corresponding ecological and economic values can be improved and the potential for pollutions can be reduced. The input and output factors can be seen in Table 3; the paper takes the first three letters to give a short-term for the factors in this analysis part. This part is to analyze the slacks, and make progress on the input and output of each city group on this basis. Scientific and reasonable optimization is conducive to realizing the most optimal land use structure.

Table 3. Summary of slacks of input and output factors of the city groups.

	PYL (2000)	WH (2000)	XJY (2000)	CZT (2000)	PYL (2005)	WH (2005)	XJY (2005)	CZT (2005)	PYL (2010)	WH (2010)
FAR	17,565.81	12,141.54	356,716.81	115,491.05	143,545.48	203,402.96	647,902.37	111,301.54	282,065.76	24,217.07
CON	7943.45	18,241.37	23,220.75	2165.35	56,315.08	46,447.90	47,722.22	9613.66	54,778.64	38,856.25
ECO	103,009.95	29,752.10	0.00	36,812.74	380,220.94	227,122.64	243,699.72	30,202.43	76,967.56	0.00
INV	52,359.85	193,986.57	533,404.58	427,900.74	45,640.84	588,068.49	0.00	606,673.91	0.00	475,709.54
LAB	52.35	56.67	0.00	151.23	278.75	158.32	15.82	218.71	107.35	150.42
ESV	2,161,125.56	2,076,313.64	1,759,700.52	449,768.73	1,204,294.50	60,810.98	268,904.44	80,595.93	1,286,006.34	91,228.77
WAS	11.47	47.02	0.00	159.21	83.41	6.30	5.65	85.83	27.59	12.34
SUL	135.22	280.56	143.14	466.28	1200.63	112.50	202.52	425.99	313.34	121.93
FIR	63.17	102.72	12.14	38.74	99.71	30.38	29.13	93.83	158.70	281.43
SEC	156.59	0.00	13.70	68.82	177.20	337.17	33.40	70.52	227.72	127.38
TER	105.61	39.46	3.90	187.36	125.19	64.81	0.75	0.69	2335.83	307.32
	XJY (2010)	CZT (2010)	PYL (2015)	WH (2015)	XJY (2015)	CZT (2015)	PYL (2020)	WH (2020)	XJY (2020)	CZT (2020)
FAR	266,797.90	26,065.09	479,828.46	366,794.66	671,361.84	129,560.57	21,979.83	100,085.56	336,390.11	49,779.53
CON	33,081.76	13,080.42	58,225.20	48,923.33	15,792.13	0.00	15,167.92	15,542.98	22,773.50	3786.50
ECO	77,843.26	15,710.24	6259.88	0.00	0.00	14,871.61	2758.74	327,514.55	866.28	4449.11
INV	407,062.82	1,875,769.44	5,692,966.97	0.00	0.00	599,826.50	5,822,738.28	6,206,309.79	3,606,866.86	7,238,377.27
LAB	72.94	163.01	201.55	237.70	10.69	121.63	42.35	101.69	2.29	36.40
ESV	640,261.14	499,817.29	374,269.74	62,219.58	303,286.41	359,972.31	2,699,105.25	661,178.44	2,066,729.26	3,921,942.00
WAS	0.73	18.06	25.31	6.58	8.41	5.34	1.68	1.53	0.43	1.55
SUL	5.09	164.73	257.11	101.04	32.77	97.04	17.71	6.08	1.63	8.47
FIR	45.69	125.24	350.45	16.38	0.00	126.49	15.94	379.30	319.07	762.86
SEC	222.26	698.01	314.30	955.92	138.91	1198.40	19.21	1714.26	225.22	3759.41
TER	139.19	408.92	3874.85	2424.61	2212.25	2041.21	13.29	5138.07	294.33	5933.15

3.4.1. Land-Use Structure

In terms of input factors, all urban agglomerations have some degree of redundancy in most years. In terms of land resources, there is a surplus of agricultural land, construction land, and other land from 2000 to 2020, which indicates a certain degree of waste in the use of land resources. However, it differs from one urban agglomeration to another in different years. For the year 2000, the main land structure problem in the Xiang-Jing-Yi City Belt is the excess input of agricultural land and construction land. For WH, the main problem is the excess input of construction land. For CZT, the main problem is the excess input of agricultural land as well as ecological and other land. For PYL, the main problem is the excess input of ecological and other land. The four agglomerations all experienced redundancy in 2005 and 2010. In 2015, there was some redundancy of agricultural land and construction land in PYL, XJY, and WH, and redundancy of agricultural land and ecological and other land in CZT. In 2020, there was overcapacity in agricultural land and construction land in XJY, and there was input overcapacity in other land in Wuhan City Circle. The results show that most cities in the middle reaches of the Yangtze River urban agglomeration have a certain degree of unreasonable land-use structure, with the most prominent problem of non-intensification of construction land. Among them, 45% of the cities had different degrees of redundancy of construction land in 2005. The comparative analysis shows that the redundancy rate of construction land differs among cities, but there is a certain commonality in the land-use structure adjustment programs between provincial capital cities and cities in urban areas.

3.4.2. Investment and Labor Force

In terms of fixed asset investment, excluding XJY and PYL in 2005 and WH and XJY in 2015, there is some redundancy in all four urban clusters in other study years. In terms of employment, most of the urban agglomerations have labor redundancy, excluding XJY in 2000. In 2000, the capital and labor redundancy in CZT is at a high level in comparison. Within the Chang-Zhu-Tan City Circle, redundancy in fixed asset investment is concentrated in Changsha, Zhuzhou, and Loudi, and redundancy in the number of employees is concentrated in Loudi and Xiangtan. In 2005, WH shows significant redundancy in investment and labor force, but there are differences among cities. The only cities having redundancy in fixed asset investment are Wuhan and Tianmen, and the only cities having redundancy in the labor force are Huanggang and Xianning. In 2010, the redundancy was mainly concentrated in CZT. In 2015, the redundancy of the labor force was mainly concentrated in Wuhan City Circle and Poyang Lake city circle; meanwhile, the redundancy of capital investment was mainly concentrated in PYL. In 2020, there is no obvious redundancy of labor force input in most of the city groups, and the urban development and ecological efficiency of land use improve to absorb the surplus labor force. However, there was a large surplus of fixed capital input in that year, which may have been due to the influence of the high percentage of land finance.

3.4.3. Ecological Output and Environmental Pollution

During the years of the study area, all four urban agglomerations included in the middle reaches of the Yangtze River urban agglomeration had the problem of insufficient ESV output, indicating that further land use control is needed to protect the ecological environment and enhance the service function of the ecosystem. Statistically, most cities in the study area had serious industrial SO_2 emissions and industrial wastewater discharge pollution in most of the years from 2000 to 2010. After 2015, the pollution was greatly modified. In terms of output insufficiency analysis, industrial wastewater discharges in the four metropolitan agglomerations are currently within a reasonable range and have no discernible effects on the improvement of land-use eco-efficiency.

3.4.4. Industrial Structure

During the study years, the shortage of economic output value was mainly concentrated in the tertiary industry. The amount of redundancy of tertiary industry output differs among the four urban groups. If the optimization results of the DEA model can be realized, in 2020, the output value of the primary industry can be increased by CNY 147.717 billion, the secondary industry by CNY 571.810 billion, and the tertiary industry by CNY 113.884 billion, which is equivalent to about 2% of the total GDP of China in that year. Industrial upgrading is an issue that must be considered to enhance the ecological efficiency of land use.

4. Discussion

The paper here proposed some suggestions and recommendations for land-use management based on the study results above.

The paper discussed the changes in land-use eco-efficiency during the years 2000 to 2020; we summarize the land-use-cover change, industrial structure change, pollution, etc., to analyze the reasons. These results point us in the direction of improvement in the green and efficient use of land resources.

Sustainable development should be emphasized throughout the entire decision-making procedure [46,47]. The government should take activities to deal with the conflicts between land use and the ecological environment [30]. It is an important guarantee for economic development and security of food rations through the combination of land use and land cultivation, the utilization of cultivated land guaranteeing the current production.

The improvement of eco-efficiency of land use should be set as one of the core factors of local government performance evaluation. The improvement of urban eco-efficiency in China depends largely on the further reforming of performance evaluation mechanisms [48]. During the process, the eco-efficiency of land use needs to be improved according to local conditions, and the four city groups in the MRYR have their own characteristics. Cities should be based on their own functional positioning, economic vitality, and resource endowments determining their land use layout [49,50], fully tapping the potential of all kinds of land, to avoid blindly expanding the city. At the same time, the thresholds should be used to limit high energy consumption and high pollution.

According to the land use and industrial layout of different cities, the division of labor and cooperation will be carried out to advance industrial upgrading. Industrial upgrading is an important way to improve the level of eco-efficiency, which is a key factor affecting energy consumption intensity and pollution emission intensity [51].

This study has some deficiencies, first of all, there is no temporal continuity in the land-use data, so the efficiency is measured intermittently. As a result, the calculated efficiency value cannot reflect the trend of change and spatial differentiation patterns, and the inflection point of efficiency values cannot be determined. Secondly, the idea of eco-efficiency only makes sense when viewed through the lens of sustainable development. Meanwhile, this article is based on the city level, which cannot take into account the differences within the region. Further study can be conducted at the county level to discuss the efficiency of land-use structures to improve the present practical guidance. Third, as the number of decision-making units increases, the system of input-output indicators could also be appropriately expanded to allow for more perspectives to consider the benefits of land use and comprehensively measure the structure of land-use efficiency. Last, but not least, a comprehensive comparison of the input and output status of the land should be made on the basis of efficiency. It is more appropriate to evaluate the effectiveness of land use by considering the negative impact of the land-use process on the environment.

5. Conclusions

China's high-quality development policy has required high-efficiency of land use, and it is of great significance to ensure green development while improving land-use efficiency. Therefore, the concept of achieving eco-efficiency should be widely used in land-use management. The paper constructed an evaluation system of land-use eco-efficiency of the urban agglomeration in MPYR using the Super-SBM model based on previous studies of the urban-land-use efficiency of various regions of China. After the analysis of the results of the eco-efficiency of the four city groups of the MRYR, the paper briefly summarized the changes in policy, population, land use, techniques, and social factors during the study period and how they possibly contribute to the evaluation results. At last, the paper analyzed the slacks of the input and output factors.

During the years 2000 to 2020, the eco-efficiency values are generally in a relatively upper-middle average. There exists an upside potential of improving the eco-efficiency in many cities. Each city's efficiency varies and is heterogeneous, yet there is a general trend of falling and then rising. Most of the high-efficiency scores occur between 2000 and 2020.

The variance between the four city groups of the MRYR urban agglomeration changed every year. In 2000, the highest average efficiency value is XJY, and the lowest is WH; In 2005, the highest is WH, and the lowest is PYL Circle. PYL and XJY experienced two ups and downs from 2000 to 2020 as they move along a "W-shaped" curve. WH and CZT show

"U-shaped" curves, with higher land use eco-efficiency in 2000 and 2020, and lower land use eco-efficiency in 2005, 2010, and 2015.

Not all capital cities or cities with higher GDP per capita had higher eco-efficiency in this study. Cities such as Nanchang, Changsha, and Wuhan, as the capital of their provinces, are also the economic center of the central region, with good location conditions and a large proportion of construction land. However, their eco-efficiency turns out to be at an average level for some years because of their environmental problems and extensive land-use pattern. Although some of the relatively developed cities have the highest pollution, their economic output has an absolute advantage, making their eco-efficiency still reach the optimal level. Some economically underdeveloped areas also showed high land-use levels, such as Pingxiang and Yiyang, because of their high level of green development. Some cities are in the middle level of both economic and the eco-efficiency, which may be because the advantages of the urban economy in this study are not very prominent, but in the process of development, extensive land use has produced higher pollution emissions, and undesirable environmental output has pulled down the overall land-use level.

In this paper, the main ecological protection policies in the research period are sorted out and the influencing factors of the policies are analyzed qualitatively. Considering China's national conditions, the promulgation and implementation of policies have a certain time consistent with the changes in the eco-efficiency of urban agglomerations. In addition to government factors, population, land-use patterns, technical progress, etc., may have significant effects on efficiency values.

The slacks analysis can be used to optimize the land-use structure and industrial structure. The optimization can be conducted from the four aspects of land use structure, investment and labor, ESV, and undesirable environmental output and industry structures. There are certain differences in the direction and magnitude of the adjustment.

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References

1. Eisenmenger, N.; Pichler, M.; Krenmayr, N.; Noll, D.; Plank, B.; Schalmann, E.; Wandl, M.T.; Gingrich, S. The Sustainable Development Goals prioritize economic growth over sustainable resource use: Critical reflection on the SDGs from a socio-ecological perspective. *Sustain. Sci.* **2020**, *15*, 1101–1110. [CrossRef]
2. Ren, Y.; Fang, C.; Lin, X. Evaluation of eco-efficiency of four major urban agglomerations in eastern coastal area of China. *Acta Geogr. Sin.* **2017**, *11*, 2047–2063.
3. Wang, Z.; Chen, J.; Zheng, W.; Deng, X. Dynamics of land use efficiency with ecological intercorrelation in regional development. *Landsc. Urban Plan.* **2018**, *177*, 303–316. [CrossRef]
4. Kuosmanen, T. Measurement and analysis of eco-efficiency: An economist's perspective. *J. Ind. Ecol.* **2005**, *9*, 15–18. [CrossRef]
5. Müller, K.; Holmes, A.; Deurer, M.; Clothier, B.E. Eco-efficiency as a sustainability measure for kiwifruit production in New Zealand. *J. Clean. Prod.* **2015**, *106*, 333–342. [CrossRef]
6. Zhang, B.; Bi, J.; Fan, Z.; Yuan, Z.; Ge, J. Eco-efficiency analysis of industrial system in China: A data envelopment analysis approach. *Ecol. Econ.* **2008**, *68*, 306–316. [CrossRef]
7. Tang, Y.; Wang, K.; Ji, X.; Xu, H.; Xiao, Y. Assessment and spatial-temporal evolution analysis of urban land use efficiency under green development orientation: Case of the Yangtze river delta urban agglomerations. *Land* **2021**, *10*, 715. [CrossRef]
8. Wang, S.; Jia, M.; Zhou, Y.; Fan, F. Impacts of changing urban form on ecological efficiency in China: A comparison between urban agglomerations and administrative areas. *J. Environ.* **2019**, *63*, 1834–1856. [CrossRef]

9. Jiang, W.; Cai, Y.; Tian, J. The application of minimum cumulative resistance model in the evaluation of urban ecological land use efficiency. *Arab. J. Geosci.* **2019**, *12*, 714. [CrossRef]
10. Liu, Y.; Fang, F.; Li, Y. Key issues of land use in China and implications for policy making. *Land Use Policy* **2014**, *40*, 6–12. [CrossRef]
11. Deng, X.; Gibson, J. Sustainable land use management for improving land eco-efficiency: A case study of Hebei, China. *Ann. Oper. Res.* **2020**, *290*, 265–277. [CrossRef]
12. Cao, W.; Zhou, W.; Wu, T.; Wang, X.; Xu, J. Spatial-temporal characteristics of cultivated land use eco-efficiency under carbon constraints and its relationship with landscape pattern dynamics. *Ecol. Indic.* **2022**, *141*, 109140. [CrossRef]
13. Kuang, B.; Lu, X.; Zhou, M.; Chen, D. Provincial cultivated land use efficiency in China: Empirical analysis based on the SBM-DEA model with carbon emissions considered. *Technol. Forecast. Soc. Chang.* **2020**, *151*, 119874. [CrossRef]
14. Hu, Y.; Liu, X.; Zhang, Z.; Wang, S.; Zhou, H. Spatiotemporal Heterogeneity of Agricultural Land Eco-Efficiency: A Case Study of 128 Cities in the Yangtze River Basin. *Water* **2022**, *14*, 422. [CrossRef]
15. Dong, J.; Wu, D. An evaluation of the impact of ecological compensation on the cross-section efficiency using SFA and DEA: A case study of Xin'an River Basin. *Sustainability* **2020**, *12*, 7966. [CrossRef]
16. Wang, M.; Sun, C.; Wang, X. Analysis of the water-energy coupling efficiency in China: Based on the three-stage SBM-DEA model with undesirable outputs. *Water* **2019**, *11*, 632. [CrossRef]
17. Lambin, E.F.; Meyfroidt, P. Global land use change, economic globalization, and the looming land scarcity. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 3465–3472. [CrossRef]
18. Wang, X.; Liu, X.; Pei, T.; Wang, Z. Potential evaluation of urban land intensive use in Beijing-Tianjin-Hebei region based on measurement of technical efficiency. *Acta Geogr. Sin.* **2019**, *74*, 1853–1865.
19. Chen, Y.; Chen, Z.; Xu, G.; Tian, Z. Built-up land efficiency in urban China: Insights from the General Land Use Plan (2006–2020). *Habitat Int.* **2016**, *51*, 31–38. [CrossRef]
20. Agegnehu, G.; Ghizaw, A.; Sinebo, W. Yield potential and land-use efficiency of wheat and faba bean mixed intercropping. *Agron. Sustain. Dev.* **2008**, *28*, 257–263. [CrossRef]
21. de Araújo, R.V.; Espejo, R.A.; Constantino, M.; de Moraes, P.M.; Taveira, J.C.; Lira, F.S.; Herrera, G.P.; Costa, R. Eco-efficiency measurement as an approach to improve the sustainable development of municipalities: A case study in the Midwest of Brazil. *Environ. Dev.* **2021**, *39*, 100652. [CrossRef]
22. Andrés, M.D.; Barragán, J.M.; Sanabria, J.G. Relationships between coastal urbanization and ecosystems in Spain. *Cities* **2017**, *68*, 8–17. [CrossRef]
23. Liu, Y.; Song, Y.; Peter, H. Examination of the relationship between urban form and urban eco-efficiency in China. *Habitat Int.* **2012**, *36*, 171–177. [CrossRef]
24. Nita, A.; Fineran, S.; Rozylowicz, L. Researchers' perspective on the main strengths and weaknesses of Environmental Impact Assessment (EIA) procedures. *Environ. Impact Assess. Rev.* **2022**, *92*, 106690. [CrossRef]
25. da Rocha, É.G.; da Rocha, P.L.B. Scientists, environmental managers and science journalists: A hierarchical model to comprehend and enhance the environmental decision-making process. *Perspect. Ecol. Conserv.* **2018**, *16*, 169–176. [CrossRef]
26. Hossu, C.A.; Oliveira, E.A. Streamline democratic values in planning systems: A study of participatory practices in European strategic spatial planning. *Habitat Int.* **2022**, *129*, 102675. [CrossRef]
27. Ma, D.; Zhang, J.; Wang, Z.; Sun, D. Spatio-temporal evolution and influencing factors of open economy development in the Yangtze River Delta area. *Land.* **2022**, *11*, 1813. [CrossRef]
28. Yu, J.; Zhou, K.; Yang, S. Land use efficiency and influencing factors of urban agglomerations in China. *Land Use Policy* **2019**, *88*, 104143. [CrossRef]
29. Sun, Y.; Ma, A.; Su, H.; Su, S.; Chen, F.; Wang, W.; Weng, M. Does the establishment of development zones really improve industrial land use efficiency? Implications for China's high-quality development policy. *Land Use Policy* **2020**, *90*, 104265. [CrossRef]
30. Gao, X.; Zhang, A.; Sun, Z. How regional economic integration influence on urban land use efficiency? A case study of Wuhan metropolitan area, China. *Land Use Policy* **2019**, *90*, 104329. [CrossRef]
31. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
32. Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
33. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
34. Tone, K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [CrossRef]
35. Costanza, R.; de Groot, R.; Farber, S.; Grasso, M.; Hannon, B.; Limburg, K.; Naeem, S.; Paruelo, J.; Raskin, R.G.; Sutton, P.; et al. The value of the world's ecosystem services and natural capital. *Nature* **1997**, *387*, 253–260. [CrossRef]
36. Xie, G.D.; Zhen, L.; Lu, C.X.; Xiao, Y.; Chen, C. Expert knowledge based valuation method of ecosystem services in China. *J. Nat. Resour.* **2008**, *23*, 911–919.
37. Du, J.; Thill, J.C.; Peiser, R.B. Land pricing and its impact on land use efficiency in post-land-reform China: A case study of Beijing. *Cities* **2016**, *50*, 68–74. [CrossRef]

38. Wu, C.; Wei, Y.D.; Huang, X.; Chen, B. Economic transition, spatial development and urban land use efficiency in the Yangtze River Delta, China. *Habitat Int.* **2017**, *63*, 67–78. [CrossRef]
39. Fu, B.; Li, Y.; Wang, Y.; Zhang, B.; Yin, S.; Zhu, H.; Xing, Z. Evaluation of ecosystem service value of riparian zone using land use data from 1986 to 2012. *Ecol. Indic.* **2016**, *69*, 873–881. [CrossRef]
40. Ding, T.; Chen, J.; Fang, Z.; Chen, Y. Assessment of coordinative relationship between comprehensive ecosystem service and urbanization: A case study of Yangtze River Delta urban Agglomerations, China. *Ecol. Indic.* **2021**, *133*, 108454. [CrossRef]
41. Shan, L.; Jiang, Y.; Liu, C.; Zhang, J.; Zhang, G.; Cui, X. Conflict or Coordination? Spatiotemporal Coupling of Urban Population–Land Spatial Patterns and Ecological Efficiency. *Front. Public Health* **2022**, *10*, 890175. [CrossRef] [PubMed]
42. Lu, X.; Kuang, B.; Li, J.; Han, J.; Zhang, Z. Dynamic evolution of regional discrepancies in carbon emissions from agricultural land utilization: Evidence from Chinese provincial data. *Sustainability* **2018**, *10*, 552. [CrossRef]
43. Yang, H.; Zheng, H.; Liu, H.; Wu, Q. NonLinear effects of environmental regulation on eco-efficiency under the constraint of land use carbon emissions: Evidence based on a Bootstrapping approach and Panel Threshold Model. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1679. [CrossRef] [PubMed]
44. Luo, Y.; Long, X.; Wu, C.; Zhang, J. Decoupling CO_2 emissions from economic growth in agricultural sector across 30 Chinese provinces from 1997 to 2014. *J. Clean. Prod.* **2017**, *159*, 220–228. [CrossRef]
45. Fukuyama, H.; Weber, W.L. A directional slacks-based measure of technical inefficiency. *Socio-Econ. Plan. Sci.* **2009**, *43*, 274–287. [CrossRef]
46. Fu, Y.; Zhang, X. Planning for sustainable cities? A comparative content analysis of the master plans of eco, low-carbon and conventional new towns in China. *Habitat Int.* **2017**, *63*, 55–66. [CrossRef]
47. Zhang, M.; Xiao, H.; Sun, D.; Li, Y. Spatial differences in and influences upon the sustainable development level of the Yangtze River Delta urban agglomeration in China. *Sustainability* **2018**, *10*, 411. [CrossRef]
48. Cheng, Y.; Shao, T.; Lai, H.; Shen, M.; Li, Y. Total-factor eco-efficiency and its influencing factors in the Yangtze River Delta urban agglomeration, China. *J. Environ. Sci.* **2019**, *16*, 3814. [CrossRef]
49. Fang, C.; Yu, D. Landscape and Urban Planning Urban agglomeration: An evolving concept of an emerging phenomenon. *Landsc. Urban Plan.* **2017**, *162*, 126–136. [CrossRef]
50. Zhou, Y.; Huang, X.; Chen, Y.; Zhong, T.; Xu, G.; He, J. The effect of land use planning (2006–2020) on construction land growth in China. *Cities* **2017**, *68*, 37–47. [CrossRef]
51. Kahn, M. Domestic pollution havens: Evidence from cancer deaths in border counties. *J. Urban Econ.* **2004**, *56*, 51–69. [CrossRef]

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How Neighbors Influence Rice–Crayfish Integrated System Adoption: Evidence from 980 Farmers in the Lower and Middle Reaches of the Yangtze River

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Abstract: Rice-aquatic animal integrated systems can alleviate food and environmental insecurity. Understanding how this practice is adopted by farmers is significant for promoting the development of the agricultural industry. Given the information inadequacy and information frictions in agricultural society in China, farmers are susceptible to the behaviors of their neighbors through social interaction. This paper defines neighboring groups that are both spatially and socially connected to identify whether neighbors influence farmers' adoption of rice–crayfish integrated systems using a sample in the lower and middle reaches of the Yangtze River in China. The findings reveal that for every one-unit increase in neighbors' adoption behavior, the probability of farmers' adoption increases by 0.367 units. Therefore, our results may have great value for policymakers seeking to take advantage of the neighborhood effect to complement formal extension systems and promote the developments of China's ecological agriculture.

Keywords: neighborhood effect; rice–crayfish integrated system; technology adoption

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1. Introduction

In recent years, rice–aquatic animal integrated systems (i.e., co-farming with aquatic animals such as crayfish, crab, soft-shelled turtle, etc.) have gained increasing attention for their potential for alleviating food and environmental insecurity. Rice–aquatic animal integrated systems can bring about high yields and low environmental impacts and have been widely explored through field experiments [1,2] and household surveys [3]. Among them, rice–crayfish integrated systems have experienced explosive growth in China since 2016 and are considered to be a valid approach for ensuring the supply of food and aquatic products, increasing farmers' incomes and promoting rural revitalization [4,5]. Rice–crayfish integrated systems allow for the efficient internal recycling of crayfish and rice. In this practice, on the one hand, the rice field provides a habitat for crayfish, and the straw in the field creates a heat preservation effect which facilitates the hatching of crayfish seedlings. Meanwhile, rice straw corrosion facilitates the growth of plankton in the water, which are regarded as nourishment for crayfish and effectively address the straw burning issue in China. On the other hand, integrated farming can take advantage of agricultural byproducts to decrease dependence on agroindustry inputs such as fertilizers and pesticides. To be more specific, crayfish digest and utilize rice straw and can eliminate the presence of pests in the straw. The excreta of crayfish also supply organic fertilizer for rice growth, and the crayfish in paddy fields constrain the use of pesticides and fertilizers due to their being sensitive to chemical inputs. Thus, integrated systems are regarded as an ecological agricultural practice.

According to the statistical data, rice–crayfish integrated systems constitute 52.95% of the total land areas used for rice–fish integrated systems. Additionally, 83.54% of the total production of crayfish is through rice–crayfish integrated systems [6]. The increased use of this type of integrated system can be partly attributed to political subsidies, field demonstrations and technical instructions from local extension agents. However, the implementation of rice–crayfish integrated systems involves intensive knowledge and requires deep insight into recycling and execution to ensure high crayfish and rice yields and a low environmental impact. Thus, farmers are not able to master the core techniques through simple learning and typical demonstration visits. Moreover, integrated systems require large investments (e.g., proprietary equipment) and involve increased flood and drought associated risks [7]. Clarifying the micro-mechanisms of farmers' adoption of rice–crayfish integrated systems is significant for promoting the development of ecological agricultural practices in general.

In Chinese culture, which emphasizes collectivism and "acquaintance", neighbors are considered to be one essential driver of family decision making [8]. Given the information inadequacy in agricultural society in China and the existing information frictions between farmers and extension agents, farmers share farming information and techniques with their neighbors and assist each other with farm work. Through these frequent and close interactions, farmers are influenced by the behaviors of their neighbors [9], which forms a neighborhood effect. Studies have demonstrated that farmers in proximity to each other tend to have similar adoption behavior toward new technologies to reduce learning costs through information sharing [10]. Even though the role of the neighborhood effect is acknowledged in the literature, many studies focus on geographical criteria [11,12] (i.e., distance and location) to define neighboring units and have not specified the strength of interactions between neighboring units. The presence of the neighborhood effect usually amplifies this effect, which implies that a multiplier effect exists through social interaction that is strongly conditioned by the geographic distance between individuals [13]. Moreover, many studies have examined the neighborhood effect on simple technology adoption (e.g., biogas adoption [14] and water conservation [15]).

Our study expands the literature in two aspects. First, we define neighboring groups at the village level using samples of small communities. Individual farmers and their neighbors are both spatially and socially connected, which indicates the existence of real— and thus more relevant—social interactions. Usually, community-based definitions of neighbors or peers are too broad and may include irrelevant reference individuals. However, this concern may not appear in our village-based sample for the following reasons. Families in one village usually have lived there for generations and the farmers are familiar with each other, which maintains strong social relationships between farming households [16]. The natural and exogenous characteristics of rural villages suggest that the definition of neighbors in our sample includes both friends and non-friend acquaintances and excludes strangers. Such village-based neighboring groups are not self-selected networks; thus, their exogeneity is unlikely to interfere with our desired outcome. Second, little empirical research has concentrated on exploring the relationship between the neighborhood effect and farmers' integrated farming system adoption. Our paper expands the existing literature by providing direct evidence of the neighborhood effect in integrated farming system adoption.

In this article, we consider both geographic and socioeconomic criteria when defining the neighbor group to examine the presence of the neighborhood effect in farmers' rice–crayfish integrated system adoption behavior. Understanding how new practices are disseminated through these interactions is helpful for developing agricultural policies that target specific agricultural areas or communities or even farmers where certain technologies should be introduced to achieve the desired impact.

The reminder of this paper is structured as follows. Section 2 is a review of the literature. Section 3 describes the data and empirical methods. In Section 4, we present the results and a discussion. Section 5 concludes.

2. Literature Review

Previous studies have identified many factors of farmers' adoption behavior and indicated that subsidies, agricultural extension services, field schools, and field demonstrations can improve farmers' adoption rates [17,18]. Studies have also suggested that household characteristics, such as age, education, farm size, and income level as well as perception of technology adoption, environmental concern, behavioral goals, and attitude have important roles [19–23]. The costs and benefits of the technology also affect farmers' adoption decisions [24,25]. Furthermore, the nudge theory, or "altering people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives," has been widely discussed as a factor in farmers' adoption behavior [26,27]. In addition to these factors, economists and policymakers have argued that individual behaviors vary with the behavior of the group through mechanisms other than economic aspects [15,28,29], namely, the neighborhood effect.

Many studies have confirmed the presence of the neighborhood effect in farmers' decision-making processes in settings ranging from rural housing demand [30], rural labor mobility [31], commercial health insurance purchasing [32], and response to climate change [33]. Exploring the impact that neighbors or social interactions have on individual farmers' technology adoption have also been widely explored. One strand of the literature focuses on the mechanism of the neighborhood effect in terms of information sharing and social norms. Xiong and Payne [34] investigated how peer effects occur and found that family members sharing experimental resources and production externalities between contiguous plots of land positively impacts farmers' Artemisia slengensis (AS) adoption. Di Falco and Doku [35] argued that the peer effect occurs through information diffusion by observing peer farmers' choices, which encourages farmers to adopt multiple climate adaption strategies at the household level. Tran-Nam and Tiet [36] considered organic farming neighbors or peers as a source of information, knowledge, and motivation to help farmers transition to organic farming. Crudeli and Mancinelli [37] focused on peer approval and examined how the social norm of being a "good farmer" influences farmers' innovation adoption.

Another strand of research has concentrated on identifying the presence of the neighborhood effect. Many studies have identified the spatial or geographic neighboring effect. Sampson and Perry [11] take spatial bands around each water right as a peer group and find that spatial neighboring effects in the adoption of LEPA (i.e., low-energy precise application) diminishes with distance. Bollinger and Burkhardt [15] found peer effects in water conservation. Their identification strategy relies on quasi-experimental variation from consumer migration in which new households move into peer groups and make water consumption and landscape changes. Kolady and Zhang [38] use location-specific survey data to define farmers' peer group through physical proximity, and the results show that spatially mediated peer effects are important in the adoption of conservation tillage and diverse crop rotation. Skevas and Skevas [20] discovered that peer effects arise from both nearby farmers' adoption of unmanned aerial vehicles and the spatial spillover of other farmers' characteristics.

More research has identified the neighborhood effect through social interactions between individuals and their neighboring group. Gao and Grebitus [39] reveal that hog farmers' genomics adoption time frames are positively correlated with other closely related hog farmers' time frames. Ward and Pede [40] define same-village membership and geographical distance as spatial network systems and demonstrate that the distance between hybrid rice adopters affects farmers' adoption of hybrid rice.

3. Data and Methods

3.1. Data

The data of this study are from a survey of rice farmers we conducted in the provinces of Hubei, Hunan, and Anhui in the middle and lower reaches of the Yangtze River of China in July 2019. These three provinces are the main originating location of rice–crayfish integrated systems in China. This region is characterized as a subtropical monsoon with a humid climate and an average annual temperature ranging between 14 °C and 18 °C and a forest-free period ranging between 210 and 270 days. The annual average precipitation is approximately

1000–1500 mm. These three provinces were chosen as the study area for the following reasons. First, they are major producers of rice and aquaculture products—especially crayfish—in China due to their climate conditions and the rich water resources in the middle and lower Yangtze Plain. Rice–crayfish integrated systems were first developed in Jianli, Hubei province, and over the years, this cultivation system has been adopted by a growing number of farmers in this region. Second, local governments in this area recognize the environmental and economic benefits of such systems and thus promote them using a wide range of policy instruments, from offering direct subsidies to farmers who adopt them to providing technical assistance through agricultural extension services. As a result, it is estimated that these three provinces have a great amount of farming areas that use rice–crayfish integrated systems, among which Hubei province ranks first [6]. A map of the study area is shown in Figure 1.

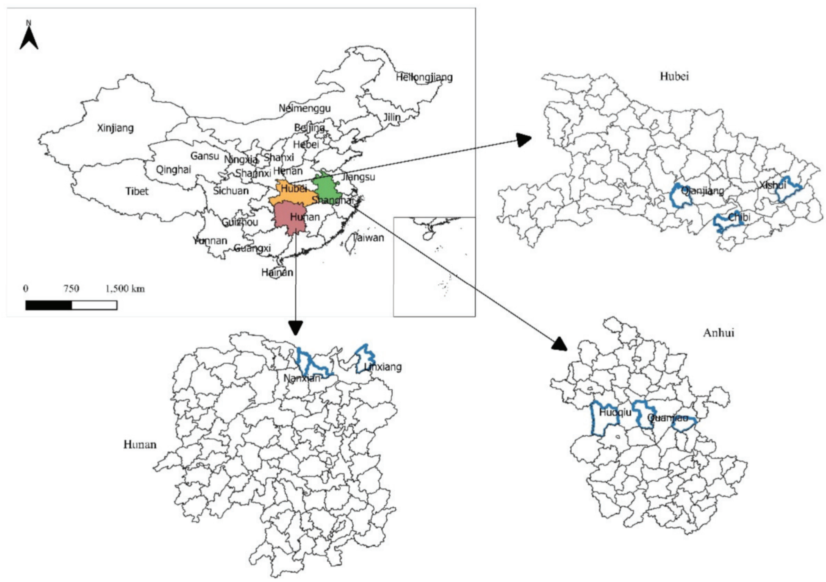

Figure 1. Location of the study area.

A multistage stratified sampling procedure was used to choose a representative sample of rice farming households in the region. In the first stage, three counties within each province were chosen to account for the distribution of land used for rice–crayfish integrated systems and the general level of economic development within these provinces. In the second stage, around 1000 rice farming households were randomly chosen from villages in each county. Most farming families have lived in their village for generations and are within walking distance of each other. We used a structured questionnaire to obtain farmers' information. The questionnaire consisted of six parts: household and farm characteristics (e.g., age, education, farm size, labor, and assets); sources of new technology; crop planting methods (e.g., the adoption of rice–crayfish integrated systems) and related inputs and outputs; farmers' utilization of agricultural socialization services (e.g., agricultural mechanization services); farmers' perception of rice–crayfish integrated systems; and village characteristics (e.g., infrastructure). We conducted face-to-face interviews with farmers through trained qualified postgraduates majoring in agricultural economic management in our research group based on a survey questionnaire. Since this study analyzes the influence of group behaviors, we deleted samples ($\leq$3) with fewer than three neighbors. After dropping observations with missing information for key variables, we obtained a final sample of 980 households, 695 of which had adopted rice–crayfish integrated systems to some degree.

3.2. Methodology and Variables

There are several situations that may have led us to mix other effects with the neighborhood effect when we observed similar behavioral outcomes between individual farmers and their neighboring group. Therefore, measuring the neighborhood effect presents several challenges [13,40–43] which include: (1) the contextual effect, which reflects the fact that neighbors' exogenous characteristics will directly affect individuals' behavior (i.e., a farmer's propensity to adopt will be affected by the mean age within their neighboring group); (2) the correlation effect, which indicates that individuals behave similarly in one group with which they tend to have similar characteristics or are confronted with a common set of unobserved characteristics (i.e., farmers may be affected by regional policies, such as the same agricultural subsidy policy, to have the same behaviors); (3) the self-selection problem, which implies that individuals select neighbors based on their preferences and backgrounds and have similar behaviors simply resulting from similar income levels or proximity; and (4) the reflection problem, by which individuals and their neighboring group make decisions or behave simultaneously. As a result, individuals forming a unilateral causal relationship with their neighboring group will cause an endogeneity problem.

To overcome the above problems, we applied a set of empirical strategies. We collected samples of 980 farming households in three major provinces in the lower and middle reaches of the Yangtze River in China in 2019, and formed plausible empirical neighbor groups given the small community nature of rural villages. In the context of our research setting, there are typically strong socio-economic ties in Chinese culture and thus we define farmers living in the same administrative village as a neighboring group. The reason for this is that choosing a village as a dataset contributes to solving the self-selection issue to some extent [30]. On the one hand, the household registration system of China and restrictions on rural–urban mobility hinders migration to villages. On the other hand, the formation of a village often spans generations [43]. Households settled in rural areas are unlikely to choose their neighbors through migration [44,45]. Moreover, this paper took neighboring farmers' background characteristics, village characteristics, and provincial dummy variables into account to limit the importance of contextual and correlation effects [43]. Last, to estimate the effect of neighboring farmers' adoption, we applied the instrumental variable method (IVs) to overcome the simultaneity issue and identify two exogenous variables as instrumental variables, "Village diversity in surnames" and "The proportion of paddy field area in the village", to improve our identification of the neighborhood effect. After that, we conducted several robustness checks to confirm the presence of the neighborhood effect.

Since the explained variable, farmers' adoption behavior, is binary, we chose the probit model as a benchmark model [45,46]. The basic formula is specified as follows:

$$Probit\ (Adoption_i^c\ = 1) = \varphi(\beta_0 + \beta_1 NAdoption_{-i}^c + \beta_2 X_i + \beta_3 Y_{-i}^c + \beta_4 Z_i + ProvinceDummy. \quad (1)$$

In this formula, $Adoption_i^c$ is an indicator of the rice–crayfish integrated system adoption of farmer i in village c (1 = yes; 0 = no). These data stem from a question in the questionnaire, namely, "Does your family adopt a rice–crayfish integrated system?"

The key explanatory variable is $NAdoption_{-i}^c$ (i.e., the neighborhood effect), which indicates the average adoption within a neighboring group, except for farmer i. The size and significance of the coefficient on β_1 are of particular interest to us. To ensure the accuracy of the results, the scope of "neighborhood" must be cautiously defined. Thus, we calculated the neighborhood effect using the following equation:

$$NAdoption_{-i}^c = \frac{\sum_1^n Adoption_i^c - Adoption_i^c}{n-1} \quad (2)$$

Equation (2) denotes neighboring farmers' behavior in this paper. Neighbors' influence should exclude the effects of the focal farmer; thus, farmer i is not included. c is the number of sampled farmers in the village.

X_i is a vector of exogenous characteristics of the sampled farming household, including the age of the head of the household, education, risk preference, job status, perception of the economic benefits of rice–crayfish integrated systems, agricultural extension training attendance, scale of operations, agricultural labors, investment, cooperation membership status, proportion of agricultural income to total household income, and the furthest distance between two plots.

Y^c_{-i} denotes a vector of neighbors' characteristic variables. To minimize the contextual effect, we controlled neighbors' head of household age, education, job status and cooperation membership status in the basic regression. The calculations followed Equation (2) (i.e., the average value within the neighboring group, but not the focal farmer in the same village).

Two measures were taken to suppress the correlation effect issue: conducting a province-varying fixed effects model and controlling village-based variables (Z_i), including the proportion of the effective irrigated area in the village and the effective traffic rate of the village's road. The details of the variables are presented in Table 1.

Table 1. Definition of variables and summary statistics.

Variable Category	Variables	Variables Description	Mean	SD
Dependent variable	Farmers' adoption behavior	Whether your family adopted rice–crayfish integrated systems in 2018? Dummy (1 = yes; 0 = no)	0.710	0.454
Explanatory variable	Neighborhood effect	Average adoption behavior in neighbors' household. (range: 0–1)	0.292	0.289
Instrumental variables	Village diversity in surnames	Whether your village is a miscellaneous surname village? (1 = yes; 0 = no)	0.699	0.459
	Proportion of paddy field area	The proportion of paddy field area to cultivated land in the village. (range: 0–1)	0.848	0.141
Household characteristics	Age	Household head age. Number	54.791	9.261
	Education	Education of the household head. Number	7.276	3.204
	Risk preference [1]	What's your risk preference? (3 = high risk preference; 2 = neutral risk preference; 1 = low risk preference)	1.63	0.765
	Job status	Whether you engaged in part-time job? (1 = yes; 0 = no)	0.33	0.47
	Perception on economic benefits	Whether you think rice–crayfish integrated systems are highly profitable? (1 = yes; 0 = no)	0.805	0.491
	Perception on population	Rice–crayfish integrated systems are popular in your village? (5 = strongly agree; 4 = agree; 3 = not sure; 2 = disagree; 1 = strongly disagree)	3.609	0.897
	Information access	You can easily get information on rice–crayfish integrated system. (5 = strongly agree; 4 = agree; 3 = not sure; 2 = disagree; 1 = strongly disagree)	3.348	1.06
	Agricultural extension training attendance	You have attended agricultural extension training many times in 2018? (5 = frequently; 4 = often; 3 = some time; 2 = rarely; 1 = none)	3.417	1.045
	Scale of operations	How many farmlands you have operated in 2019. (mu)	91.655	202.729
	Agricultural labors	How many agricultural labors in your family? Number	2.028	0.68
	Own capital investment proportion	What's the proportion of own possessed capital investment to the whole agricultural investment? (%)	90.099	20.949
	Cooperation membership status	Is your family any member of the village cooperation? (1 = yes; 0 = no)	0.191	0.393
	Proportion of agricultural income	What's the proportion of agricultural income to total household income? (%)	0.693	0.272
	Plots distance	How far away is your furthest two plots? (kilometers)	0.653	1.895

Table 1. *Cont.*

Variable Category	Variables	Variables Description	Mean	SD
Neighborhood characteristics	g_age	The average age of household heads within neighboring group. Number	54.791	4.421
	g_education	The average education of household heads within neighboring group. Number	7.276	1.48
	g_job status	The average part-time job of household heads within neighboring group. Number	0.33	0.167
	g_corperation membership status	The average member of corporation of household heads within neighboring group. Number	0.191	0.189
Village characteristics	Agents	How many agents who buy rice and crayfish within the village? Number	7.297	8.038
	Effective irrigated area	What's the proportion of effective irrigated area in villages? (%)	94.548	11.708
	Mechanical plough road	What's the effective traffic rate of the village mechanical plough road? (%)	90.536	17.835
Region variables	Anhui	Household from Anhui province. (1 = yes; 0 = no)	0.33	0.47
	Hunan	Household from Hunan province. (1 = yes; 0 = no)	0.335	0.472
	Hubei	Household from Hubei province. (1 = yes; 0 = no)	0.334	0.472

[1] The measurement method of 'risk preference' is by asking famers the following question. If there are two varieties of rice (Seed A and Seed B), their yields may vary in the following three scenarios, what would you choose? (1 jin = 0.5 kg; 1 mu = 666 m^2) ① A.900–1100 jin/ mu, B.800–1300 jin/ mu; ② A.900–1100 jin/ mu, B.700–1600 jin/ mu; ③ A.900–1100 jin/ mu, B.600–1800 jin/ mu. If the farmer chooses A in the three scenarios, we define them as low-risk preference; if the farmer chooses B in the three scenarios, we define them as high-risk preference. Otherwise, we define them as neutral risk preference. SD denotes standard deviation; One mu is about 0.0667 hm^2.

As mentioned above, endogenous threats that arise from simultaneity should be controlled [45–47]. We applied the IV method to control the reflection problem [29]. We followed Gaviria and Raphael [48], Li and Zang [45] and Ling and Zhang [49] and select two exogenous natural characteristic variables as instruments. It must be clarified that the IV variables were not related to the individual adoption probability of the focal farmer because these two variables were considered exogenous natural characteristics and did not significantly affect the adoption behavior of individual farmers. Second, they were related to the mean adoption behavior of the endogenous neighborhood farming group.

4. Empirical Results and Discussion

4.1. Baseline Results of the Neighborhood Effect on Farmers' Adoption Behavior

In this study, we began by identifying the neighborhood effect in farmers' rice–crayfish integrated system adoption behavior. The empirical results are shown in Table 2, which reports the probit model, fixed effect (FE), and instrumental variable (IV) estimates in Column 1, Column 3, and Column 5, respectively. To compare the coefficients, all results are reported as the marginal effect of the variables in all tables, and all specifications control the impact of household characteristics, neighboring farmers' characteristics, and village characteristics.

First, in Models 1 and 2, it can be seen that the coefficients on the neighborhood effect are both positive and significant at the 1% level, as expected. The size and significance of the coefficients do not change much (i.e., from 0.426 to 0.379), which indicates that farmers' probability of adoption increases by 0.379 percentage points for each percentage point increase in the neighbors' adoption rate. The results of Models 1 and 2 preliminarily confirm that the average integrated system adoption behavior within neighboring groups have a significantly positive influence on farmers' adoption behavior. Thus, the neighborhood effect exists in farmers' rice–crayfish integrated systems adoption.

Our focused specification is Model 3 (i.e., the IV method). As Manski [28] points out, individuals and their reference group can affect each other simultaneously, which can cause an endogeneity problem. We applied the instrumental variable method to solve this problem. For instruments, we consider whether the village is diverse in surnames and the proportion of paddy field area to cultivated land. The maximum likelihood estimation (MLE) is used to acquire the marginal effect of the IV probit model. The results are shown in Model 3 in Table 2.

Table 2. Neighborhood effect in farmers' adoption behavior.

Panel A						
Variables	Model 1: Probit		Model 2: FE		Model 3: IV Probit	
	Coef.	P	Coef.	P	Coef.	P
Neighborhood adoption behavior (NE)	0.426 ***	(0.034)	0.379 ***	(0.042)	0.367 ***	(0.124)
Age	−0.003 ***	(0.001)	−0.003 ***	(0.001)	−0.003 **	(0.001)
Educ	−0.005 *	(0.003)	−0.005 *	(0.003)	−0.005 *	(0.003)
Risk preference	0.020	(0.013)	0.020	(0.013)	0.020	(0.013)
Job status	−0.050 ***	(0.019)	−0.049 ***	(0.019)	−0.050 **	(0.020)
Perception on economic benefits	0.043 **	(0.019)	0.039 **	(0.019)	0.037 *	(0.020)
Perception on population	0.030 ***	(0.010)	0.027 ***	(0.010)	0.027 **	(0.012)
Information access	0.075 ***	(0.011)	0.077 ***	(0.011)	0.077 ***	(0.015)
Extension training attendance	−0.011	(0.009)	−0.012	(0.009)	−0.012	(0.010)
Scale of operations	−0.000	(0.000)	−0.000	(0.000)	−0.000	(0.000)
Agricultural labors	−0.009	(0.013)	−0.010	(0.013)	−0.010	(0.014)
Investment proportion	−0.002 ***	(0.001)	−0.002 ***	(0.001)	−0.002 **	(0.001)
Cooperation membership status	0.076 ***	(0.029)	0.072 **	(0.029)	0.072 ***	(0.027)
Proportion of agricultural income	−0.084 **	(0.037)	−0.089 **	(0.037)	−0.089 **	(0.042)
Plots distance	−0.008 **	(0.003)	−0.007 **	(0.003)	−0.008	(0.005)
g_age	0.003	(0.003)	0.001	(0.003)	0.001	(0.006)
g_educ	0.005	(0.008)	0.003	(0.009)	0.003	(0.009)
g_Job status	0.063	(0.053)	0.051	(0.053)	0.047	(0.062)
g_ corperation Membership status	−0.103 *	(0.053)	−0.097 *	(0.053)	−0.096	(0.065)
Agents	0.004 **	(0.001)	0.004 ***	(0.002)	0.004	(0.003)
Effective_irrigated_area	−0.000	(0.001)	−0.000	(0.001)	0.000	(0.001)
Mechanical_plough_road	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Hubei			0.056 **	(0.027)	0.052	(0.044)
Anhui			0.002	(0.026)	−0.006	(0.027)
Panel B: First-stage estimation results						
Village diversity in surnames					−0.011 ***	(0.001)
Proportion of paddy field area					0.027 ***	(0.004)
First-stage F value—Weak identification test					61.23	
DWH *p*-Value—Endogeneity test					0.090	
Amemiya-Lee-Newey minimum chi-sq statistic *p*-Value—Over-identification test					0.632	

***, **, * denotes $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. The 'Coef.' presented in Panel A is the marginal effects (dy/dx) of the variables, taking Hunan as the reference group.

Column 5 in Table 2 presents the IV probit estimates. The results suggest that as neighboring groups' adoption improves by one percentage point, and farmers' likelihood of rice–crayfish integrated systems adoption increases by 0.367 percentage points. Compared to Models 1 and 2, the coefficient on neighborhood effect has a noticeable decrease. This result also proved that the probit and FE models both overestimate the neighborhood effect. Taken together, this IV probit estimation supports the hypothesis that changes in neighbors' adoption behaviors will in turn affect the focal farmer's adoption behavior. One possible explanation for this finding is that focal farmers presume that their neighbors possess superior information. It is also possible that certain farmers are afraid to become "special" under the cultural background of the "Doctrine of the Mean" in China, so they tend to behave like their neighbors. This finding is in accordance with those of Di Falco and Doku [35] and Tran-Nam and Tiet [36].

The first-stage estimation results in Panel B indicate that the first IV ("Village diversity in surnames") negatively affects neighbors' adoption behavior, and "The proportion of paddy field area to cultivated land in the village" positively affects it. The degree of communication and trust between the farming households in mixed villages is relatively low compared to that in non-mixed villages, and the mutual influence between the farmers is relatively small, which may decrease the adoption effect. Rice–crayfish integrated systems are suitable for production in flat and water-rich fields, and good natural conditions may increase farmers' output and revenue. Therefore, the higher the proportion of paddy field area in the village, the higher the possibility that farmers in the village will adopt integrated systems.

In addition, we empirically examined the validity of the instrumental variables using a series of tests. To exclude the assumption of weak instrumental variables, we used the two-step method (2SLS) to report the first-stage estimates. As shown in Panel B in Table 2, the F-statistic is 61.23 with a p-value of less than 1% (0.000), which implies that the weak-instrument issue should not be a concern in our estimates. The Amemiya–Lee–Newey minimum p-value of the over-identification test is 0.632, which is higher than 0.1. This result indicates that the joint null hypothesis should not be rejected, and the over-identification restriction is satisfied. Additionally, the p-value of the Durbin-Wu-Hausman test is 0.090, which rejects the null hypothesis. This result proves that variable of the neighborhood effect (*NE*) is endogenous, which implies the existence of the endogeneity problem. Thus, the chosen variables are valid as the instrumentals for the neighborhood effect.

Moreover, many control variables have a significant effect on farmers' adoption behavior (e.g., 'information access' is an indicator to measure a farmer's openness). Farmers who have more information access are more likely to obtain pro-adoption information and be open-minded to produce market-oriented products. This conclusion has been suggested in previous studies, which find that accesses to extension services and peers predict technology adoption [50,51]. The "perception of economic benefits" and "perception of population" items reflect farmers' perception and judgement of rice–crayfish integrated systems, both of which result in a higher probability of adoption behavior. Investment proportion indicates the farmer's adoption capacity; the higher the proportion of their own capital investment to the whole agricultural investment, the less likely they are to adopt. A possible reason for this finding is that their self-owned funds are relatively sufficient, thus indicating that their economic situation is good. This proves that the original allocation efficiency of farmers' funds, land, and labor is high. Therefore, farmers are unwilling to adopt time-consuming and laborious practices to increase their household income. Moreover, there is a positive correlation relation between cooperation membership and agents, as the cooperation may disseminate more technology information and supply related inputs to encourage adoption. Agents can relieve farmers' concerns about product distribution after adoption. This result has important implications that related agricultural administrative departments and extension agents should emphasize to expand the channels of rice–crayfish integrated system knowledge dissemination.

4.2. Robustness Checks

In this section, we performed several robustness tests to further validate the stability of the results. The results are presented in Table 3. These robustness checks have confirmed the presence of the neighborhood effect on farmers' adoption behavior.

In Column 1, we deleted farmer samples with fewer than five neighbors to eliminate the issues that farmers interact with alternative social groups or have less opportunity to interact with neighboring groups; that is, farmers with fewer than five neighbors may choose other groups to acquire agricultural information or are even unlikely to get a chance to form a community with others. After excluding the samples, the coefficient on key explanatory variable 'neighborhood effect' increased (from 0.379 to 0.383) and remained significantly positive.

Another concern was that we took the average adoption rate within neighboring groups in a village as the proxy variable to define the 'neighborhood effect'. Considering rice–crayfish integrated systems are capital-intensive, farmers' adoption behavior may be affected by neighbors having the same levels of income, instead of by the mean within neighboring group [49]. Thus, we eliminated the sample farmers in the top 30% of high-income earners in the village. The result in Column 2 reveals that the neighborhood effect was still significant.

Table 3. Robustness checks of the neighborhood effect on farmers' adoption behavior.

	Robustness Checks 1	Robustness Checks 2	Robustness Checks 4	Robustness Checks 5
	coef. (*p*-Value)	coef. (*p*-Value)	coef. (*p*-Value)	coef. (*p*-Value)
Neighborhood effect	0.383 *** (0.122)	0.413 *** (0.128)	0.803 *** (0.148)	0.372 *** (0.100)
Instrumental variables	YES	YES	YES	YES
Household characteristics	Controlled	Controlled	Controlled	Controlled
Neighborhood characteristics	Controlled	Controlled	Controlled	Controlled
Village characteristics	Controlled	Controlled	Controlled	Controlled
Provincial dummies	Controlled	Controlled	Controlled	Controlled
Observations	930	727	980	980

*** denotes $p < 0.01$.

Then, we modified the estimation model. In Column 3 of Table 3, we show the results of the ordinary least squares (OLS) estimation. The neighborhood effect remained significantly positive, which further validated the robustness of our findings.

As a final check, we followed other studies [52] in introducing external group information, which is independent from neighborhood farming groups, to construct IV variables. Then, we selected the mean adoption behavior of neighboring farmers' relatives and friends as IV variables (The validity of the instrumental variable is verified). The average number of adoptions within relatives and friends of neighboring farmers will have an impact on neighboring farmers' adoption behavior, but it will not affect focal farmers, which meets the requirements of instrumental variables. Furthermore, the neighbors' relatives and friends do not live in the same village, which further suppresses the association effect. The estimations in Column 5 of Table 3 demonstrate that the neighborhood effect is significant and thus the results are confirmed.

5. Conclusions

Rice–crayfish integrated systems create both economic and ecological benefits. To study how this practice experienced explosive growth in China is significant for promoting the development of ecological agricultural practices in general. Farmers are subject to information inadequacies information frictions; thus, they are susceptible to their neighbors' behavior via social interaction. In this paper, we identify the role of the neighborhood effect on farmers' adoption behavior using 980 rural households in the middle reaches of the Yangtze River in China. To solve the potential identification problem, this paper adopts a set of empirical strategies. To control the self-selection problem, we use rural household survey data to define neighboring groups that are both spatially and socially connected. We control a series of neighboring farmers' characteristics and village characteristics to eliminate the contextual and correlation effects. We apply the instrumental variables (IV) method to address the simultaneity problem. The empirical results reveal that a one-unit increase in neighbors' adoption behavior increases the adoption probability of individual farmers by 0.367 units, which provides evidence of the significance of the neighborhood effect in farmers' rice–crayfish integrated system adoption decisions. The four robustness tests also confirm the presence of the neighborhood effect in farmers' adoption behavior.

Based on the above findings, this paper improves the understanding of farmers' adoption in ecological agricultural practices in rural China. When the agricultural administrative institutions or extension agents attempt to develop relevant policies or improve farmers' adoption behavior, they should not be confined to an economic perspective. The networking or social interaction between farmers should be fully exploited. Therefore, neighborhood effect can be seen as an effective approach to complement formal extension systems and promote the development of China's ecological agriculture.

Finally, we reflect on the limitations of this paper. First, although this paper has addressed several challenges associated with our measurement of the neighborhood effect, we did not conduct a further investigation into effects such as the snowballing or social multiplier effects [13] given the limitations of cross-sectional data used in our study. Therefore, future studies may target the social multiplier effect using longitudinal data. Second, we have confirmed that the neighborhood effect matters in farmers' adoption behavior, but we did not explore the mechanism of the neighborhood effect on farmers' adoption behavior. It is highly suggested that future studies analyze how neighbors influence farmers' adoption behaviors. Third, the adoption of farming practices is a process, and we only used a binary variable to measure adoption, which cannot reflect farmers' dynamic adoption behaviors. Future studies may, therefore, extend this work by utilizing panel data.

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References

1. Zhang, J.; Hu, L.; Ren, W.; Guo, L.; Tang, J.; Shu, M.; Chen, X. Rice-soft shell turtle coculture effects on yield and its environment. *Agric. Ecosyst. Environ.* **2016**, *224*, 116–122. [CrossRef]
2. Bashir, M.A.; Wang, H.; Sun, W.; Zhai, L.; Zhang, X.; Wang, N.; Rehim, A.; Liu, H. The implementation of rice-crab co-culture system to ensure cleaner rice and farm production. *J. Clean. Prod.* **2021**, *316*, 128284. [CrossRef]
3. Yuan, P.; Wang, J.; Chen, S.; Guo, Y.; Cao, C. Certified rice-crayfish as an alternative farming modality in waterlogged land in the Jianghan Plain region of China. *Agron. J.* **2021**, *113*, 4568–4580. [CrossRef]
4. Ministry of Agriculture and Rural Affairs of P.R. China. Development of Rice and Fishery Comprehensive Breeding Industry. General Guidelines. 2022. Available online: http://www.gov.cn/zhengce/zhengceku/2022-11/01/content_5723093.htm (accessed on 15 November 2022).
5. Chen, Y.; Yu, P.; Chen, Y.; Chen, Z. Spatiotemporal dynamics of rice-crayfish field in Mid-China and its socioeconomic benefits on rural revitalisation. *Appl. Geogr.* **2022**, *139*, 102636. [CrossRef]
6. China Fisheries Association. Crayfish Industry Development Report in China. 2022. Available online: http://www.china-cfa.org/xwzx/xydt/2022/0531/732.html (accessed on 15 June 2022).
7. Bashir, M.A.; Liu, J.; Geng, Y.; Wang, H.; Pan, J.; Zhang, D.; Rehim, A.; Aon, M.; Liu, H. Co-culture of rice and aquatic animals: An integrated system to achieve production and environmental sustainability. *J. Clean. Prod.* **2020**, *249*, 119310. [CrossRef]
8. Bian, Y. Bringing strong ties back in: Indirect connection, bridges, and job search in China. *Am. Sociol. Rev.* **1997**, *62*, 266–285. [CrossRef]
9. Eun, C.S.; Wang, L.; Xiao, S.C. Culture and R2. *J. Financ. Econ.* **2015**, *115*, 283–303. [CrossRef]
10. Dessart, F.; Barreiro-Hurlé, J.; Van Bavel, R. Behavioural factors affecting the adoption of sustainable farming practices: A policy-oriented review. *Eur. Rev. Agric. Econ.* **2019**, *46*, 417–471. [CrossRef]

11. Sampson, G.S.; Perry, E.D. Peer effects in the diffusion of water-saving agricultural technologies. *Agric. Econ.* **2019**, *50*, 693–706. [CrossRef]
12. Müller, S.; Rode, J. The adoption of photovoltaic systems in Wiesbaden, Germany. *Econ. Innov. New. Technol.* **2013**, *22*, 519–535. [CrossRef]
13. Atefi, Y.; Pourmasoudi, M. Measuring peer effects in sales research: A review of challenges and remedies. *J. Pers. Sell. Sales Manag.* **2019**, *39*, 264–274. [CrossRef]
14. Qing, C.; He, J.; Guo, S.; Zhou, W.; Deng, X.; Xu, D. Peer effects on the adoption of biogas in rural households of Sichuan Province, China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 61488–61501. [CrossRef]
15. Bollinger, B.; Burkhardt, J.; Gillingham, K. *Peer Effects in Water Conservation: Evidence from Consumer Migration*; National Bureau of Economic Research: Cambridge, MA, USA, 2018.
16. Fei, H.-T.; Hamilton, G.G.; Zheng, W. *From the Soil, the Foundations of Chinese Society: A Translation of Fei Xiaotong's Xiangtu Zhongguo, with an Introduction and Epilogue*; University of California Press: Berkeley, CA, USA, 1992.
17. Cremades, R.; Wang, J.; Morris, J. Policies, economic incentives and the adoption of modern irrigation technology in China. *Earth Syst. Dyn.* **2015**, *6*, 399–410. [CrossRef]
18. Cai, J.; Chen, Y.; Hu, R.; Wu, M.; Shen, Z. Discovering the impact of farmer field schools on the adoption of environmental-friendly technology. *Technol. Forecast. Soc. Change* **2022**, *182*, 121782. [CrossRef]
19. Ghimire, R.; Huang, W.-C. Household wealth and adoption of improved maize varieties in Nepal: A double-hurdle approach. *Food Secur.* **2015**, *7*, 1321–1335. [CrossRef]
20. Skevas, T.; Skevas, I.; Kalaitzandonakes, N. The role of peer effects on farmers' decision to adopt unmanned aerial vehicles: Evidence from Missouri. *Appl. Econ.* **2022**, *54*, 1366–1376. [CrossRef]
21. Gao, L.; Arbuckle, J. Examining farmers' adoption of nutrient management best management practices: A social cognitive framework. *Agric. Hum. Values* **2022**, *39*, 535–553. [CrossRef]
22. Tensi, A.F.; Ang, F.; van der Fels-Klerx, H.J. Behavioural drivers and barriers for adopting microbial applications in arable farms: Evidence from the Netherlands and Germany. *Technol. Forecast. Soc. Change* **2022**, *182*, 121825. [CrossRef]
23. Sarma, P. Farmer behavior towards pesticide use for reduction production risk: A Theory of Planned Behavior. *Cleaner Circ. Bioecon.* **2022**, *1*, 100002. [CrossRef]
24. Weersink, A.; Fulton, M. Limits to profit maximization as a guide to behavior change. *Appl. Econ. Perspect. Policy* **2020**, *42*, 67–79. [CrossRef]
25. DeVincentis, A.J.; Solis, S.S.; Bruno, E.M.; Leavitt, A.; Gomes, A.; Rice, S.; Zaccaria, D. Using cost-benefit analysis to understand adoption of winter cover cropping in California's specialty crop systems. *J. Environ. Manag.* **2020**, *261*, 110205. [CrossRef]
26. Thaler, R.H.; Sunstein, C.R. *Nudge: Improving Decisions about Health, Wealth, and Happiness*; Penguin: London, UK, 2009.
27. Liu, D.; Qi, S.; Xu, T. Visual observation or oral communication? The effect of social learning on solar photovoltaic adoption intention in rural China. *Energy Res. Soc. Sci.* **2023**, *97*, 102950.
28. Manski, C.F. Identification of endogenous social effects: The reflection problem. *Rev. Econ. Stud.* **1993**, *60*, 531–542. [CrossRef]
29. Angrist, J.D. The perils of peer effects. *Labour. Econ.* **2014**, *30*, 98–108. [CrossRef]
30. Zhang, A.; Ni, P.; Ling, C. Peer effects in rural housing demand: Evidence from China. *China. Econ. Rev.* **2022**, *73*, 101787. [CrossRef]
31. Chen, Y.; Jin, G.Z.; Yue, Y. *Peer Migration in China*; National Bureau of Economic Research Working Paper No. 15671; National Bureau of Economic Research: Cambridge, MA, USA, 2010.
32. Han, K.; Tan, J. How neighbours influence commercial health insurance purchase: Evidence from 2451 rural households in west China. *J. Dev. Effect.* **2021**, *13*, 329–341. [CrossRef]
33. Ma, J.; Zhou, W.; Guo, S.; Deng, X.; Song, J.; Xu, D. The influence of peer effects on farmers' response to climate change: Evidence from Sichuan Province, China. *Clim. Change* **2022**, *175*, 9. [CrossRef]
34. Xiong, H.; Payne, D.; Kinsella, S. Identifying mechanisms underlying peer effects on multiplex networks. *J. Artif. Soc. Simul.* **2018**, *21*, 6.
35. Di Falco, S.; Doku, A.; Mahajan, A. Peer effects and the choice of adaptation strategies. *Agric. Econ.* **2020**, *51*, 17–30. [CrossRef]
36. Tran-Nam, Q.; Tiet, T. The role of peer influence and norms in organic farming adoption: Accounting for farmers' heterogeneity. *J. Environ. Manag.* **2022**, *320*, 115909. [CrossRef] [PubMed]
37. Crudeli, L.; Mancinelli, S.; Mazzanti, M.; Pitoro, R. Beyond individualistic behaviour: Social norms and innovation adoption in rural mozambique. *World Dev.* **2022**, *157*, 105928. [CrossRef]
38. Kolady, D.; Zhang, W.; Wang, T.; Ulrich-Schad, J. Spatially mediated peer effects in the adoption of conservation agriculture practices. *J. Agric. Appl. Econ.* **2021**, *53*, 1–20. [CrossRef]
39. Gao, S.; Grebitus, C.; Schmitz, T. Effects of risk preferences and social networks on adoption of genomics by Chinese hog farmers. *J. Rural. Stud.* **2022**, *94*, 111–127. [CrossRef]
40. Ward, P.S.; Pede, V.O. Capturing social network effects in technology adoption: The spatial diffusion of hybrid rice in Bangladesh. *Aust. J. Agric. Resour. Econ.* **2015**, *59*, 225–241. [CrossRef]
41. Manski, C.F. Economic analysis of social interactions. *J. Econ. Perspect.* **2000**, *14*, 115–136.
42. Krishnan, P.; Patnam, M. Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption? *Am. J. Agric. Econ.* **2013**, *96*, 308–327. [CrossRef]

43. Loh, C.-P.A.; Li, Q. Peer effects in adolescent bodyweight: Evidence from rural China. *Soc. Sci. Med.* **2013**, *86*, 35–44. [CrossRef] [PubMed]
44. Liu, H.; Sun, Q.; Zhao, Z. Social learning and health insurance enrollment: Evidence from China's New Cooperative Medical Scheme. *J. Econ. Behav. Organ.* **2014**, *97*, 84–102. [CrossRef]
45. Li, Q.; Zang, W.; An, L. Peer effects and school dropout in rural China. *China Econ. Rev.* **2013**, *27*, 238–248. [CrossRef]
46. Bertrand, M.; Luttmer, E.F.P.; Mullainathan, S. Network Effects and Welfare Cultures*. *Q. J. Econ.* **2000**, *115*, 1019–1055. [CrossRef]
47. Chen, Z.; Jiang, S.; Lu, M.; Sato, H. How do Heterogeneous Social Interactions affect the Peer Effect in Rural-Urban Migration?: Empirical Evidence from China. *Econ. Lett.* **2008**, *80*, 123–129. [CrossRef]
48. Gaviria, A.; Raphael, S. School-Based Peer Effects and Juvenile Behavior. *Rev. Econ. Stat.* **2001**, *83*, 257–268. [CrossRef]
49. Ling, C.; Zhang, A.; Zhen, X. Peer Effects in Consumption Among Chinese Rural Households. *Emerg. Mark. Financ. Trade* **2018**, *54*, 2333–2347. [CrossRef]
50. Genius, M.; Koundouri, P.; Nauges, C.; Tzouvelekas, V. Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *Am. J. Agric. Econ.* **2014**, *96*, 328–344. [CrossRef]
51. Thinda, K.; Ogundeji, A.; Belle, J.; Ojo, T. Understanding the adoption of climate change adaptation strategies among smallholder farmers: Evidence from land reform beneficiaries in South Africa. *Land Use Policy* **2020**, *99*, 104858. [CrossRef]
52. Bramoullé, Y.; Djebbari, H.; Fortin, B. Identification of peer effects through social networks. *J. Econom.* **2009**, *150*, 41–55. [CrossRef]

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Improvement Pathways for Urban Land Use Efficiency in the Beijing-Tianjin-Hebei Urban Agglomeration at the County Level: A Context-Dependent DEA Based on the Closest Target

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Abstract: One of the most effective ways to achieve sustainable land use and the regional coordinated development of urban agglomerations lies in improving the urban land use efficiency (ULUE) of both large, medium, and small cities and small towns. However, in previous studies, less attention has been paid to pathways for potential improvement, especially at the county level. The main purpose of this paper is to examine potential improvement paths for the ULUE at the county level in urban agglomerations, while attempting to provide more practical targets for improvement and formulate more reasonable improvement steps for inefficient counties. Therefore, a total of 197 counties in the Beijing-Tianjin-Hebei urban agglomeration (BTHUA) in 2018 were taken as examples to build a context-dependent data envelopment analysis (DEA) model based on the closest target. In addition, by utilizing methods such as the significant difference test and system clustering analysis, the shortest path and steps to achieve efficiency were identified for inefficient counties, and the characteristics of improvement paths at different levels were summarized. Furthermore, improvement pathways were compared for two dimensions: administrative type and region. The results showed that the causes of polarization for ULUE at different levels were mainly reflected in more complex targets to be improved in the middle- and low-level counties than at high levels. Improving environmental and social benefits was essential to achieving efficiency in most inefficient counties, especially at the middle and low levels. The improvement paths for inefficient counties between different administrative types, as well as the prefecture-level cities, were heterogeneous. The results of this study can provide a policy and planning basis for improving urban land use. This study is of practical significance in accelerating the development of urbanization and the promotion of regional coordination and sustainable development.

Keywords: urban land use efficiency; Beijing-Tianjin-Hebei urban agglomeration; improvement pathways; county level

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1. Introduction

Cities are centers of economic activity, innovation, and culture in countries and regions [1]. Large-scale urbanization has led to the ongoing expansion of urban construction while also accelerating the development of urban economies. Nevertheless, it has also caused a series of problems, such as the extensive utilization of urban land [2], reductions in cultivated land [3], intensified energy consumption [4], environmental pollution [5], traffic congestion [6], etc. These have threatened the sustainable development of countries and regions, and it has been proven that the improvement of urban land use efficiency (ULUE) is not only a precondition for promoting urban sustainable development but also a way to balance the development of urban economies and sustainable land use [7]. Hence, it is necessary to change the mode from the extensive one to an intensive one during the process of urban land use. Moreover, significant attention should be paid to the integration of the economic, social, and ecological benefits of land use in order to promote sustainable development for cities [8].

Urban agglomerations are the most dynamic and high-potential regions in China and they play an irreplaceable role in promoting urbanization [9]. In recent years, studies on the ULUE of urban agglomerations have become increasingly popular, including studies on single urban agglomerations such as Beijing-Tianjin-Hebei [10] and the Yangtze River Delta [11], as well as comparative studies of multiple other urban agglomerations [12]. Scholars have mainly emphasized two categories of problems in research on ULUE. The first is referred to as "efficiency evaluation". Establishing the evaluation index system and determining evaluation methods are the preconditions for evaluating ULUE. With advances in the study of the various conceptions of ULUE, evaluation indexes have evolved from a single index focusing on economic output to a comprehensive index system considering economic, social, and ecological benefits [13]. In the comprehensive index system, the role of environmental factors in ULUE changed from a constraint condition on the quality of economic development to an essential component of comprehensive benefits [14,15]. In terms of evaluation methods, the SFA method has the advantage of having a more explicit economic meaning [16], while data envelopment analysis (DEA) is more suitable for evaluating comprehensive problems with multiple targets [17]. Therefore, the DEA method is used for ULUE by most scholars [18]. The other category is referred to as the "mechanism of efficiency". Among these approaches, analyzing influencing factors for ULUE helps to understand the driving mechanism behind urban land use [19]. The mechanism research provides guidance for the formulation of macro-level policies. Various influencing factors for ULUE have been addressed extensively in the previous literature [20–22].

However, the endogenous differences, meaning equal efficiency scores but significantly different redundant structures in decision making units (DMU), were ignored in the previous literature on mechanism studies. The DEA methods can not only quantify the performance of DMUs, but can also provide improvement benchmarks for inefficient DMUs [23]. Through projection analysis—in other words, comparing the gap between actual and target inputs and outputs—the causes of inefficiency can be identified from a micro-level perspective, and a path to improving efficiency can be determined. The study of the improvement paths for the ULUE is an extension and complement of the above two categories of issues. On the one hand, the analysis of improvement paths further identifies the input and output redundancy of inefficient DMUs based on the efficiency evaluation. On the other hand, compared with the indirect mechanistic analysis of the influencing factors, the analysis of the improvement paths is a direct causal analysis based on efficiency decomposition. However, there are few studies related to efficiency improvement in research on ULUE. Moreover, only a few scholars have conducted empirical analyses at the city level. Fu et al. utilized the slack-based measures (SBM) to evaluate the ULUE of 13 cities in Jiangsu Province and compared the redundancy of undesirable outputs among cities [24]. Han et al. measured the input redundancy of 287 cities in China by constructing an SBM model and revealed the distribution characteristics and regional differences of different redundant factors [25]. Two research perspectives were shown for improvement path analysis in ULUE. One was to analyze which resources are misallocated or wasted from a reasonableness perspective. The other was to identify improvement priorities based on potential targets in economic, social, and environmental benefits from a development perspective, compared to the extent to which different aspects contribute to improving the overall efficiency.

The previous study on improvement paths of ULUE mainly had two deficiencies. One was that the previous ones were too theoretical. More specifically, the practicality of targets for improvement and the actual implementation ability of the research objects was often neglected. The other deficiency was that there were few empirical studies, and the research setting scale was limited. Firstly, from the improvement target perspective, selecting targets that are more in line with experience is a precondition for determining potential pathways for improvement. The improvement targets for inefficient DMUs depend on the distance function of different DEA models [26]. In research on ULUE, DEA models such as Charnes, Cooper, and Rhodes (CCR), slack-based measures (SBM), and their extended models were often used by scholars [27,28]. However, the potential improvements of inefficient DMUs might be overestimated by the traditional DEA model based on the "furthest" targets; meanwhile, the improvement targets obtained in this manner may not be practical targets for inefficient DMUs [29]. Some scholars have pointed out these problems and proposed using DEA models based on the closest target. Minimum distance to a strong efficient frontier (MinDS) is a non-radial DEA model based on the closest target, proposed by Aparicio [30]. The projected point on the frontier obtained by the MinDS model is the nearest efficient projection, meaning achieving efficiency with less effort, to the inefficient DMUs. At present, the closest-target method has been applied to many research fields, such as carbon emission efficiency [31], port efficiency [26], and financial efficiency [32], but, so far, not ULUE.

From the improvement steps perspective, there are certain limitations in analyzing the improvement paths for ULUE utilizing single-frontier DEA models. Previous studies have pointed out that the ULUE of urban agglomerations in China is generally low, and there is an obvious polarization phenomenon [8,33]. In reality, it is difficult to significantly reduce the input or increase the output in the short term. Therefore, the empirical results obtained by using traditional DEA models lack practical significance. Despite the fact that the closest-target DEA model can identify the nearest improvement targets, it may still be difficult to achieve efficiency in one step for inefficient DMUs at short-term time scales. The context-dependent DEA model was proposed by Seiford and Zhu [34]. This model identifies all evaluated DMUs at different layers, which can be seen as multiple frontiers. The efficient projection of inefficient DMUs on the top frontier can be obtained as the ultimate targets, which can be seen as intermediate targets on other frontiers [35]. Thus, the context-dependent DEA model is based on the closest target (context-dependent MinDS, CD-MinDS), which is conducive to exploring a more reasonable and feasible improvement pathway for inefficient DMUs.

In addition, the development strategy of new-type urbanization has been advanced in China since 2012, which pursues the coordinated development of large, medium, and small cities and small towns based on the context of urban agglomerations. However, most existing ULUE studies have been carried out at the city level, mainly focusing on the performance of urban areas while neglecting the evaluation of surrounding county towns. County towns are essential parts of China's urban system and necessary spaces for promoting industrialization and urbanization [36]. Therefore, it is necessary to take county towns into account in the ULUE study of urban agglomerations. In addition, urban areas were generally evaluated as a whole in research carried out at the city level. In recent years, however, "city–county mergers" have become the primary way for the government to advance urbanization [37]. There are many differences between inner cities and suburbs regarding functional orientation, development levels, and so on. Hence, the ULUE study of urban agglomerations at the county level is helpful in understanding the features and differences of various administrative units, such as inner cities, suburbs, county-level cities, and county towns. From an epistemological perspective, county-level ULUE studies can help to understand more comprehensively and accurately the characteristics and differences in the relative efficiency of different territorial units within urban agglomerations. From the perspective of the ULUE mechanism study, taking county units as research objects can help to further reveal the differences in the causes of different administrative types of inefficient counties in urban agglomerations. The problems of the extensive use of urban land and unbalanced regional development have been still faced by different regions in the Beijing-Tianjin-Hebei urban agglomeration (BTHUA), which is the epitome of China's urban agglomerations at this point [36]. Therefore, as a research context, the BTHUA is very typical.

In summary, this paper selected 197 counties in the BTHUA as a case study. It utilized the context-dependent DEA based on the closest target to identify the improvement paths for the ULUE. This paper intended to answer the following research questions: (1) Could using context-dependent DEA based on the closest target provide a more practical and reasonable improvement path for inefficient counties than traditional DEA methods? (2) What were the main characteristics of inefficient counties with different levels of efficiency in terms of improvement paths and the impact of economic, social, and environmental benefits on improving efficiency? (3) Were there differences in the improvement paths for inefficient counties by administrative types and regions, and how can we improve the efficiency of different inefficient counties? This paper, by supplementing the existing research methods on urban agglomeration ULUE, adds to the body of empirical research conducted at the county level, thereby assisting China and other developing countries in promoting sustainable urbanization and regionally coordinated development.

2. Materials and Methods

2.1. Study Area

The BTHUA, located in the northern part of the North China Plain (36°03′–42°40′ N, 113°27′–119°50′ E), includes two municipalities, Beijing and Tianjin, as well as the other cities in Hebei Province. According to the China Statistical Yearbook, in 2018, the urban population of the BTHUA reached 74.24 million, accounting for 5.32% of the country's total population. The gross domestic product (GDP) was 8513.989 billion yuan, making up 9.47% of the national GDP. The urban construction land area was around 3 million hectares, accounting for 7.63% of the total construction land area of the country. China currently has four primary administrative levels: national, provincial, prefecture-level city, and county. The county-level administrative districts, including counties, districts, and county-level cities, are included in the prefecture-level city's administrative area. In this paper, the districts are further divided into inner cities and suburbs. A total of 197 counties in the BTHUA were selected as research subjects, including 36 inner cities, 43 suburbs, 21 county-level cities, and 97 county towns. There are only two types of counties in Beijing and Tianjin, with 6 inner cities and 10 suburbs, respectively. Hebei Province has a total of 165 counties, including 24 inner cities, 23 suburbs, 21 county-level cities, and 97 county towns.

2.2. Index System and Data Sources

The index system proposed in this paper aims to reflect the relation between input and output in urban economic and social activities, as well as the role of urban land as a geographical space. At present, China's urbanization has evolved from a period of rapid growth to high-quality development. Therefore, significant attention must be paid to the coordinated development of economic, social, and environmental benefits for urban land use. In particular, not only the level of economic output but also the social welfare and environmental quality should be considered in the examination of efficiency [38]. Therefore, as shown in Table 1, the labor input was expressed as the number of employees per land area and the capital input was expressed as the amount of the fixed asset investment per land area in this paper. In terms of the output of economic benefits, the development level of urban productivity was reflected by the added value of the secondary and tertiary industries per land area. In terms of social benefits, the living and consumption level of residents was expressed by the total retail sales of consumer goods per land area. In addition, the public service level was reflected by the density of points of interest (POI), i.e., the number of POIs per land area [39]. These include four types of data—namely, science and education cultural services, medical care services, transportation facilities and services, government agencies, and social organizations. In terms of environmental benefits, as the BTHUA is among the regions with the most serious air pollution problems in China, air quality improvement is an important goal of high-quality development in this region. In this paper, the annual average concentration of particulate matter (PM2.5) was taken as the undesirable output to reflect the level of environmental quality [40].

Table 1. Urban land use efficiency measurement indexes.

Types	Names	Details
Input index	Employees per land area	Number of employees in the secondary and tertiary industries/Construction land area
	Fixed asset investment per land area	Fixed asset investment of the whole society/Construction land area
Desirable output index	Added value of the secondary industry per land area	Added value of the secondary industry/Construction land area
	Added value of the tertiary industry per land area	Added value of the tertiary industry/Construction land area
	Per capita disposable income of urban residents	Per capita disposable income of urban residents
	Density of POI	Number of POI (medical care services, living facilities, science and education cultural services)/Construction land area
	Green coverage rate in built-up area	Greenland area/Construction land area
Undesirable output index	Concentration of PM2.5	Annual average concentration of PM2.5 concentration

Among the relevant data, data on employees, fixed asset investment, the added value of secondary and tertiary industries, the per capita disposable income of urban residents, and the BGR were derived from the 2019 Beijing Area Statistical Yearbook, Tianjin Statistical Yearbook, and the statistical yearbooks of all prefecture-level cities in Hebei Province.

2.3. Research Methods

2.3.1. DEA

To explore the influence of different improvement targets and steps on efficiency improvement, several DEA methods were employed in this paper to measure the same sample. First of all, in order to measure the influence of different improvement targets, the SBM model and MinDS model was used to calculate an efficiency score, which served as the basis for the identification of improvement targets. Second, the CD-MinDS model was used to identify the efficiency levels for inefficient counties and measure the gap between inefficient counties and improvement targets, including ultimate and intermediate targets.

SBM and its extended models are among the most widely used DEA models in ULUE research. This model, proposed by Tone et al. in 2001, measures DMU efficiency by the slack of input and output [41]. The model works as follows:

$$\min\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{q+g}\left(\sum_{r=1}^{q}\frac{s_r^+}{y_{rk}}+\sum_{h=1}^{g}\frac{s_h^-}{z_{hk}}\right)}$$
$$\text{s.t.}\begin{cases}\sum\lambda_j x_{ij}+s_i^- = x_{ik}\\ \sum\lambda_j y_{rj}+s_r^+ = y_{rk}\\ \sum\lambda_j z_{hj}+s_h^- = z_{hk}\\ \lambda_j,\ s_i^-, s_r^+, s_h^- \geq 0\end{cases} \tag{1}$$

In this model, ρ represents the efficiency value of DMU. s_r^+, s_i^- and s_h^- are the slack of the i input, the r desirable output and the h undesirable output, respectively. λ_j is the weight variable of the j unit. x_{ik}, y_{rk} and z_{hk} are the DMU_k input, desirable and undesirable output values of DMUs, respectively. However, the objective function of the SBM model is to minimize the efficiency value ρ, i.e., to maximize the redundancy of the input and output values. From the perspective of the distance function, the projection point of the DMU is the furthest point on the frontier, meaning that the input and output values for DMUs must be adjusted to the greatest extent. This is obviously contrary to the actual needs of the evaluated objects.

To this end, Aparicio et al. propose the MinDS model to improve the practicality of the SBM model [29]. The objective function of the MinDS model is to maximize the efficiency value ρ by increasing the mixed-integer linear constraint, with the effective DMUs as the reference set and confined to the same hyperplane. The model is described as follows:

$$\max\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{q+g}\left(\sum_{r=1}^{q}\frac{s_r^+}{y_{rk}}+\sum_{h=1}^{g}\frac{s_h^-}{z_{hk}}\right)}$$
$$\text{s.t.}\begin{cases} \vdots \\ -\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{q}\mu_r y_{rj} - \sum_{h=1}^{g}\tau_h z_{hj} + d_j = 0 \\ v_i, \mu_r, \tau_h \geq 1 \\ d_j \leq M b_j, \lambda_j \leq M\left(1-b_j\right), b_j \in \{0,1\}, j \in E \end{cases} \tag{2}$$

The constraint conditions of the MinDS model consist of three parts, among which the first part is the same as the constraint conditions of the SBM model. The common purpose of the second and third parts is to ensure that the reference rods lie in the same hyperplane.

In combination with the MinDS model, the context-dependent model proposed by Seiford and Zhu [34] was employed to provide staged intermediate targets for inefficient counties. The reference set $J^l = \left\{DMU_j, j = 1, \cdots, n\right\}$ was defined as the set containing all DMUs. The iterative reference set $J^{l+1} = J^l - E^l$ was defined such that $E^l = \left\{DMU_k \in J^l \middle| \rho = 1\right\}$ was the set of effective units in the reference set J^l. When $l = 1$, the model was the MinDS model, E^l constituted the global frontier, and the units in the set were effective units. When $l = 2$, the new subset J^2 was taken as the reference set and recalculated. E^2 constituted the second-level frontier. The units in the set were inefficient units whose efficiency level was lower than that of the effective units, but higher than that of other inefficient units. All DMUs were divided into different sets by circular calculation. The model is described as follows:

$$\max\rho^* = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{q+g}\left(\sum_{r=1}^{q}\frac{s_r^+}{y_{rk}}+\sum_{h=1}^{g}\frac{s_h^-}{z_{hk}}\right)}$$
$$\text{s.t.}\begin{cases} \sum_{j\in E^l}\lambda_j x_{ij} + s_i^- = x_{ik} \\ \sum_{j\in E^l}\lambda_j y_{rj} + s_r^+ = y_{rk} \\ \sum_{j\in E^l}\lambda_j z_{hj} + s_h^- = z_{hk} \\ \sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{q}\mu_r y_{rj} - \sum_{h=1}^{g}\tau_h z_{hj} + d_j = 0 \\ \lambda_j \geq 0 \\ s_i^-, s_r^+, s_h^- \geq 0 \\ d_j \leq M b_j, \lambda_j \leq M\left(1-b_j\right), b_j \in \{0,1\} \\ E^l = \left\{DMU_k \in J^l \mid \rho(l,k) = 1\right\} \\ l_0 \in \{2, \cdots, L\} \\ p \in \{1, \cdots, l_0 - 1\} \end{cases} \tag{3}$$

In this model, the reciprocal of ρ^* was the progress value of DMU_k based on E^{l_0-p}, representing the improvement degree required for DMU_k to raise the efficiency level to E^{l_0-p},. Here, $1/\rho^* > 1$, and the higher the $1/\rho^*$ value, the greater the improvement degree. When DMU_k had multiple superior frontiers, $\rho^*(p+1) < \rho^*(p)$. In addition, the improvement ratio of input and output elements (I/O elements) in DMU_k was used to characterize the statistical redundancy for each element—that is, the ratio of the slack of each element to the actual value. The improvement ratios of input, desirable output and undesirable output are as follows:

$$\frac{s_i^-}{x_{ik}}, \frac{s_r^+}{y_{rk}}, \frac{s_h^-}{z_{hk}} \quad (4)$$

2.3.2. Paired-Samples *t*-Test and One-Way ANOVA

To determine reasonable improvement targets and steps, the mean difference significance test was used to judge whether the results obtained by the DEA model were statistically different. The paired-samples *t*-test can be used to test whether there is a significant difference in the mean values of the two groups' paired sample data. As mentioned above, in terms of DEA principles, the shortest improvement paths for inefficient counties can be identified by the closest target. In other words, the MinDS model proposes more practical ways to improve efficiency for inefficient counties, enabling them to become efficient with less effort. To verify the validity of the MinDS model for the ULUE study, the MinDS model was compared with the SBM model, which was widely used to evaluate ULUE. Specifically, suppose that the efficiency scores of the SBM model are significantly lower than that of the MinDS model. In this case, it indicates that the MinDS model can identify the more practical paths for improving ULUE in inefficient counties. Furthermore, the one-way ANOVA test can be used to test for significant differences between multiple sample data. Therefore, the improvement steps of inefficient counties were determined via a one-way ANOVA test according to the improvement degrees of inefficient counties at different levels. Suppose that the improvement degree significantly differs based on the global frontier in inefficient counties at different levels. In this case, the improvement steps for inefficient counties at low levels are unreasonable, and the intermediate targets should be added to reduce the improvement degrees of each step. Finally, the overall improvement degrees of inefficient counties were compared to test whether there were significant differences between one-step and step-by-step by the paired-samples *t*-test. If the overall improvement degree of the step-by-step is less than that of the one-step, then a more practical and reasonable improvement path can be identified by the CD-MinDS model. Otherwise, the improvement path needs to be weighed between the one-step and step-by-step.

2.3.3. System Clustering Analysis

As an exploratory method, system clustering analysis can be divided into variable clustering (Mode R) and sample clustering (Mode Q). The method classifies objects with similar properties according to the degree of closeness between variables or samples. In this paper, Mode Q systematic clustering was used to identify the similarity of redundant elements among inefficient counties based on the adjusted cosine similarity, and this was used to classify the key elements for improvement at each stage.

3. Results

3.1. Efficiency of the Closest and Furthest Targets

In order to compare the influence of different improvement targets on inefficient counties, the efficiency scores based on the furthest target (the SBM model) and the closest target (the MinDS model) were measured according to Formulas (1) and (2), and the results were compared by using the paired-samples *t*-test. The most effective and ineffective counties obtained by the two models were the same, 26 and 171, respectively. As shown in Table 2, the efficiency scores based on the nearest target were significantly higher than those of the furthest target ($p < 0.01$), and there was a significant correlation between them ($p < 0.01$). This shows that the influence of different measurement benchmarks was clear when both the frontier and inefficient counties were the same in the two groups of samples. For inefficient counties, taking the projection identified by the nearest-target method as the improvement goal can achieve the same effect with relatively small improvements.

Table 2. Paired-samples *t*-test results based on efficiency scores of the SBM and MinDS models.

Samples	Mean	N	*t*-Value	Sig.	Correlation	Sig.
SBM MinDS	0.364 0.731	197	−38.009	0.001	0.822	0.001

Note: N—number of samples.

According to Formula (3), the inefficient counties were stratified to further distinguish the efficiency level among inefficient counties. As shown in Figure 1, the counties of the BTHUA were divided into seven levels. The counties located at the frontier of the first level (global frontier) were effective counties, and those located at the frontier (local frontier) of the 2nd–7th levels were inefficient counties. The efficiency level of counties at the same level was the same, and showed a decreasing trend from first to seventh. The number of counties in the 2nd–5th levels was relatively large (30–35), while that in the seventh level was relatively small (13). From the regional perspective, the counties of Beijing and Tianjin occupied most of the counties in the first level. Most of the counties in the 3rd–7th levels were in Hebei. This indicates that the efficiency levels of Beijing and Tianjin counties in the BTHUA were similar, and the efficiency performance was better. In contrast, the efficiency levels of counties in Hebei Province ranged more widely and the efficiency performance was relatively poor.

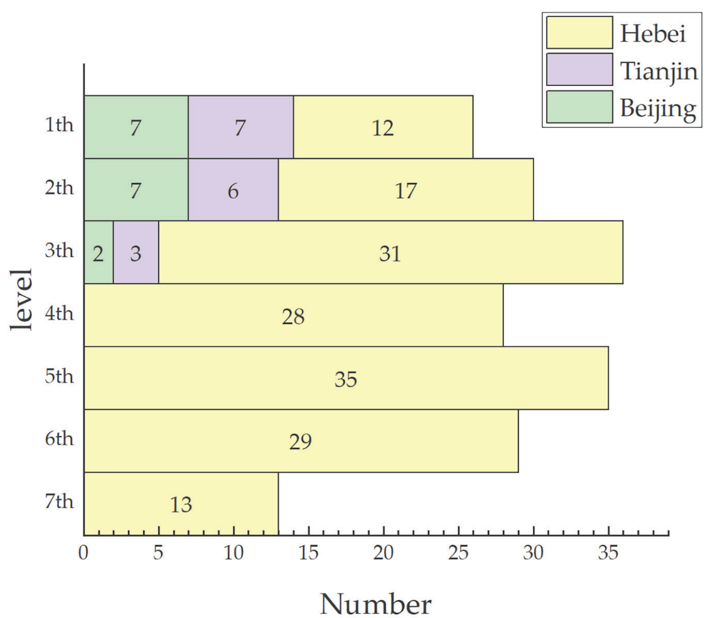

Figure 1. Number and regional distribution of nine efficiency levels in counties.

3.2. Intermediate Targets and Steps for Improvement

In order to compare the improvement degrees for inefficient counties at different levels, the progress values based on the global frontier were calculated according to Formula (3). This was done in order to characterize the improvement degrees required to reach the efficient level. The results were then compared by using ANOVA. As shown in Table 3, the Levene statistic was 1.709, with a significance level of over 0.05, meeting the requirements of ANOVA. The F statistic for the ANOVA test was 7.524, with a significance level of less than 0.05, indicating that there were significant differences in the average improvement degrees of the counties at various levels. Through multiple comparisons among different levels of counties (Figure 2), it was found that there were significant gradient differences in the improvement degrees for counties at different levels. There were significant differences among high-level (the second level), middle-level (the third and fourth levels), and low-level (the 5th–7th levels) counties, but there were no significant differences within the groups. The improvement degree was the highest in low-level counties, followed by middle-level counties and then high-level counties. This shows that the improvement process for counties at all levels was asynchronous, and it was obviously longer in middle and low-level counties. Therefore, it is necessary to further set intermediate targets and formulate progressive improvement steps.

Table 3. Homogeneity of variance and F-value test of global progress values of counties at different levels.

Test Variable	Classification	Levene Statistic	F-Value
Global progress value	2nd–7th level	1.709	7.524 ***

Note: *** show significance at the 1% level, respectively.

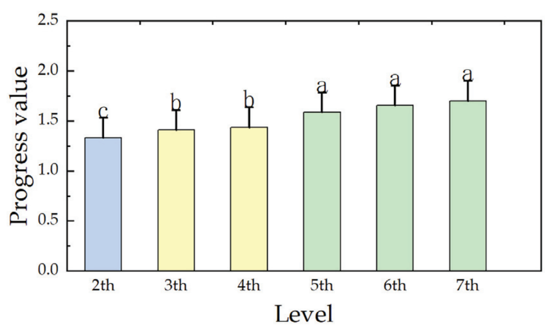

Figure 2. Comparison of global progress values of counties at different levels. Note: Different letters represent a significant difference at 5% level.

The intermediate targets are determined according to the differences in their improvement degrees. In terms of the 5th–7th levels of counties, the improvement degrees based on the global frontier were significantly greater than that of the high- and middle-level counties, with the smallest difference for the fourth level of counties. Therefore, the fourth level can be regarded as the intermediate target of the first step, and the second level can be regarded as the intermediate target of the second step, dividing the improvement process into three steps. Similarly, the frontiers for the second level are taken as the intermediate targets for counties at the 3rd–4th levels. The improvement processes for three groups of counties at high, middle and low levels have one, two and three steps, respectively. Table 4 presents the inspection results based on intermediate targets. It should be noted that the improvement degrees for the second and third steps were calculated by taking the target input and output of the previous step as the actual input and output of this step. It can be seen from the results that there was no significant difference in terms of the improvement degrees of counties at all levels during the three steps, and the average improvement degree in the three steps was relatively low. This means that the improvement process for middle- and low-level counties can be decomposed by setting intermediate targets so that the improvement degree of each step is in a more reasonable range. Therefore, it is appropriate to take the frontiers of the second and fourth levels as the intermediate targets of the middle- and low-level counties.

Table 4. Homogeneity of variance and F-value test of local progress values of counties at different levels.

Test Variable	Classification	Mean	Levene Statistic	F Value
Local progress value (1st step)	2nd–7th level	1.436	1.178	0.856
Local progress value (2nd step)	3rd–7th level	1.367	1.359	1.554
Local progress value (3rd step)	5th–7th level	1.321	1.530	1.622

To further explore the reasons that there were various improvement degrees, the redundancy (improvement ratio) of elements of input and output in inefficient counties was calculated based on Formula (4) and the redundant quantity in each county was counted. Figure 3 presents the statistical redundancy of the elements of input and output in the case of one-step and step-by-step in high-, middle- and low-level counties, as well as the proportions of different redundant quantities. On the whole, middle- and low-level counties had larger redundant quantities and greater redundancy, indicating that there are more aspects to be improved in middle- and low-level counties, with more difficulties during the improvement. The establishment of intermediate targets plays a role in screening and focusing on the improvement elements. In other words, when the local frontiers that are more similar to themselves are considered as benchmarks, there are smaller quantities and lower redundancy. Therefore, setting intermediate targets can help to recognize the main weaknesses of each stage, and improvement in these aspects may be a shorter path to advance efficiency.

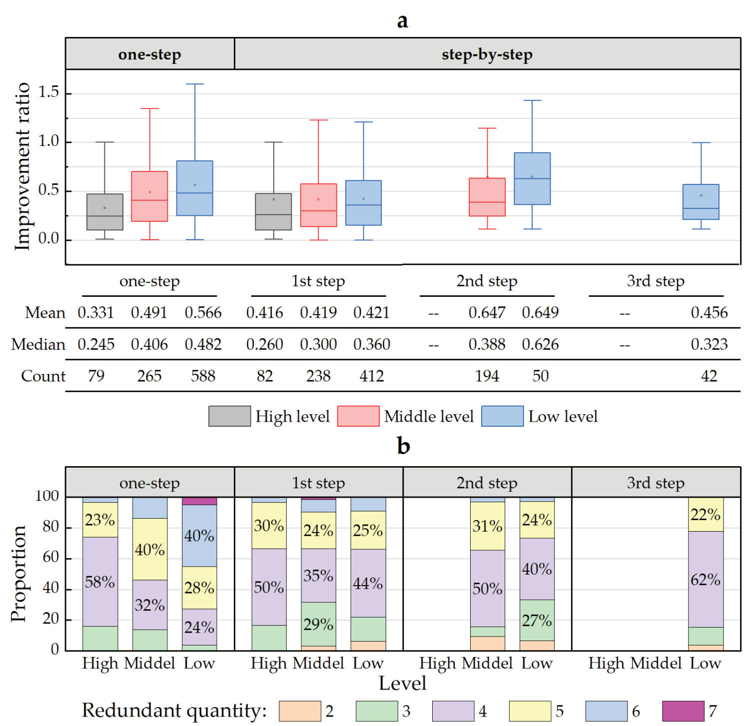

Figure 3. Differences for input and output redundancy among high-, middle- and low-level counties. (**a**): boxplot of redundancy improvement ratio for counties at each level. (**b**): proportion structure of the redundant quantities of counties at each level.

In addition, paired-samples *t*-tests were used to compare the progress values for the two groups to further explore the overall improvement degrees for both one-step and step-by-step. The slack of the elements of input and output during the step-by-step method was the sum of the slack in each stage. As shown in Table 5, there was a significant difference between the progress values for the two groups ($p < 0.01$). The progress value in terms of step-by-step was considerably lower than that of the one-step context, showing a significant correlation between the two ($p < 0.01$). Thus, the method of step-by-step is a shorter path for middle- and low-level counties to achieve efficiency using a step-by-step method, which supports the conclusion above.

Table 5. Paired-samples *t*-test results for progress values of the one-step and the step-by-step contexts.

Samples	Mean	N	*t*-Value	Sig.	Correlation	Sig.
step-by-step one step	1.327 1.504	184	−12.913	0.001	0.826	0.001

Note: N—number of samples.

3.3. Improvement Elements of Inefficient Counties

In this paper, the Q-type system clustering method was used to classify the input and output redundancy of inefficient counties for exploring the characteristics of improvement elements at each stage. In Figure 4, the six improvement elements in the first step are shown. On the whole, one improvement element had the most prominent improvement ratio in each type, which was significantly higher than that of other redundancies, indicating the existence of one major improvement element. From the perspective of the improvement elements, there were mainly deficiencies in economic, social, and environmental benefits, reflecting the low degree of intensive utilization of urban land in inefficient counties, and the continuation of the extensive land use mode, to some extent. In terms of the number of counties of various types, the number of counties with tertiary industry as the key improvement element was the largest (47), followed by counties with the secondary industry, resident income, AQI or BGR as the major improvement element. It was revealed that the improvement elements in the first step were diverse. The types of improvement elements in the second and third steps were slightly fewer than in the first step, both showing four types (Figure 5). In these two steps, most counties needed to further improve the output of economic and environmental benefits on the basis of the first step to achieve the final goal. This means that the output of economic and environmental benefits in the middle- and low-level counties was generally insufficient, with a large gap compared with the highest level in the urban agglomeration. In terms of the numbers of counties, in the second step, counties taking the BGR as the improvement element were obviously greater in number. In the third step, similarly, the number of counties with the BGR and tertiary industry as the improvement element was larger. This initially reflects that BGR and tertiary need to be focused on both in the middle- and low-level counties.

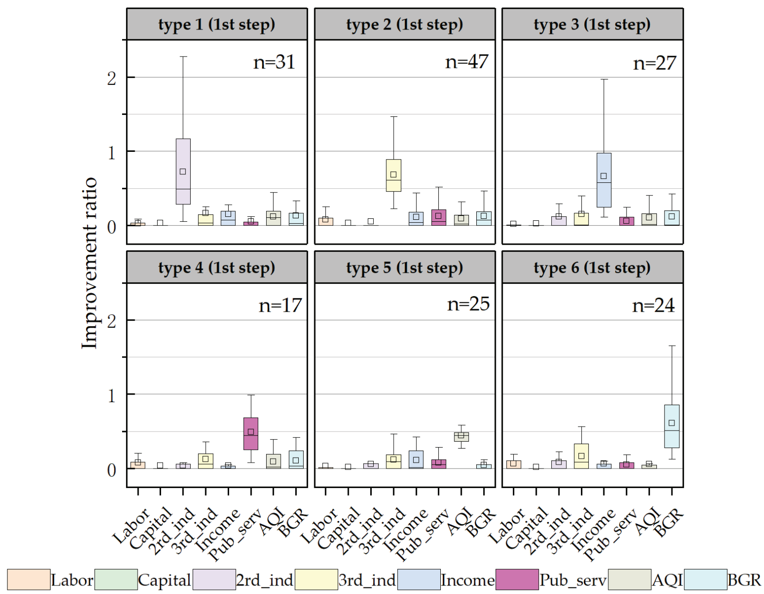

Figure 4. Types of key improvement elements in the first step. Note: 2nd_ind—secondary industry; 3rd_ind—tertiary industry; Income—resident income; Pub_serv—public services; AQI—air quality; BGR—green development level.

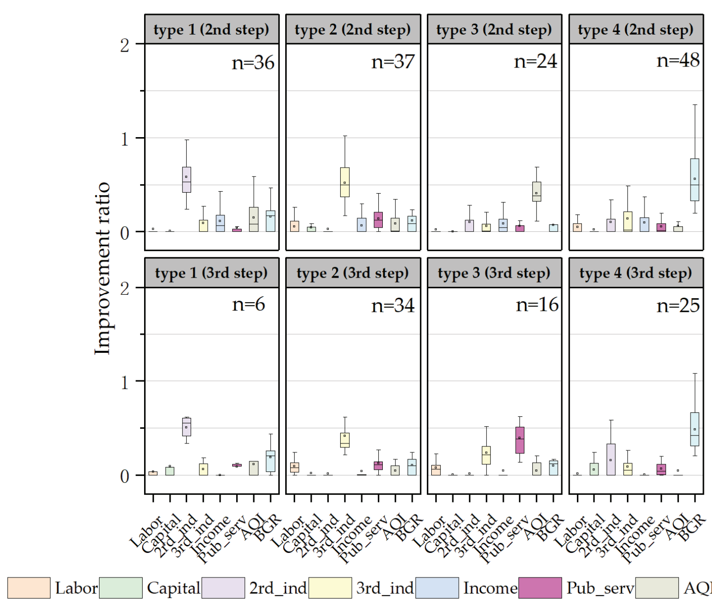

Figure 5. Types of key improvement elements in the second and third steps. Note: 2nd_ind—secondary industry; 3rd_ind—tertiary industry; Income—resident income; Pub_serv—public services; AQI—air quality; BGR—green development level.

Combining the improvement elements in different steps, 54 ULUE improvement paths were formed in 171 inefficient counties (Figure 6). The number of paths was the largest in low-level counties, followed by middle-level counties and high-level counties. On the whole, most high-level counties needed to focus on improving economic benefits. In addition to economic benefits, middle- and low-level counties generally needed to promote social or environmental benefits. On the basis of the similarity in terms of improvement elements, 54 improvement paths could be summarized as the economic (Ec.), economic–social (Ec.–Soc.), economic–environmental (Ec.–Env.), social–environmental (Soc.–Env.) and economic–social–environmental (Ec.–Soc.–Env.). The number of counties was the largest for the Ec.–Env. category (68), followed by Ec. (45), Ec.–Soc.–Env. (24), Soc.–Env. (18) and Ec.–Soc. (16). Figure 7 shows the proportions of various improvement elements in high-, middle- and low-level counties from both short-term and long-term perspectives. In the short term, the improvement elements for high-level counties were mainly those related to tertiary industry. The improvement elements for middle- and low-level counties had significant heterogeneity, and the proportion of each element did not exceed 25%. In the long run, the middle- and low-level counties were characterized by great differences in terms of the social and environmental domains. The middle-level counties had a more significant direction of improving efficiency in the social context, while the environmental domain was more critical for low-level counties as key improvement elements.

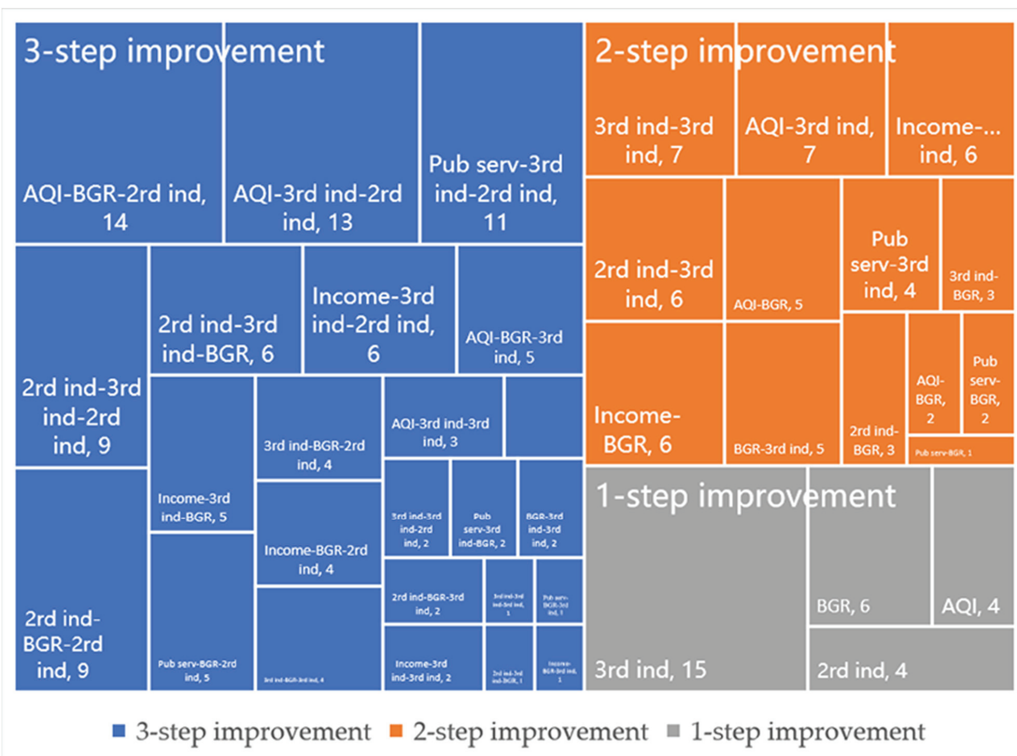

Figure 6. Forty-one improvement paths in inefficient counties. Note: 2nd_ind—secondary industry; 3rd_ind—tertiary industry; Income—resident income; Pub_serv—public services; AQI—air quality; BGR—green development level.

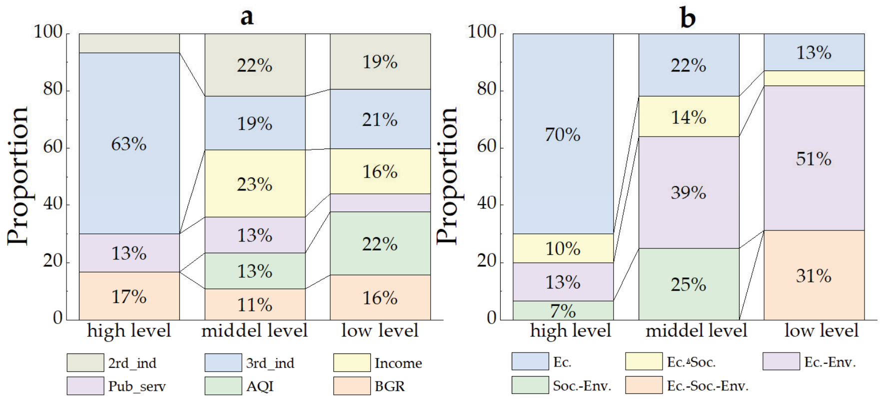

Figure 7. (**a**): Proportions of short-term improvement element of high-, middle- and low-level counties. (**b**): proportions of long-term improvement element of high-, middle- and low-level counties. Note: 2nd_ind—secondary industry; 3rd_ind—tertiary industry; Income—resident income; Pub_serv—public services; AQI—air quality; BGR—green development level.; Ec.—economic; Ec.–Soc.—economic–social; Ec.–Env.—economic–environmental; Soc.–Env.—social–environmental; Ec.–Soc.–Env.—economic–social–environmental.

3.4. Improvement Paths of Different Types and Regions

In this section, the improvement paths of the inefficiency units were compared further from the dimensions of administrative types and regions (prefecture-level cities). Figure 8 presents the proportions of high-, middle- and low-level counties that are different types and located in regions. From the perspective of administrative types, most of the inner cities, suburbs and county-level cities were high-level and middle-level counties, while the county towns were mostly low-level counties. In terms of regions, the difference was obvious between cities; however, it was not significant within the cities. There were mainly high-level counties in Beijing and Tianjin. Four cities in Hebei along Beijing and Tianjin, and the Langfang–Tangshan–Qinhuangdao Axis, were mainly middle-level counties. The majority of the six cities in the central south were low-level counties. The results above mean that, in terms of improvement steps, the regional difference is more prominent, showing a pattern of difference between the north and south. The urban land use and management may have boundary effects—namely, the urban land use levels of various counties within the city area are relatively similar.

Figure 9 demonstrates the differences in improvement elements in terms of different types of settlements and regions. From the short-term perspective, the proportions of improvement elements of the four types of counties were all less than 35%. Furthermore, the improvement elements with the highest proportion are in inner cities and suburbs, which belong to tertiary industry. In contrast, the highest proportion of elements in county-level cities and county towns are public services and air quality. This phenomenon also took place within the cities where improvement elements presented obvious heterogeneity, as well. From a longer-term perspective, the improvement elements for county-level cities and county towns were relatively concentrated, similar to the seven cities in Hebei. Specifically, county-level cities and county towns were mainly associated with the economic and environmental contexts, which is the same as four cites—the traditional industrial city. In addition, two cities in Northern Hebei, Chengde, and Zhangjiakou, were associated mainly with the social context in Northern Hebei. The traditional industrial city in Southern Hebei, as well as Xingtai and Handan, were mainly associated with the economic–social–environmental contexts. It is evident that the functional layout of each region within cities is not currently reasonable, and some portions of cities have common problems in terms of the process of efficiency improvement, which needs to be advanced in general.

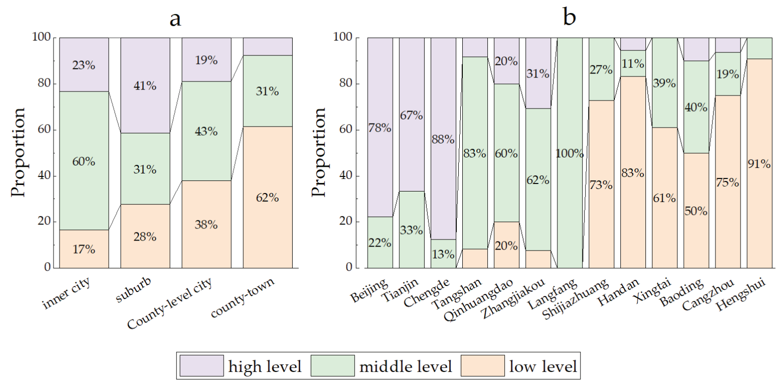

Figure 8. (**a**): Proportions of high-, middle- and low-level counties within county towns, county-level cities, suburbs and inner cities. (**b**): Proportions of high-, middle- and low-level counties within 13 prefecture-level cities in Beijing-Tianjin-Hebei urban agglomeration.

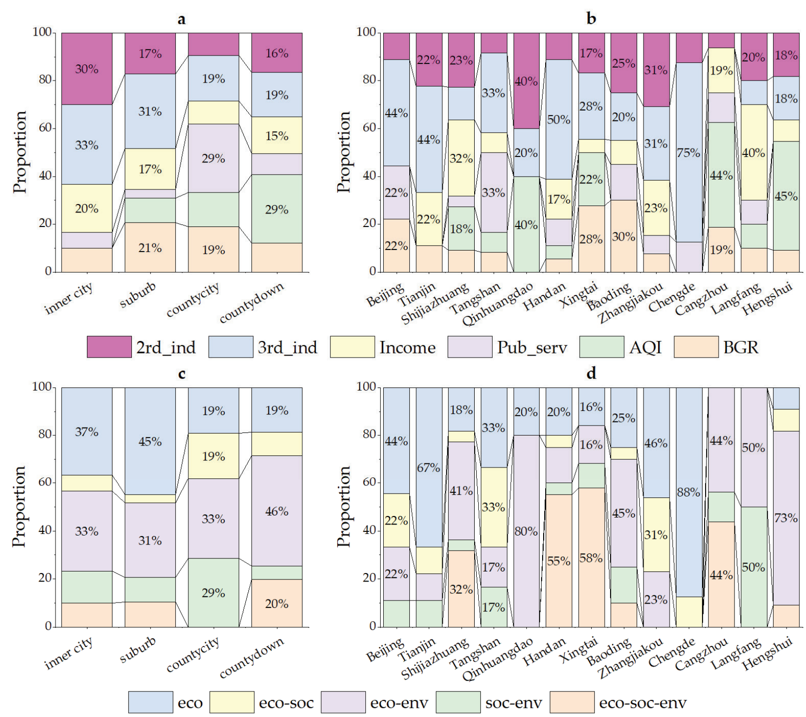

Figure 9. (**a**) Proportions of medium- and short-term improvement elements in four types of counties (inner cities, suburbs, county-level cities and county towns). (**b**) Proportions of medium- and short-term improvement elements within 13 prefecture-level cities. (**c**) Proportions of medium- and long-term improvement elements in four types of counties. (**d**) Proportions of medium- and long-term improvement elements within 13 prefecture-level cities.

In this paper, cross-analyses from the dimensions of administrative types and cities were conducted and presented in the form of a matrix heat chart (Figure 10) in order to further examine whether there were common features in the short-term improvement elements of inefficient counties belonging to different types and located in various regions. In Figure 10, there are 52 regional units composed of 4 administrative types and 13 cities. This concentration reflects the proportion of the dominant improvement elements in the unit, i.e., the ratio of the number of counties with that improvement element to the total number of counties in the unit. It can be seen that 16 region units shared consistency in short-term improvement elements, accounting for 30.77%, distributed in seven cities. According to the number of these units, the improvement element was dominated by air quality, followed by green space, public services, secondary industry and resident income. The results demonstrate that a small number of regions in the BTHUA have common features in the short-term improvement elements, with a relatively scattered distribution.

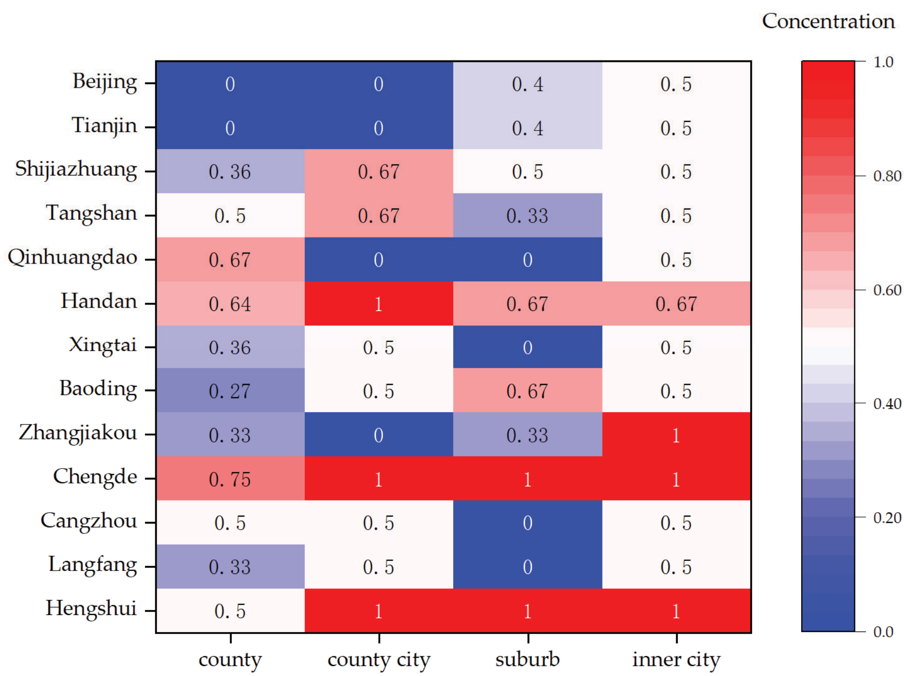

Figure 10. Concentration of short-term improvement elements in inefficient counties with different administrative types and located in various prefecture-level cities. Note: The concentration indicates the proportion of the dominant improvement elements in the unit, i.e., the ratio of the number of counties with that improvement element to the total number of counties in the unit. 2nd_ind—secondary industry; 3rd_ind—tertiary industry; Income—resident income; Pub_serv—public services; AQI—air quality; BGR—green development level.

4. Discussion

4.1. Theoretical Implications

The DEA method has been widely adopted in ULUE research. In this paper, improvement paths for inefficient counties in the BTHUA were analyzed by combining the nearest target and context-dependent DEA. The results show that, with the same technology frontier and in the same inefficient counties, selecting different benchmarks as improvement targets can have a significant impact on redundant information. From the perspective of efficiency improvement, it is a more desirable choice for inefficient counties to achieve the same effect with relatively small adjustments. In previous studies, the SBM model was mainly used to evaluate ULUE [42]. However, the SBM model maximized the redundancy of input and output, thus leading to an underestimation of efficiency. This paper has compared the results based on the nearest target (MinDS) and the furthest target (SBM) by utilizing paired-samples *t*-tests, indicating that the efficiency of MinDS was significantly greater than that of SBM. This means that identifying the redundant information of inefficiency units through the context-dependent DEA based on the closest target helps to find shorter improvement paths. Moreover, the principle of the nearest target method is to take the projection of the most similar actual input and output of the inefficiency county as the evaluation benchmark. Therefore, the redundant information and improvement targets at the basis of the method are more practical and instructive.

Adding intermediate targets is helpful in providing shorter improvement paths for middle- and low-level counties and the improvement degrees, keeping them within a reasonable range at different stages. With the CD-MinDS model, improvement degrees for inefficient counties were calculated and compared under the conditions of both the single benchmark (one-step) and the multi-level benchmark (step-by-step). According to our results, improvement degrees during the step-by-step improvement were significantly lower than those during the one-step. The reason is that the inefficient counties in urban agglomerations have high heterogeneity in terms of land use modes, economic and social development levels, etc. The number of counties constituting the global frontier is small and relatively homogeneous in type. The evaluation results based on a single benchmark may be prone to miscalculation due to heterogeneity, leading to the overestimation of potential improvements. As the types of counties constituting the local frontier are more diverse and more similar to the evaluated counties, the miscalculation caused by heterogeneity is reduced to some extent. In addition, for middle- and low-level counties, the improvement information provided by a single benchmark is too general, while the intermediate targets can serve as a guide and help to better understand the key improvement elements at each step.

In this study, the improvement paths of ULUE were analyzed for the BTHUA in 2018 at the county level. The results showed that, among the 197 counties, there were 184 inefficient counties, including 21 high-level counties, 59 middle-level counties and 104 low-level counties. Significant gradient differences were evident in the improvement degrees for high-, middle- and low-level counties. There was also a large gap between the efficiency level for most counties and the highest efficiency level of the urban agglomeration. Within the urban agglomeration, there was a spatial non-equilibrium characteristic of polarization. In other words, the efficiency level for each county in the core city was the highest and the differences were considerable between surrounding cities versus within the cities. This is again consistent with an overall pattern of high levels in the north and low levels in the south. The results were similar to those of other studies on other urban agglomerations in China, such as those in the Yangtze River Delta [11], the Pearl River Delta [42] and the Shandong Peninsula [43]. These results are in accordance with the findings of Fang et al. that the urban agglomerations in China are still in the initial stage of development or the fast-growing stage, emphasizing the fact that the sustainable development of urban agglomerations should follow an agglomerated effect strategy and borrowed size [44]. In addition, compared to the existing study, the causes of efficiency differences were further analyzed by identifying redundancy characteristics in inefficient counties at different levels as improvement elements. The improvement elements of high-, middle- and low-level counties were classified to reveal the direction of improvement of ULUE. The types of improvement elements were more concentrated in the high-level counties, and the economic contexts, especially the tertiary industry, accounted for the majority. The types of improvement elements are more diverse in the middle- and low-level counties compared to the high-level counties. Specifically, the short-term improvement elements in most middle- and low-level counties are social or environmental contexts, and the share of each element is below 25%. Meanwhile, the long-term improvement elements in these counties contain two to three improvement elements, with a high percentage of them containing both economic and environmental contexts, followed by economic, social and environmental or social and environmental. The results indicate that the cause of the polarization of ULUE in the BTHUA is the presence of more weaknesses in the outputs of middle- and low-level counties. On the other hand, environmental and social benefits are the key to improving ULUE in the short term in middle- and low-level counties. They are also necessary conditions to achieve full efficiency.

Industrial growth enhances overall economic strength [21], as well as ULUE. However, increasing the share of services in the industrial structure is considered to be a more general view to promote higher ULUE [45,46]. In addition, stressing the regulation of environmental pollution and increasing public service expenditures also have a significant positive impact on ULUE [47,48]. In this study, however, the improvement paths for inefficient counties were identified from the micro-level perspective. The results showed that obvious heterogeneity was manifested in the improvement elements for inefficient counties with different administrative types and regions. From the short-term perspective, the improvement elements in most inner cities are economic contexts. In contrast, the improvement elements in county-level cities and county towns are mainly social or environmental contexts. Similarly, the improvement elements of inefficient counties in Beijing and Tianjin are mainly economic contexts, while inefficient counties in most of Hebei's prefecture-level cities are social or environmental. From a long-term perspective, the types of improvement elements in county cities and county-level cities are more concentrated, mostly economic–environmental, while the improvement elements in inner cities and suburbs are mainly economic or economic–environmental. The types of improvement elements of inefficient counties within each prefecture-level city in Hebei are more concentrated, mostly economic–environmental and a few economic. In contrast, the improvement elements in Beijing and Tianjin are more diverse, including economic, economic–social and economic–environmental. The results demonstrate that the causes of ineffectiveness are different across the administrative types and regions of counties and that inefficient counties need to be targeted for improvement according to their critical weaknesses to achieve efficiency. Future ULUE studies on urban agglomerations should take into account the heterogeneous background of the research subjects, while at the same time comprehensively analyzing and discussing the influence mechanisms and efficiency improvement from both macro- and micro-level perspectives.

4.2. Policy Implications

In the past decade or so, China has experienced a surge in urbanization. For example, during the period between 2012 and 2018, all 13 prefecture-level cities except Xingtai and Cangzhou in the BTHUA expanded their urban scales by the means of a "city–county merger". In terms of ULUE, large-scale urbanization has not brought significant efficiency advantages, especially in the Hebei cities. As China's old industrial bases and resource-based cities, these cities are facing the dilemma of transforming and upgrading their leading industries. In terms of accelerating the restructuring of economies, local governments have guided the transfer of secondary industries, which are mainly labor-intensive and resource-intensive, from the inner cities to suburbs and surrounding counties. This leads high-tech industries and producer services to be the new driving forces for urban development. Through the improvement elements of various counties within the prefecture-level cities, it is evident that, in the inner cities, the secondary and tertiary industries make up major proportions. In the suburbs and county towns, on the other hand, secondary industries and air quality account for more. On the one hand, this reflects the ineffectiveness of the main urban areas in attracting and nurturing emerging industries, as well as the continuation of the extensive urban land use mode in peripheral areas. On the other hand, this reflects a lack of industrial support and collaboration capacity within the cities. Therefore, it is necessary to strengthen the coordinating role of regional governments and to break down the administrative barriers between cities. This allows them to benefit from the other's comparative advantages through cross-city collaboration, which promotes effective urban land use in each region of the urban agglomeration.

In the BTHUA, inefficient counties belonging to different types and located in various regions have obvious heterogeneity in the improvement degrees and elements, indicating that more precise governance must be implemented. The governance of urban agglomerations needs to focus on adopting policies based on regional and special planning, while adhering to systematic and comprehensive approaches. From an administrative type perspective, the inner city is a multifunctional center within the prefecture-level city limits, generating a substantial economic radiation role in the surrounding areas. The improvement of the inner cities in the BTHUA, mainly in Hebei, was economic output, including secondary and tertiary industries. Inner cities with relatively low efficiency should continue the strategy of industrial transformation. It is vital to devise more positive industrial and land use policies to increase the share of productive services and high-tech industries in the economic output and promote the redevelopment of inefficient urban land. The suburbs bear the function of taking over the industrial transfer from the inner cities and are potentially densely populated areas in the urbanization process. The direction for improving ULUE in the suburbs was mainly economic and environmental, primarily tertiary industry and BGR. The suburbs should adopt the strategy of city–industry integration to provide more attractive talent policies and focus on improving the business environment to improve the local industrial structure. Meanwhile, it is necessary to implement a sustainable urban operation model and expand the size of urban green spaces. County-level cities and county towns are satellite towns closely linked to the central urban areas and regional centers that surround the rural hinterland. Compared with the inner cities and suburbs, most county-level cities and county towns have more improvement elements and steps. A long-term and tailored development plan is essential. For instance, industrial-oriented county towns should adopt a strategy of industrial upgrading and subsidize R&D and innovation for township enterprises to achieve higher-quality economic output, thereby improving local living standards and reducing negative environmental impacts.

4.3. Limitations and Future Improvements

This study has certain limitations. First, this is a study on ULUE for a single urban agglomeration, the BTHUA. Considering the diversity and complexity of cities in China, it is necessary to include a wider range of urban agglomerations as samples for research. Second, this paper used cross-sectional data to explore the improvement paths for ULUE at the county level. In the future, introducing panel data will be required to further identify and compare the improvement paths for inefficient counties in the process of dynamic change. Moreover, in terms of the construction of the evaluation index system, in order to explore green use and sustainable development for urban land more thoroughly, data sources must be further broadened in the future by including energy consumption, carbon emissions, etc., in the evaluation and analysis of ULUE. In addition, in terms of research methods, this paper has mainly discussed efficiency improvement for inefficient counties from the micro-level perspective. From the macro-level perspective, however, the improvement of ULUE is also influenced by various exogenous drivers. Therefore, in the future, making further efforts to combine micro- and macro-level perspectives will be necessary to explore the mechanisms and improvement paths for ULUE.

5. Conclusions

In this study, the nearest targets and context-dependent DEAs were combined to evaluate and identify ULUE and improvement paths for 197 counties in the BTHUA in 2018. The improvement targets and steps for inefficient counties were compared and analyzed using ANOVA and paired-samples *t*-tests. The improvement elements for inefficient counties were classified and summarized according to the Q-type system clustering method, and improvement paths for inefficient counties belonging to different types and located in various regions were further compared. The main conclusions are as follows. (1) Compared to previous DEA methods for ULUE, better-matched improvement targets are identified by CD-MinDS, resulting in significantly shorter improvement paths. The decomposition of the improvement process by adding intermediate targets helps to identify more reasonable steps and more practical guidance for middle- and low-level counties during the step-by-step method. (2) The inefficient counties in the BTHUA account for more than 85% of the total, and the improvement processes for inefficient counties at high, middle and low levels have one, two and three steps, respectively. The types of improvement elements are more concentrated in the high-level counties and more diverse in the middle- and low-level counties. The economic benefits have a widespread impact on the improvement efficiency of inefficient counties at all levels. However, the environmental and social benefits have a crucial impact on achieving full efficiency for most middle- and low-level counties. (3) The obvious heterogeneity is revealed in the improvement elements for inefficient counties with different administrative types and regions in the short and long term. The inefficient counties should make targeted improvements to achieve efficiency by addressing their critical weaknesses at different stages.

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References

1. Fang, C.; Yu, D. Urban agglomeration: An evolving concept of an emerging phenomenon. *Landsc. Urban Plan.* **2017**, *162*, 126–136. [CrossRef]
2. Liu, Y. Introduction to land use and rural sustainability in China. *Land Use Policy* **2018**, *74*, 1–4. [CrossRef]
3. Deng, X.; Huang, J.; Rozelle, S.; Zhang, J.; Li, Z. Impact of urbanization on cultivated land changes in China. *Land Use Policy* **2015**, *45*, 1–7. [CrossRef]
4. Zheng, W.; Walsh, P.P. Economic growth, urbanization and energy consumption—A provincial level analysis of China. *Energy Econ.* **2019**, *80*, 153–162. [CrossRef]
5. Liang, L.; Wang, Z.; Li, J. The effect of urbanization on environmental pollution in rapidly developing urban agglomerations. *J. Clean. Prod.* **2019**, *237*, 117649. [CrossRef]
6. Moody, J.; Wang, S.; Chun, J.; Ni, X.; Zhao, J. Transportation policy profiles of Chinese city clusters: A mixed methods approach. *Transp. Res. Interdiscip. Perspect.* **2019**, *2*, 100053. [CrossRef]
7. Zhao, J.; Zhu, D.; Cheng, J.; Jiang, X.; Lun, F.; Zhang, Q. Does regional economic integration promote urban land use efficiency? Evidence from the Yangtze River Delta, China. *Habitat Int.* **2021**, *116*, 102404. [CrossRef]
8. Jingxin, G.; Jinbo, S.; Lufang, W. A new methodology to measure the urban construction land-use efficiency based on the two-stage DEA model. *Land Use Policy* **2022**, *112*, 105799. [CrossRef]
9. Fang, C.; Ren, Y. Analysis of emergy-based metabolic efficiency and environmental pressure on the local coupling and telecoupling between urbanization and the eco-environment in the Beijing-Tianjin-Hebei urban agglomeration. *Sci. China Earth Sci.* **2017**, *60*, 1083–1097. [CrossRef]
10. Lu, W.; Zhang, G. Green development efficiency of urban agglomerations in a developing country: Evidence from Beijing-Tianjin-Hebei in China. *Environ. Dev. Sustain.* **2022**, 1–24. [CrossRef]
11. Tan, S.; Hu, B.; Kuang, B.; Zhou, M. Regional differences and dynamic evolution of urban land green use efficiency within the Yangtze River Delta, China. *Land Use Policy* **2021**, *106*, 105449. [CrossRef]
12. Yu, J.; Zhou, K.; Yang, S. Land use efficiency and influencing factors of urban agglomerations in China. *Land Use Policy* **2019**, *88*, 104143. [CrossRef]

13. Wu, J.; Lu, W.; Li, M. A DEA-based improvement of China's green development from the perspective of resource reallocation. *Sci. Total Environ.* **2020**, *717*, 137106. [CrossRef] [PubMed]
14. Liu, S.; Xiao, W.; Li, L.; Ye, Y.; Song, X. Urban land use efficiency and improvement potential in China: A stochastic frontier analysis. *Land Use Policy* **2020**, *99*, 105046. [CrossRef]
15. Wu, C.; Wei, Y.D.; Huang, X.; Chen, B. Economic transition, spatial development and urban land use efficiency in the Yangtze River Delta, China. *Habitat Int.* **2017**, *63*, 67–78. [CrossRef]
16. Song, Y.; Yeung, G.; Zhu, D.; Xu, Y.; Zhang, L. Efficiency of urban land use in China's resource-based cities, 2000–2018. *Land Use Policy* **2022**, *115*, 106009. [CrossRef]
17. Schiavina, M.; Melchiorri, M.; Freire, S.; Florio, P.; Ehrlich, D.; Tommasi, P.; Pesaresi, M.; Kemper, T. Land use efficiency of functional urban areas: Global pattern and evolution of development trajectories. *Habitat Int.* **2022**, *123*, 102543. [CrossRef]
18. Zhang, J.; Chang, Y.; Zhang, L.; Li, D. Do technological innovations promote urban green development?—A spatial econometric analysis of 105 cities in China. *J. Clean. Prod.* **2018**, *182*, 395–403. [CrossRef]
19. Chen, Y.; Chen, Z.; Xu, G.; Tian, Z. Built-up land efficiency in urban China: Insights from the General Land Use Plan (2006–2020). *Habitat Int.* **2016**, *51*, 31–38. [CrossRef]
20. Lu, X.; Wang, M.; Tang, Y. The Spatial Changes of Transportation Infrastructure and Its Threshold Effects on Urban Land Use Efficiency: Evidence from China. *Land* **2021**, *10*, 346. [CrossRef]
21. Chen, W.; Shen, Y.; Wang, Y.; Wu, Q. The effect of industrial relocation on industrial land use efficiency in China: A spatial econometrics approach. *J. Clean. Prod.* **2018**, *205*, 525–535. [CrossRef]
22. Wang, A.; Lin, W.; Liu, B.; Wang, H.; Xu, H. Does Smart City Construction Improve the Green Utilization Efficiency of Urban Land? *Land* **2021**, *10*, 657. [CrossRef]
23. Ding, T.; Yang, J.; Wu, H.; Liang, L. Land use efficiency and technology gaps of urban agglomerations in China: An extended non-radial meta-frontier approach. *Socio-Econ. Plan. Sci.* **2022**, *79*, 101090. [CrossRef]
24. Fu, Y.; Zhou, T.; Yao, Y.; Qiu, A.; Wei, F.; Liu, J.; Liu, T. Evaluating efficiency and order of urban land use structure: An empirical study of cities in Jiangsu, China. *J. Clean. Prod.* **2021**, *283*, 124638. [CrossRef]
25. Han, X.; Zhang, A.; Cai, Y. Spatio-Econometric Analysis of Urban Land Use Efficiency in China from the Perspective of Natural Resources Input and Undesirable Outputs: A Case Study of 287 Cities in China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 7297. [CrossRef] [PubMed]
26. Lim, S.; Bae, H.; Lee, L.H. A study on the selection of benchmarking paths in DEA. *Expert Syst. Appl.* **2011**, *38*, 7665–7673. [CrossRef]
27. Wu, H.; Fang, S.; Zhang, C.; Hu, S.; Nan, D.; Yang, Y. Exploring the impact of urban form on urban land use efficiency under low-carbon emission constraints: A case study in China's Yellow River Basin. *J. Environ. Manag.* **2022**, *311*, 114866. [CrossRef] [PubMed]
28. Wang, Z.; Chen, J.; Zheng, W.; Deng, X. Dynamics of land use efficiency with ecological intercorrelation in regional development. *Landsc. Urban Plan.* **2018**, *177*, 303–316. [CrossRef]
29. Aparicio, J.; Pastor, J.T. A well-defined efficiency measure for dealing with closest targets in DEA. *Appl. Math. Comput.* **2013**, *219*, 9142–9154. [CrossRef]
30. Aparicio, J. A survey on measuring efficiency through the determination of the least distance in data envelopment analysis. *J. Cent. Cathedra* **2016**, *9*, 143–167. [CrossRef]
31. Liu, X.; Zhu, Q.; Chu, J.; Ji, X.; Li, X. Environmental Performance and Benchmarking Information for Coal-Fired Power Plants in China: A DEA Approach. *Comput. Econ.* **2019**, *54*, 1287–1302. [CrossRef]
32. An, Q.; Wu, Q.; Zhou, X.; Chen, X. Closest target setting for two-stage network system: An application to the commercial banks in China. *Expert Syst. Appl.* **2021**, *175*, 114799. [CrossRef]
33. Chakraborty, S.; Maity, I.; Dadashpoor, H.; Novotný, J.; Banerji, S. Building in or out? Examining urban expansion patterns and land use efficiency across the global sample of 466 cities with million+ inhabitants. *Habitat Int.* **2022**, *120*, 102503. [CrossRef]
34. Seiford, L.M.; Zhu, J.J.O. Context-dependent data envelopment analysis—Measuring attractiveness and progress. *Omega* **2003**, *31*, 397–408.
35. Ramón, N.; Ruiz, J.L.; Sirvent, I. Two-step benchmarking: Setting more realistically achievable targets in DEA. *Expert Syst. Appl.* **2018**, *92*, 124–131. [CrossRef]
36. Bao, W.; Yang, Y.; Zou, L. How to reconcile land use conflicts in mega urban agglomeration? A scenario-based study in the Beijing-Tianjin-Hebei region, China. *J. Environ. Manag.* **2021**, *296*, 113168. [CrossRef] [PubMed]
37. Li, Z.; Yan, R.; Zhang, Z.; Sun, Y.; Zhang, X. The Effects of City-County Mergers on Urban Energy Intensity: Empirical Evidence from Chinese Cities. *Int. J. Environ. Res. Public Health* **2021**, *18*, 8839. [CrossRef] [PubMed]
38. Lu, X.-H.; Ke, S.-G. Evaluating the effectiveness of sustainable urban land use in China from the perspective of sustainable urbanization. *Habitat Int.* **2018**, *77*, 90–98. [CrossRef]
39. Wang, S.; Xu, G.; Guo, Q. Street centralities and land use intensities based on points of interest (POI) in Shenzhen, China. *SPRS Int. J. Geo-Inf.* **2018**, *7*, 425. [CrossRef]
40. Chen, M.; Guo, S.; Hu, M.; Zhang, X. The spatiotemporal evolution of population exposure to PM2. 5 within the Beijing-Tianjin-Hebei urban agglomeration, China. *J. Clean. Prod.* **2020**, *265*, 121708. [CrossRef]
41. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]

42. Yang, C.; Xia, R.; Li, Q.; Liu, H.; Shi, T.; Wu, G. Comparing hillside urbanizations of Beijing-Tianjin-Hebei, Yangtze River Delta and Guangdong–Hong Kong–Macau greater Bay area urban agglomerations in China. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102460. [CrossRef]
43. Cui, X.; Fang, C.; Wang, Z.; Bao, C. Spatial relationship of high-speed transportation construction and land-use efficiency and its mechanism: Case study of Shandong Peninsula urban agglomeration. *J. Geogr. Sci.* **2019**, *29*, 549–562. [CrossRef]
44. Fang, C.L.; Wang, Z.B.; Ma, H.T. The theoretical cognition of the development law of China's urban agglomeration and academic contribution. *Acta Geogr. Sin.* **2018**, *73*, 651–665.
45. Qiao, W.; Huang, X. Change in Urban Land Use Efficiency in China: Does the High-Speed Rail Make a Difference? *Int. J. Environ. Res. Public Health* **2021**, *18*, 10043. [CrossRef]
46. Yao, M.; Zhang, Y.J.S. Evaluation and optimization of urban land-use efficiency: A case study in Sichuan Province of China. *Sustainability* **2021**, *13*, 1771. [CrossRef]
47. Lu, J.; Li, B.; Li, H. The influence of land finance and public service supply on peri-urbanization: Evidence from the counties in China. *Habitat Int.* **2019**, *92*, 102039. [CrossRef]
48. Zhang, J.; Kang, L.; Li, H.; Ballesteros-Pérez, P.; Skitmore, M.; Zuo, J. The impact of environmental regulations on urban Green innovation efficiency: The case of Xi'an. *Sustain. Cities Soc.* **2020**, *57*, 102123. [CrossRef]

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The Proactive Effects of Built Environment on Rural Community Resilience: Evidence from China Family Panel Studies

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Abstract: Rural community resilience (RCR) is crucial to rural sustainable development in the context of rural decline globally. Previous studies seem to underestimate the role of the built environment (BE) in the proactive aspect of RCR (P-RCR), that is, a rural community's ability to cope with change proactively. This study explores BE's effects on P-RCR with a holistic framework involving objective BE (OBE), perceived BE (PBE), place attachment (PA) and P-RCR, using structural equation modeling (SEM) based on a sample of 7528 rural respondents from eastern, central and western China. The results are as follows: (1) Both OBE (population density and accessibility) and PBE (perceptions of facilities, surrounding environment and safety) can significantly affect P-RCR in terms of social, economic and environmental dimensions. (2) In all regions, PBE's impacts were consistent and positive on social and economic dimensions at both the individual and community levels (except the community-level economic dimension in western regions), but negative on the individual-level environmental dimension; OBE's impacts were varied among regions. (3) In certain regions, PA and PBE were mediators in the BE-P-RCR relationship. This study can help researchers to construct a more detailed picture of the BE-P-RCR relationship and identify BE-related factors that contribute to P-RCR enhancement.

Keywords: rural community resilience; objective built environment; perceived built environment; place attachment; China

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1. Introduction

Fostering rural community resilience (RCR) is gaining increasing attention along with a series of rural issues confronted by many rural communities around the world, such as depopulation, economic depression, employment reduction and increasing disaster vulnerability [1–4]. RCR explains rural communities' reactive and proactive responses to disturbances for their survival and development [5–7], providing new theoretical perspectives and strategies for rural communities to deal with the abovementioned issues [2–4,8]. Two aspects of RCR have been observed [6]. The reactive aspect of RCR (R-RCR), which ensures a rural community's original state of maintenance and short-term recovery in the face of disturbances, typically involves the community's ability to resist and absorb disturbance [6,9]. Additionally, the proactive aspect of RCR (P-RCR), which facilitates a rural community's long-term survival and prosperity despite constant changes, usually combines personal and collective ability to respond to change proactively with diverse community resources [5,6,10]. Through this proactive aspect, resilient rural communities can deliberately utilize and develop those resources to adapt to change and transform themselves into a new state that is usually more resilient than the original one [6,10,11]. The enhancement of RCR not only improves the viability of rural communities exposed to fast-onset disasters, but also allows them to adapt to slow-onset demographic, socioeconomic and environmental changes more successfully and find new development pathways to overcome adversities [7,12,13]. Fostering RCR has been viewed as essential to reduce and prevent disaster risks in rural areas [3], to maintain rural populations, to improve rural life quality and diversify rural economies in the context of rural decline [2,8,14].

As a result, researchers have shown great interest in factors that enhance or undermine RCR [15], including built environment (BE) factors [16]. BE refers to "all of the physical structures and elements of the human-made environments in which we live, work, travel, and play" [17], as well as the design and planning of these structures and elements (e.g., urban design, land use planning, building codes) [18]. Whether a community can withstand and rapidly recover from disasters usually depends on the performance of BE during these disasters [19], and BE is also seen as an important resource for communities coping with constant change [10]. In previous studies, great attention has been paid to BE's impacts on R-RCR. A range of BE attributes or components that dramatically influence the level of R-RCR have been identified, including lifelines and critical infrastructure, quality of building construction, land use planning, and design codes [16,20]. However, with respect to P-RCR, the effects of BE are either omitted [21] or limited in a facility-economy way. Most researchers tend to simplify BE to "infrastructure" or "facility" and view it as one of the indicators comprising the economic dimension of P-RCR due to its monetary value for rural communities [22–24]. For example, facilities provide services for the needs of people and companies, attracting businesses that help rural communities develop their economic resources [25]. One of the reasons leading to RCR researchers' disproportional attention to BE might be that the role of BE in P-RCR is not as explicit as in the process of rural communities withstanding disasters.

Nevertheless, studies in rural health, psychology and environmental psychology indicate that BE, either objectively measured (OBE) or perceived (PBE), is not dispensable to P-RCR and has multiple approaches to influence P-RCR not merely through the facility-economy way. Researchers focusing on rural health and the resilience of individuals find that "facilities" also are of non-monetary value to rural communities and their resilience by offering locations for people's social interactions and influencing social networks through perceived availability (PBE attribute) [26–28]. The non-facility BE attributes, for example, perceived aesthetics of buildings and streets (PBE attribute), have impacts on rural communities' economic diversity by attracting settlers to the area [28], and objectively measured population density (OBE attribute) is associated with the environmental conditions of rural communities [29]. Those social, economic and environmental factors are the key elements that constitute three fundamental dimensions of P-RCR [30]. Moreover, environmental psychology researchers note that place attachment (PA) can be impacted by OBE or PBE [31], while PA is an important factor closely related to P-RCR [32]. These findings imply that OBE/PBE may indirectly affect P-RCR through PA.

However, although a few researchers test the links between rural people's perceptions of facilities and P-RCR in case studies [2], the implications of OBE and PBE have not yet been further examined simultaneously and holistically in empirical studies on P-RCR. In addition, there is also a lack of a framework that depicts BE's effects on P-RCR from an integrative perspective. To fill this gap, we explored whether and how OBE and PBE affect P-RCR in different dimensions with a holistic framework and structural equation modeling (SEM) based on a sample of 7528 rural community residents from China. This sample was nationally representative and divided into eastern, central, and western region groups according to communities' geographic locations. The reasons we selected Chinese rural communities as our research objects were as follows. First, compared to developed countries, resilience research on communities attracts limited attention in developing economies, with a particular gap in research in China regarding P-RCR [33]. Moreover, these communities are experiencing demographic and socioeconomic changes that have been seen as global issues in rural areas or termed as rural decline [1]. Therefore, research on the relationship between BE and P-RCR in China will help domestic as well as international researchers develop a more detailed picture of RCR in the context of rural decline globally. Second, what those resilience communities need to improve urgently is the proactive aspect. Along with rapid urbanization and industrialization, the rural population in China began to decrease dramatically in 1995 [34]. The size of the rural population declined by about 0.36 billion from 1995 (0.86 billion) to 2021 (0.50 billion) [35]. The outmigration of rural laborers has accompanied this, leading to the reduction in human resources in traditional agriculture, a decline in the agricultural income of rural households, hollowed-out villages and the deterioration of traditional values [36]. To solve rural problems including depopulation, lack of economic opportunity and the weakening of agricultural social cohesion, a "rural revitalization strategy" was proposed in China in 2017 [37]. As a continuation of this strategy, the Chinese government issued the "Rural Revitalization Strategic Plan (2018–2022)" in 2018, with the revitalization of rural communities as its essential part [38]. Against this backdrop, fostering P-RCR in China is critical and urgent because, for revitalization and sustainable development, rural communities undergoing these changes require intentional adaptation and transformation rather than maintenance of their original state, which hardly exists amid constant socioeconomic change [13]. Further, those changes also weaken RCR in China, including P-RCR [33,38]. In the face of such changes, the resilience of rural communities faces challenges in community resources as well as residents' willingness and capacity to assume responsibility for community development [39]. Third, exploring the BE-P-RCR relationship is key to P-RCR enhancement and sustainable rural reconstruction in China. Top-down and bottom-up BE reconstruction have long been seen as important approaches to reverse the trend of rural decline and as strategies for achieving rural renaissance in China [40,41]. A series of policies with a central focus on BE have been implemented since 2005, including new rural reconstruction and scenic rural development [42]. However, though remarkable achievements have been made in these reconstruction efforts, there are criticisms that farmers' interests and social connections are often ignored in those BE transformations, causing social contradictions [41,42] that decrease P-RCR. As a result, investigating BE's influences on P-RCR is necessary for a better rural BE and improved P-RCR in China. It can be useful for planners and architects identifying specific BE attributes that reinforce P-RCR as well as contribute to sustainable rural reconstruction.

Specifically, in this study, we focused on the following questions:

1. Do OBE and PBE significantly affect P-RCR in the social, economic and environmental dimensions?
2. How do OBE and PBE affect these dimensions, respectively?
3. Does PA or PBE play a mediating role in the BE-P-RCR relationship?

2. Theoretical Framework of the BE-P-RCR Relationship

We propose a holistic framework (Figure 1) to depict the BE-P-RCR relationship based on an extensive literature review on BE, P-RCR and PA, which we will explain in the following subsections. We applied this framework as our research scheme and the basis of the structural equation models we used for statistical analysis in Section 3. In this framework, there were six paths in total, including the paths from OBE to PBE, OBE to P-RCR, OBE to PA, PBE to P-RCR, PBE to PA and PA to P-RCR. These paths represent the OBE-PBE relationship and the potential ways OBE and PBE affect P-RCR in the social (Soc), economic (Eco) and environmental (Env) dimensions.

2.1. The Path from OBE to PBE

We used both PBE and OBE to explore BE's impacts on P-RCR, and we recognized that OBE has effects on PBE based on the framework proposed by Marans [43]. Except for distinctions in measurement approach, the differences between OBE and PBE have led to considerations of the OBE-PBE relationship [43,44] and the issues of relying solely on one approach to explore BE [45]. Many researchers have noticed that OBE cannot be equal to PBE, even considering the similar environmental attributes, since different people might have different views on the same objective attributes [43,44]. To further explain this, Marans [43] asserts that PBE reflects people's perceptions and assessments of OBE, which is influenced by their past experiences and OBE itself, and OBE has impacts on people's satisfaction with their community through PBE. In addition, Lewicka [45] suggests that depending merely on residents' perceptions of BE in PA studies is less reliable due to the biases that may exist in these perceptions. As a result, our framework incorporated both OBE and PBE with a pathway from OBE to PBE.

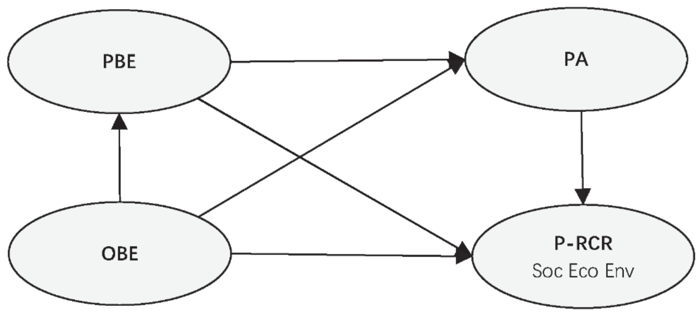

Figure 1. Theoretical framework of the BE-P-RCR relationship. PBE = perceived built environment; OBE = objective built environment; PA = place attachment; P-RCR = the proactive aspect of rural community resilience; Soc = social dimension of P-RCR; Eco = economic dimension of P-RCR; Env = environmental dimension of P-RCR.

2.2. Direct Paths from OBE/PBE to P-RCR with Three Fundamental Dimensions

2.2.1. Three Fundamental Dimensions of P-RCR

Social, economic and environmental capital are fundamental to P-RCR. P-RCR relies on the personal and collective agency of members [6,11,46], as well as community resources or capital (e.g., social, economic, environmental, and cultural capital) that can be deployed to deal with change [10,11,47]. It is enhanced through deliberate development and engagement of these resources or capital by community members [10], and well-developed capital often represents a high level overall or specific dimensions of P-RCR [22,23]. Soc, Eco and Env are seen as fundamental dimensions of P-RCR [5], because they embody community members' willingness and ability to work together [10] as well as the critical resources or capital communities use to respond to change [11,47]. Soc, including factors such as the social networks between individuals and groups [30], trust [30], and happiness [13], is fundamentally about the community members' willingness and capacity to participate in actions for coping with change [10]. Eco is the financial base of a rural community and its members and includes components such as community economic well-being [47], individual financial stability [13], and economic diversity [24]. Env often refers to the ecological conditions of a rural community such as soil conditions [47], water quality [47] and biodiversity [48], and the pro-environmental attitudes or behaviors of the community members [5].

2.2.2. The Influences of OBE/PBE on P-RCR

The existing work suggests that OBE/PBE may influence P-RCR in terms of all three dimensions. Regarding Soc, BE components such as schools, stores, and recreational and healthcare facilities provide physical spaces for rural residents' social interactions [26,28]. Consequently, the low perceived availability of facilities or infrastructures weakens rural people's social networks and lead to a decrease in resilience [28]. Moreover, although lacking validation in rural communities, researchers find that objectively measured accessibility and perceived adequacy of facilities have independent impacts on social capital in suburban communities [49], and perceptions of safety are associated with social capital in urban communities [50]. Concerning Eco, facilities contribute to the rural economy in multiple ways (e.g., financial and retail services, job provision, tourism encouragement, consumption) [27], which implies that accessibility may be important for the economic dimension of P-RCR. Meanwhile, the attractiveness of BE, such as aesthetic perceptions of buildings and streetscapes, is helpful in the economic diversification of rural communities [28]. Regarding Env, it is plausible that some PBE attributes (e.g., perceptions of litter and refuse) are associated with garbage pollution in rural China [29]. Some researchers also notice that insufficient facilities decrease residents' willingness to participate in environmental projects [51], and the population density (objectively measured) of Chinese rural communities can influence their environment [29].

2.2.3. Direct Paths from OBE/PBE to Different Dimensions of P-RCR

It should be noted that the abovementioned influences of OBE/PBE on P-RCR might be direct, indirect or both. We assume that OBE/PBE affects P-RCR in both ways. Direct paths from OBE/PBE to P-RCR are included in the framework.

2.3. The Path from PA to P-RCR

PA is described as "an emotional connection to a place" [52] (p. 560). Usually, PA has been seen as a good thing for P-RCR, since it motivates rural people's participation in community organizations and helps them cope with social, economic and environmental problems and disasters in most cases [32,53], though some researchers also notice the adverse effects of certain kinds of PA on RCR [54].

2.4. The Path from OBE/PBE to PA

In rural or agriculture studies relevant to BE, researchers have found the importance of OBE/PBE to PA. For example, Bunkus et al. [55] emphasize that population density reflecting the quantity of interactions impacts farmers' PA in Germany directly and indirectly; Christiaanse and Haartsen [56] confirm that the decreasing numbers of rural facilities have disrupted the PA between rural people and these facilities and resulted in negative emotional reactions and collective actions; researchers also recognize that within the context of Chinese rural land consolidation, rural residents' perceptions of BE are closely related to their place identity [57], which has been viewed as an important component of PA [58].

3. Materials and Methods

3.1. Data

The data used in this study were derived from China Family Panel Studies (CFPS). CFPS, conducted by the Institute of Social Science Survey (ISSS) of Peking University, is a national and comprehensive social survey aiming to collect longitudinal data at the individual, family and community levels in contemporary China for research on Chinese social phenomena [59]. It covers 25 provinces, municipalities or autonomous regions in China (except Hong Kong, Macao, Taiwan, Xinjiang, Qinghai, Inner Mongolia, Ningxia and Hainan) and is carried out in waves every 2 years [59]. The data of CFPS contain many datasets, including datasets related to communities and adult family members. We used different datasets and waves of CFPS (Table 1), because the variables in our study involved many aspects of rural life that connect with several CFPS datasets released so far, and parts of these variables were collected in different waves.

Table 1. Datasets and CFPS waves used in this study.

Variables	Data Source (Datasets)	Data Source (Waves)
OBE	community	CFPS 2014
PBE	adult	CFPS 2016
PA	adult	CFPS 2016
P-RCR	community; adult	CFPS 2014
P-RCR	adult	CFPS 2016

OBE = objective built environment; PBE = perceived built environment; P-RCR = the proactive aspect of rural community resilience; CFPS 2014/2016 = China Family Panel Studies in 2014/2016.

Specifically, we combined the variables of OBE and P-RCR (Soc, Env and part of Eco) from CFPS 2014 (datasets on communities and adults), the variables of PBE, P-RCR (Eco pertaining to individuals) and PA from 2016 (adult dataset) by linking "community ID" after keeping all samples of rural communities (communities in rural areas and urban residential areas newly transformed from villages). However, we excluded the respondents who had moved to a new residential address or had a primary job and income change during 2014–2016, for these respondents may make less reliable evaluations of OBE and individual economic well-being in the context of our study. At last, we obtained a sample of 7528 rural community respondents in China.

We divided this sample into three groups based on the geographic locations of 25 provinces (municipalities or autonomous regions). These were the groups of eastern regions (n = 2719), central regions (n = 2130) and western regions (n = 2679) (Table 2). This was because besides the community-scale factors, factors outside the community can also influence RCR (e.g., regional policies, markets and natural resources) [13,22]. External factors, such as unbalanced rural industrial development and rural income inequality in coastal and inland regions in China [60,61], could interfere with our study, which concentrated on community-scale BE impacts on P-RCR. As a result, the effects of BE on P-RCR in this study were explored separately using three groups of data. STATA Version15 was used for data cleaning and grouping.

Table 2. The eastern, central and western regions.

Regions	Provinces, Municipalities or Autonomous Regions	Sample Size
Eastern	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi	2719
Central	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan	2130
Western	Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu	2679

3.2. Variables

3.2.1. OBE

For our research purpose, OBE in this study was quantified with accessibility and population density [49,62,63]. We measured these two variables using the equations proposed by Sun et al. [64]. In CFPS 2014, the data relating to OBE included size of community administrative area (square kilometers), permanent resident population and numbers of facilities (stores, kindergartens, primary schools, middle schools, hospitals or clinics, pharmacies, churches, ancestral halls, temples, activity facilities or community service centers for the elderly, nursing homes, physical exercise facilities and playgrounds) in the community. Based on Sun et al.'s study [64], we treated population density and accessibility of facilities as two observation variables of OBE and calculated them as follows:

$$d = P/A \tag{1}$$

$$a = N/A \tag{2}$$

where d is population density, a is accessibility, P is permanent resident population of the community, N is the number of facilities in the community, A is size of administrative area (square kilometers). A higher proportion accounted for higher population density and better accessibility.

3.2.2. PBE and PA

For PBE assessment, we used the data on residents' perceptions of their neighborhood BE in CFPS 2016. It contains overall perceptions of public facilities, safety and surrounding environment of neighborhood (e.g., aesthetics and noise), which have been seen as critical PBE attributes in studies pertaining to a rural context, social capital or PA [65,66]. We treated PBE as a latent variable consisting of these three kinds of perceptions. PA was estimated using data from the residents' evaluations of their emotional attachment to the community in CFPS 2016. All indicators of PBE and PA were rated with a 5-point scale, ranging from 1 (very good or very much) to 5 (very poor or not at all). We reversed the code for the convenience of explaining that a higher score represented a better perception of BE.

3.2.3. Key Dimensions of P-RCR

In this study, P-RCR was quantified based on the framework explored by Markantoni et al. [5], which integrated the frameworks proposed by Steiner and Markantoni [13] and Wilson [30] to measure Soc, Eco and Env at the individual and community levels. Since this framework focuses on socioeconomic changes of rural areas and estimates the three key dimensions of P-RCR through both individual and collective levels, it seemed appropriate for our study.

At the individual level, Soc was assessed by happiness [13], and based on Shen and Jia [67], we used self-evaluated happiness (10-point scale, ranging from "lowest" to "highest"), life satisfaction (5-point scale, ranging from "very unsatisfied" to "very satisfied") and confidence in the future (5-point scale, ranging from "not confident at all" to "very confident") derived from CFPS 2014 as the measurement indicators of happiness. Individual-level Eco was evaluated by personal financial stability [13], and the data on income satisfaction (5-point scale, ranging from "very unsatisfied" to "very satisfied"), overall job satisfaction (5-point scale, ranging from "very unsatisfied" to "very satisfied") and working environment satisfaction (5-point scale, ranging from "very unsatisfied" to "very satisfied") obtained from CFPS 2016 were used to measure this stability. Individual-level Env was estimated on the basis of pro-environmental attitudes or behavior [5], using the severity of environmental problems rated by adult respondents (10-point scale, ranging from "not severe" to "extremely severe") in CFPS 2014 as the indicator. This was because people facing severe environmental problems are more likely to support environmental protection [68]. At the community level, Soc, Eco and Env were measured in terms of trust in neighborhood [30], community economic well-being [47] and biodiversity [48], respectively. The data obtained from CFPS 2014 (adult dataset) were used to quantify these dimensions, including neighborhood trust (10-point scale, ranging from "distrustful" to "very trustworthy"), net income per capita (CNY) and the proportion of forest and/or land with fruit trees in the community administrative area. For all levels, a higher rating score, income or proportion represented better PBE or greater Soc, Eco and Env.

3.2.4. Covariate

The covariate was the socioeconomic status of residents. Lewicka [45] asserts that the predictors of PA include physical factors (e.g., objective BE features) as well as social factors (e.g., safety, social ties), and the relative importance of these factors depends on residents' socioeconomic status in some cases. Since PA was an important endogenous variable in our study, overlooking the differences in residents' socioeconomic status might have led to imprecision in our study. Therefore, we used socioeconomic status as the covariate and employed the data on self-reported social and economic status (5-point scale, ranging from lowest to highest) obtained from CFPS 2014 (adult dataset) to measure this covariate.

3.2.5. Questions Used for Variable Measurement

Specific questions used to derive indicators of PBE, PA, different dimensions of P-RCR and the covariate are displayed in Table 3.

Table 3. Questions used to derive indicators of PBE, PA, P-RCR and the covariate.

Variables		Indicators	Questions	Source
PBE		Community Environment	How is the surrounding environment of your community (noise, trash disposal, etc.)? (reversed code ranging from 1 = very poor to 5 = very good)	CFPS 2016 Full Questionnaires
		Safety	How is the public safety around your community? (reversed code ranging from 1 = very poor to 5 = very good)	
		Public Facilities	What do you think of the public facilities around your community? (reversed code ranging from 1 = very poor to 5 = very good)	
P-RCR	Individual-level	Social Dimension	1. Are you happy? (ranging from 1 = lowest to 10 = highest) 2. How confident are you about your future? (ranging from 1 = not confident at all to 5 = very confident) 3. Are you satisfied with your life? (ranging from 1 = very unsatisfied to 5 = very satisfied)	CFPS 2014 Full Questionnaires; CFPS 2016 Full Questionnaires
		Economic Dimension	1. How satisfied are you with your current income from this job? (ranging from 1 = very unsatisfied to 5 = very satisfied) 2. In general, how satisfied are you with this job? (ranging from 1 = very unsatisfied to 5 = very satisfied) 3. How satisfied are you with the working environment in this job? (ranging from 1 = very unsatisfied to 5 = very satisfied)	
		Environmental Dimension	How would you rate the severity of the environmental problem in China? (ranging from 1 = not severe to 10 = extremely severe)	
	Community-level	Social Dimension	How much do you trust your neighborhood? (ranging from 1 = distrustful to 10 = very trustworthy)	CFPS 2014 Full Questionnaires
		Economic Dimension	The net income per capita in your village (yuan)	
		Environmental Dimension	1.The total area of forest and/or land with fruit trees in your village (mu) 2. What is the current administrative area of your village/residential community? (kilometer^2/mu)	
PA		Emotional Attachment	How would you rate your emotional attachment to your community? (ranging from 1 = very good to 5 = very poor)	CFPS 2016 Full Questionnaires
Covariate		Self-reported Socioeconomic Status	1. What is your relative income level in your local area? (ranging from 1 = lowest to 5 = highest) 2. What is your social status in your local area? (ranging from 1 = lowest to 5 = highest)	CFPS 2014 Full Questionnaires

BE = built environment; PBE = perceived built environment; P-RCR = the proactive aspect of rural community resilience; PA = place attachment. CFPS 2014/2016 = China Family Panel Studies in 2014/2016.

3.3. Methods

Structural equation modeling (SEM) has been an important tool for analyzing the interactions between the physical environment and rural society [55,57]. SEM consists of a measurement model that can measure the reliability and validity of latent variables, and a structural equation that can be used to analyze the paths between the constructs.

The reasons we employed SEM as an analytical tool in this study were manifold. First, SEM allows researchers to investigate complex relationships between multiple constructs in a single model and provides an easier way to discuss the model [55,69]. Therefore, it fit well with our study, which attempted to explore the associations between OBE, PBE, PA and three different dimensions of P-RCR in one holistic framework. Second, SEM is usually applied to verify a theoretical hypothesis by analyzing observations and latent variables through statistical procedures including path analysis, regression and structural equations [55,57]. As a result, it could be a useful tool for testing the BE-P-RCR relationship we postulated in this study. The statistical analysis in this study was built on three steps:

1. Step one: Measurement model testing and descriptive statistical analysis

In this step, confirmatory factor analysis (CFA) was performed using different groups of data and AMOS Version 26. Meanwhile, descriptive statistical analysis was conducted using STATA Version15.

2. Step two: Structural equation model building

In this step, two basic structural equation models were established based on the framework shown in Figure 1, including the individual-level model (with the variables of OBE, PBE, PA and Soc, Eco, Env at the individual level) and the community-level model (with the variables of OBE, PBE, PA and Soc, Eco, Env at the community level). Figure 2 demonstrates the structure of the two basic models.

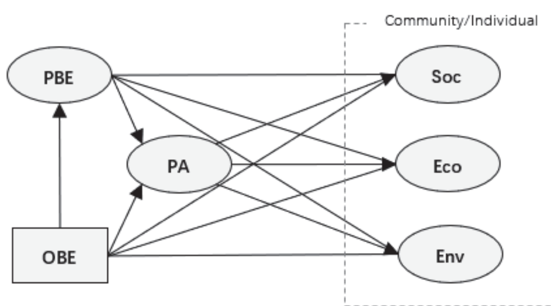

Figure 2. The structure of individual- and community-level models (Source: authors).

3. Step three: Application of structural equation model

Since population density and accessibility are highly correlated, these two indicators were examined separately in the basic models for multicollinearity reduction. Consequently, there were four models we needed to explore:

1. Individual-level model with population density (Model 1);
2. Individual-level model with accessibility (Model 2);
3. Community-level model with population density (Model 3);
4. Community-level model with accessibility (Model 4).

Each model was tested using three groups of data separately; therefore, 12 models were applied using AMOS Version 26, and the paths to all endogenous variables were controlled for the covariate.

4. Results

4.1. The Results of CFA and Descriptive Statistics

All composite reliability (CR) values for latent variables with multiple indicators derived from three groups of data were above 0.6 ($0.776 \geq CR \geq 0.631$), indicating a high degree of internal consistency [70] (Table A1). For acceptable convergent validity, generally an average variance extracted (AVE) value should be 0.5 or above [70]. However, Chin [71] suggests that most loadings should be at least 0.60 to ensure each measure can explain half or more of the variance in the latent variable, which indicates that the threshold of the AVE value should be at least 0.36. In this study, all AVE values exceeded or were close to 0.5 ($0.539 \geq \text{AVE} \geq 0.428$), except AVE for PBE and individual-level Soc in western regions (above 0.36) (Table A1). Moreover, the square root of the AVE value for each latent variable with multiple indicators was greater than the values of its correlations with other multiple indicator variables, demonstrating a high discriminant validity of our models (Table A2).

Table 4 displays the average population density (natural logarithm) and the standard deviation (sd) in eastern, central and western regions, which were 5.649 (sd = 1.461), 5.885 (sd = 1.352), and 5.196 (sd = 1.234), respectively. The average accessibility (natural logarithm) and the standard deviation in eastern, central and western regions were 0.728 (sd = 1.426), 0.855 (sd = 1.353), and 0.239 (sd = 1.263), respectively. Most respondents evaluated PBE as fair, as the median values for public facilities, surrounding environment and public safety in three regions were all 3 ("fair" option), while the interquartile ranges (IQR) of these values were all 1, which represents a central tendency of these values. Moreover, respondents are somewhat emotionally attached to their communities (all Median = 4, IQR $\leq$ 2). On average, respondents reported similar levels of life satisfaction (Mean $\approx$ 3.8) and confidence in their future (Mean $\approx$ 4.1) in all regions, but higher happiness levels in the eastern and central regions (Mean $\approx$ 7.5) than in the western regions (Mean $\approx$ 6.9). Most respondents reported their income (all Median = 3, IQR $\leq$ 2), working environment (all Median = 3, IQR = 1 except Median = 4 in central regions) and overall job satisfaction (all Median = 3, IQR = 1) as fair. Eastern and central region respondents reported higher average severity of environmental problems, neighborhood trust degree and net income per capita (natural logarithm) than their western region counterparts. The average biodiversity (natural logarithm) and the standard deviation were 6.978 (sd = 5.765) in eastern, 4.453 (sd = 5.531) in central and 6.925 (sd = 5.853) in western regions.

Table 4. Descriptive statistics for the covariate, individual- and community-level variables derived from samples of the eastern (n = 2719), central (n = 2130) and western regions (n = 2679).

	Eastern Regions				**Central Regions**				**Western Regions**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Variables	**Median (Mean)**	**IQR (sd)**	**Min**	**Max**	**Median (Mean)**	**IQR (sd)**	**Min**	**Max**	**Median (Mean)**	**IQR (sd)**	**Min**	**Max**
Population Density *	(5.649)	(1.461)	2.907	9.076	(5.885)	(1.352)	2.907	9.076	(5.196)	(1.234)	2.907	8.976
Accessibility *	(0.728)	(1.426)	−2.676	4.605	(0.855)	(1.353)	−2.676	4.605	(0.239)	(1.263)	−2.676	3.519
Public Facilities	3	1	1	5	3	1	1	5	3	1	1	5
Surrounding Environment	3	1	1	5	3	1	1	5	3	1	1	5
Public Safety	3	1	1	5	3	1	1	5	3	1	1	5
Emotional Attachment	4	1	1	5	4	1	1	5	4	2	1	5
Happiness	(7.534)	(2.269)	0	10	(7.484)	(2.250)	0	10	(6.904)	(2.403)	0	10
Life Satisfaction	(3.782)	(1.051)	1	5	(3.874)	(1.009)	1	5	(3.823)	(1.021)	1	5
Confidence in the Future	(4.053)	(1.046)	1	5	(4.144)	(1.004)	1	5	(4.031)	(1.052)	1	5
Income Satisfaction	3	2	1	5	3	1	1	5	3	1	1	5
Working Environment Satisfaction	3	1	1	5	4	1	1	5	3	1	1	5
Overall Job Satisfaction	3	1	1	5	3	1	1	5	3	1	1	5
Severity of Environmental Problems	(6.541)	(2.845)	0	10	(6.447)	(2.770)	0	10	(6.078)	(2.698)	0	10
Trust in Neighborhood	(6.895)	(2.260)	0	10	(6.894)	(2.218)	0	10	(6.455)	(2.258)	0	10
Net Income Per Capita (CNY) *	(8.517)	(0.798)	6.685	9.903	(8.181)	(0.647)	6.685	9.903	(7.976)	(0.691)	6.685	9.107
Biodiversity *	(6.978)	(5.765)	0	14.57	(4.453)	(5.531)	0	14.57	(6.925)	(5.853)	0	14.57

* We took the natural logarithm of these variables. Biodiversity = proportion of forest (and/or land with fruit trees) land area in administrative area. sd = standard deviation; IQR = interquartile range.

4.2. Analysis of the Results of the Structural Equation Model

All 12 models had acceptable goodness of fit. Because in each model, the Chi-square/degrees of freedom < 5, the comparative fit index > 0.95, the root mean square error of approximation < 0.05, and the standardized root mean square residual was below 0.05.

The specific fits of each model are shown in Appendix A Table A3. As shown in Figure 2, direct effects included the impacts of direct paths from OBE/PBE to three dimensions of P-RCR. The indirect effects consisted of the impacts of paths from OBE to three dimensions of P-RCR through PA and first PA, then PBE, as well as the paths from PBE to three dimensions of P-RCR via PA. Total effects were the sum of direct effects and indirect effects. It represents all of the effects an exogenous variable had on an endogenous variable in this study.

To examine whether and how BE influenced three dimensions of P-RCR, we first focused on whether there were positive or negative significant total effects of OBE/PBE on three dimensions of P-RCR, since it was more rational to infer that BE can affect P-RCR when significant total effects of BE are identified. Then, we paid attention to the indirect effects that PA or PBE can mediate. We highlighted the mediating role that PA and PBE play in the BE-P-RCR relationship when the total effects of OBE/PBE on P-RCR are significant. This study did not elaborate on the significant mediation effects related to insignificant total effects.

4.2.1. Total and Indirect Effects of PBE on P-RCR

Table 5 shows that the total effects of PBE on Soc and Eco were significant and positive in all three regions at the individual and community levels, apart from community-level Eco in the western regions (significant and negative). Regarding Env, significant and negative total effects of PBE were identified at the individual level in all regions, while at the community level, the total effects of PBE were negative in the eastern regions, positive in central regions and insignificant in western regions.

Table 5. Total, direct and indirect effects of PBE on P-RCR in terms of Soc, Eco and Env.

Pathways and Effects	Dimensions	Model 1		Model 2		Model 3		Model 4	
		Point Estimate	Standard Error	Point Estimate	Standard Error	Point Estimate	Standard Error	Point Estimate	Standard Error
Eastern Regions									
PBE→PA→ Indirect Effects	Soc	**0.058** ***	0.010	**0.057** ***	0.010	**0.164** ***	0.029	**0.163** ***	0.029
	Eco	**0.031** ***	0.009	**0.031** ***	0.009	**−0.022** **	0.009	**−0.022** **	0.009
	Env	0.047	0.033	0.048	0.033	−0.067	0.064	−0.076	0.064
Direct Effects	Soc	0.172	0.031	0.172	0.031	0.274	0.091	0.277	0.091
	Eco	0.434	0.037	0.432	0.037	0.132	0.031	0.133	0.031
	Env	−0.654	0.122	−0.658	0.122	−0.711	0.230	−0.682	0.230
Total Effects	Soc	**0.230** ***	0.030	**0.230** ***	0.030	**0.438** **	0.085	**0.440** **	0.086
	Eco	**0.465** ***	0.035	**0.463** ***	0.035	**0.110** ***	0.029	**0.111** ***	0.029
	Env	**−0.607** ***	0.113	**−0.611** ***	0.113	**−0.778** **	0.213	**−0.758** **	0.214
Central Regions									
PBE→PA→ Indirect Effects	Soc	**0.021** **	0.008	**0.021** **	0.008	**0.102** ***	0.029	**0.101** ***	0.029
	Eco	0.005	0.009	0.005	0.009	0.001	0.008	0.000	0.007
	Env	**0.091** **	0.034	**0.091** **	0.034	−0.095	0.068	−0.075	0.068
Direct Effects	Soc	0.099	0.033	0.099	0.033	0.556	0.115	0.549	0.115
	Eco	0.494	0.038	0.492	0.038	0.090	0.029	0.089	0.028
	Env	−0.713	0.132	−0.712	0.132	0.666	0.262	0.765	0.271
Total Effects	Soc	**0.121** ***	0.031	**0.120** ***	0.031	**0.658** ***	0.111	**0.651** ***	0.111
	Eco	**0.499** ***	0.036	**0.497** ***	0.036	**0.091** **	0.027	**0.089** **	0.027
	Env	**−0.622** ***	0.123	**−0.622** ***	0.123	**0.571** **	0.247	**0.689** **	0.256
Western Regions									
PBE→PA→ Indirect Effects	Soc	0.013	0.008	0.014	0.008	0.040	0.029	0.040	0.029
	Eco	0.016	0.009	0.016	0.009	0.003	0.008	0.002	0.008
	Env	0.043	0.032	0.043	0.033	0.054	0.073	0.045	0.073
Direct Effects	Soc	0.081	0.031	0.086	0.031	0.226	0.116	0.239	0.116
	Eco	0.533	0.051	0.537	0.051	−0.090	0.035	−0.080	0.036
	Env	−0.461	0.142	−0.466	0.143	−0.150	0.299	−0.189	0.301
Total Effects	Soc	**0.094** **	0.030	**0.099** **	0.030	**0.267** *	0.110	**0.279** *	0.110
	Eco	**0.549** ***	0.048	**0.553** ***	0.049	**−0.087** **	0.033	**−0.078** *	0.033
	Env	**−0.418** **	0.135	**−0.423** **	0.135	−0.097	0.281	−0.144	0.283

Underlined and bold values represent significant total and mediation effects (5000 bootstrap samples, 95% bias-correct confidence level). *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. PBE = perceived built environment; PA = place attachment; Soc = social dimension; Eco = economic dimension; Env = environmental dimension; "PBE→PA→" refers to the pathways from PBE to Soc/Eco/Env through PA.

In eastern regions, the mediation effects of PA were found in the relationships between PBE and Soc/Eco at the individual and community levels. In central regions, PA significantly mediated the effects of PBE on Soc (individual- and community-level) and individual-level Env. No mediation effect of PA was observed in the western regions.

4.2.2. Total and Indirect Effects of OBE on P-RCR

The values in Table 6 illustrate that the total effects of population density and accessibility on Soc were significant and negative in the eastern regions at the individual level. Referring to Eco, in the eastern regions, a significant and negative total effect of accessibility on Eco was only identified at the individual level. The values listed in Tables 7 and 8 show that in the central and western regions, both accessibility and population density had significant total effects on Eco at the individual and community levels. Regarding Env, the total effects of population density and accessibility were significant at the community level but insignificant at the individual level in all regions.

Concerning indirect effects, the values in Table 6 indicate that both PA and PBE significantly mediated the influences of OBE (population density/accessibility) on individual-level Soc and accessibility on individual-level Eco in the eastern regions. However, when considering all of the indirect paths from OBE to individual-level Soc in the eastern regions, OBE had insignificant total indirect effects on individual-level Soc, since the effects of OBE on Soc through the PBE path (negative) and firstly PA, then the PBE, path (negative) offset the PA path effects (positive). The values in Tables 6–8 demonstrate that PBE could also be a mediator in the relationship between OBE and community-level Env in the eastern and central regions, as well as between OBE and Eco in the western regions.

Table 6. Total, direct and indirect effects of OBE on P-RCR (eastern regions).

Pathways and Effects (Eastern Regions)	Dimensions	Model 1		Model 2		Model 3		Model 4	
		Point Estimate	Standard Error	Point Estimate	Standard Error	Point Estimate	Standard Error	Point Estimate	Standard Error
OBE→PBE→PA→ Indirect Effects	Soc	**−0.002** ***	0.001	**−0.002** ***	0.001	−0.005	0.002	−0.005	0.002
	Eco	−0.001	0.000	−0.001	0.000	0.001	0.000	0.001	0.000
	Env	−0.002	0.001	−0.002	0.001	0.002	0.002	0.002	0.002
OBE→PBE→ Indirect Effects	Soc	**−0.006** ***	0.002	**−0.006** ***	0.002	−0.009	0.004	−0.009	0.004
	Eco	−0.015	0.004	**−0.014** ***	0.004	−0.004	0.002	−0.004	0.002
	Env	0.022	0.007	0.022	0.007	**0.024** **	0.011	**0.022** **	0.010
OBE→PA→ Indirect Effects	Soc	**0.005** ***	0.002	**0.004** **	0.002	0.014	0.005	0.011	0.004
	Eco	0.003	0.001	**0.002** **	0.001	−0.002	0.001	−0.001	0.001
	Env	0.004	0.003	0.003	0.003	−0.006	0.006	−0.005	0.005
Total Indirect Effects	Soc	−0.003	0.003	−0.004	0.003	−0.001	0.006	−0.004	0.006
	Eco	−0.013	0.005	**−0.013** **	0.005	−0.006	0.002	−0.005	0.002
	Env	0.025	0.008	0.023	0.008	0.020	0.012	**0.020** *	0.012
Direct Effects	Soc	−0.018	0.009	−0.020	0.009	−0.013	0.028	0.000	0.029
	Eco	−0.003	0.010	−0.014	0.010	0.019	0.012	0.027	0.012
	Env	0.027	0.036	0.012	0.036	−0.314	0.076	−0.225	0.078
Total Effects	Soc	**−0.021** *	0.010	**−0.023** *	0.010	−0.014	0.028	−0.004	0.029
	Eco	−0.017	0.010	**−0.028** **	0.010	0.013	0.012	0.022	0.012
	Env	0.051	0.035	0.035	0.036	**−0.294** **	0.076	**−0.206** *	0.077

Underlined and bold values represent significant total and mediation effects (5000 bootstrap samples, 95% bias-correct confidence level). *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. PBE = perceived built environment; PA = place attachment; Soc = social dimension; Eco = economic dimension; Env = environmental dimension. "OBE→PBE→PA→" refers to the pathways from OBE to Soc/Eco/Env first through PBE, then PA; "OBE→PBE→" refers to the pathways from OBE to Soc/Eco/Env through PBE. "OBE→PA→" refers to the pathways from OBE to Soc/Eco/Env first through PA.

Table 7. Total, direct and indirect effects of OBE on P-RCR (central regions).

Pathways and Effects (Central Regions)	Dimensions	Model 1		Model 2		Model 3		Model 4	
		Point Estimate	Standard Error	Point Estimate	Standard Error	Point Estimate	Standard Error	Point Estimate	Standard Error
OBE→PBE→PA→ Indirect Effects	Soc	−0.000	0.000	−0.001	0.000	−0.002	0.001	−0.003	0.001
	Eco	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Env	−0.002	0.001	−0.002	0.001	0.002	0.002	0.002	0.002
OBE→PBE→ Indirect Effects	Soc	−0.002	0.002	−0.002	0.002	−0.014	0.007	−0.014	0.007
	Eco	−0.011	0.006	−0.012	0.006	−0.002	0.001	−0.002	0.001
	Env	0.017	0.010	0.018	0.009	**−0.016** *	0.011	**−0.019** *	0.012
OBE→PA→ Indirect Effects	Soc	−0.001	0.001	−0.001	0.001	−0.005	0.004	−0.006	0.004
	Eco	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000
	Env	−0.005	0.003	−0.005	0.004	0.004	0.005	0.004	0.005
Total Indirect Effects	Soc	−0.004	0.002	−0.004	0.002	−0.021	0.009	−0.022	0.009
	Eco	−0.012	0.006	**−0.013** *	0.006	−0.002	0.001	−0.002	0.001
	Env	0.010	0.009	0.010	0.009	−0.010	0.011	−0.013	0.012
Direct Effects	Soc	−0.003	0.010	−0.008	0.010	0.028	0.035	−0.008	0.035
	Eco	0.049	0.011	0.046	0.011	−0.077	0.010	−0.101	0.009
	Env	−0.045	0.044	−0.043	0.043	−0.453	0.083	0.324	0.085
Total Effects	Soc	−0.007	0.010	−0.013	0.010	0.007	0.035	−0.030	0.035
	Eco	**0.037** **	0.012	**0.033** **	0.012	**−0.079** ***	0.010	**−0.103** ***	0.009
	Env	−0.035	0.044	−0.033	0.043	**−0.463** ***	0.083	**0.311** ***	0.085

Underlined and bold values represent significant total and mediation effects (5000 bootstrap samples, 95% bias-correct confidence level). *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. PBE = perceived built environment; PA = place attachment; Soc = social dimension; Eco = economic dimension; Env = environmental dimension. "OBE→PBE →PA→" refers to the pathways from OBE to Soc/Eco/Env first through PBE, then PA; "OBE→PBE→" refers to the pathways from OBE to Soc/Eco/Env through PBE. "OBE→PA→" refers to the pathways from OBE to Soc/Eco/Env first through PA.

Table 8. Total, direct and indirect effects of OBE on P-RCR (western regions).

Pathways and Effects (Western Regions)	Dimensions	Model 1		Model 2		Model 3		Model 4	
		Point Estimate	Standard Error	Point Estimate	Standard Error	Point Estimate	Standard Error	Point Estimate	Standard Error
OBE→PBE→PA→ Indirect Effects	Soc	−0.001	0.000	−0.001	0.000	−0.002	0.001	−0.002	0.001
	Eco	−0.001	0.000	−0.001	0.000	0.000	0.000	0.000	0.000
	Env	−0.002	0.002	−0.002	0.002	−0.002	0.003	−0.002	0.004
OBE→PBE→ Indirect Effects	Soc	−0.004	0.002	−0.004	0.002	−0.010	0.006	−0.011	0.006
	Eco	**−0.024** ***	0.006	**−0.026** ***	0.006	**0.004** **	0.002	**0.004** **	0.002
	Env	0.021	0.008	0.023	0.008	0.007	0.013	0.009	0.015
OBE→PA→ Indirect Effects	Soc	−0.001	0.001	0.000	0.000	−0.002	0.002	−0.001	0.001
	Eco	−0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.000
	Env	−0.002	0.002	−0.001	0.002	−0.002	0.004	−0.001	0.003
Total Indirect Effects	Soc	−0.005	0.002	−0.005	0.002	−0.013	0.006	−0.014	0.006
	Eco	**−0.025** ***	0.006	**−0.027** ***	0.006	**0.004** **	0.002	**0.004** *	0.002
	Env	0.017	0.008	0.019	0.008	0.002	0.013	0.006	0.014
Direct Effects	Soc	0.007	0.009	0.020	0.009	0.035	0.036	0.064	0.035
	Eco	−0.010	0.012	0.000	0.011	0.087	0.011	0.105	0.010
	Env	−0.019	0.043	−0.035	0.042	0.562	0.092	0.343	0.089
Total Effects	Soc	0.002	0.009	0.014	0.009	0.022	0.036	0.049	0.035
	Eco	**−0.035** **	0.012	**−0.028** **	0.011	**0.090** ***	0.011	**0.109** ***	0.009
	Env	−0.003	0.042	−0.016	0.041	**0.564** ***	0.090	**0.349** ***	0.088

Underlined and bold values represent significant total and mediation effects (5000 bootstrap samples, 95%. bias-correct confidence level). *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. PBE = perceived built environment; PA = place attachment; Soc = social dimension; Eco = economic dimension; Env = environmental dimension. "OBE→PBE→PA→" refers to the pathways from OBE to Soc/Eco/Env first through PBE, then PA; "OBE→PBE→" refers to the pathways from OBE to Soc/Eco/Env through PBE. "OBE→PA→" refers to the pathways from OBE to Soc/Eco/Env first through PA.

5. Discussion

5.1. Significant Effects of PBE/OBE on Three Dimensions of P-RCR

Our findings show that both PBE and OBE significantly affected three dimensions of P-RCR. PBE had significant total effects on three dimensions of P-RCR in all regions at both the individual and community levels (except community-level Env in western regions). OBE significantly affected individual-level Soc (eastern regions), Eco (individual- and community-level Eco in central and western regions; individual-level Eco in eastern regions) and community-level Env (all regions). These findings statistically support that the way BE influences P-RCR is varied rather than constrained in a facility-economy approach.

5.2. Differences between Effects of PBE/OBE on Three Dimensions of P-RCR

PBE's impacts on P-RCR were consistent among regions regarding Soc, Eco and individual-level Env. PBE was positively associated with Soc and Eco in all regions at both levels, with the single exception of community-level Eco in the western regions. This indicates that better PBE leads to a greater P-RCR in Soc and Eco in most cases. This is in line with the findings based on a Western context that perceived adequacy of facilities, attractive BE and feelings of safety contribute to richer social capital and greater economic resilience [28,49,50]. Referring to Env, a negative link between PBE and individual-level Env was observed. One of the potential explanations for why PBE predicts residents' negative attitudes toward environmental protection is that residents' willingness and actions to protect the environment are frequently associated with environmental deterioration [68]. However, good PBE is more likely to correlate with a good residential environment. In terms of community-level Env, PBE's impacts showed an inconsistency in different regions. In central regions, better evaluations of PBE increased the likelihood of higher forest (and/or fruit tree) coverage in rural communities. It may be evidence of the finding that sufficient facilities or infrastructure raise farmers' willingness to participate in the Grain-for-Green Project in China [51]. However, this was not applicable for explaining the correlations between PBE and community-level Env in the eastern (negative) and western regions (insignificant). Therefore, further research is needed to ascertain the relationship between PBE and community-level Env.

Compared to PBE, OBE's impacts on the three dimensions of P-RCR were varied in different regions and levels. This implies that regional disparities may be critical to OBE's impacts on P-RCR, and OBE plays different roles in fostering individual- and community-level P-RCR. For instance, our results show that in the eastern coastal regions where rural industrial development levels were higher and rural income inequality levels were lower [60,61], higher population density or accessibility may result in lower levels of happiness and undermine Soc, but no similar correlation was found in inland central and western regions where rural industrial development levels were lower, and income inequality levels were higher. In terms of OBE's impacts on different levels of P-RCR, in central regions, higher population density or accessibility may have contributed to a greater Eco at the individual level but not at the community level; the exact reverse was the case in the western regions.

5.3. The Significant Mediation Roles PA and PBE Play in the BE-P-RCR Relationship

Our findings indicate that there are two significant mediation roles that PA plays in the BE-P-RCR relationship. One is the positive role in P-RCR enhancement. PA provides a critical indirect path through which better PBE bring an increment in Soc (eastern and central regions) and individual-level Eco (eastern regions). It counteracts the negative effects of OBE (accessibility/density) on happiness and OBE (accessibility) on personal financial stability in the eastern regions. It offsets the adverse effects of PBE on residents' attitudes toward environmental protection in the central regions. The other is the negative role in P-RCR enhancement. In the eastern regions, it reduces the positive impacts PBE has on community economic well-being. This suggests that the mediation effects of PA are not always beneficial to P-RCR, which is in line with the findings that different types of PA play different roles in RCR [54]. For example, residents with stability-oriented PA are often unwilling to change their current economic lifestyle closely related to rural facilities and services, which may not be good for enhancing community-level resilience [54].

In the western regions, OBE significantly influences Eco through PBE, and in eastern regions, accessibility has significant impacts on individual-level Eco through PBE. This supports the OBE-PBE relationship proposed by Marans [43] and the impacts of OBE/PBE on Eco. PBE also mediates the influences of OBE on community-level Env in the eastern and central regions, although the mechanisms remain unclear.

5.4. Strengths and Limitations

This study focused on the questions of whether and how BE affects P-RCR, subjects that attracted less attention in previous studies but are crucial to RCR enhancement. We investigated the effects of OBE/PBE on three dimensions of P-RCR using SEM based on the empirical data obtained from CFPS and a holistic framework combining OBE/PBE, PA and P-RCR. Our findings provide a more-detailed picture of the BE-P-RCR relationship and new empirical evidence of BE's multi-effects on P-RCR in terms of Soc, Eco and Env.

This study has several limitations. First, it was difficult to determine whether BE positively or negatively influences the overall level of P-RCR based on our study, since OBE and PBE had inverse effects on the same dimension at different levels in specific regions, and their effects on different dimensions were also inverse sometimes. Nevertheless, our findings are useful for researchers in understanding BE's impacts on specific dimensions and levels of P-RCR. Second, as stated earlier, the mechanism leading to PBE's impacts on community-level Env is still unclear. This may be a result of our measurement strategies (e.g., using biodiversity for community-level Env measurement) and data limitation. Therefore, more data and sophisticated research designs are required to understand the relationships between PBE and Env in future study. Third, the data we used in this study was collected in different waves, which might not have been beneficial for our research in terms of reliability. However, many researchers recognize that it is acceptable to apply data obtained from different waves of CFPS in the same analysis or SEM model considering the reality of China [64,72]. Moreover, we restricted respondents' residential addresses, income and professions when using 2014 and 2016 data for reliability improvement. As a result, applying data derived from 2014 to 2016 in this study would still be acceptable and reliable. Fourth, although our sample covered a large number of rural communities in China, our study was cross-sectional and limited to causality assessment. We could not verify the potential reciprocal causation between BE and P-RCR in this study, though resilient rural communities may intentionally increase built capital investments that improve BE qualities. This is not only because the exact pathways and scales by which P-RCR affects BE are still unclear, but also because the cross-sectional data can not statistically estimate reciprocal causation due to the lack of temporal precedence [73]. An improved model and panel data are needed in future studies. At last, the datasets we used were not recent, though they were the most recent datasets available in relation to BE in the released CFPS datasets. However, we believe the advantages of using these datasets were evident and that our findings are still valid for the current realities. The reasons are as follows. First, these datasets were longitudinal and nationally representative, providing high-quality and large sample-size data. Moreover, they can be updated in the future and facilitate our follow-up study with panel data. Second, at the core of our study was the BE-P-RCR relationship, which closely relates to psychological factors not easily changing with time, such as human cognition, emotions and behaviors. This means that for this study, the time factor might not be decisive. The consistency between our findings and some earlier study results discussed in the discussion section might be seen as evidence.

5.5. Implications

The results of our study imply that BE's impacts on P-RCR are multifaceted and should be fully considered in RCR study and practice, especially with regard to Soc and

Eco. When assessing or analyzing P-RCR in terms of Soc and Eco, rather than simplifying BE as facilities that purely increase rural communities' economic resilience, specific PBE and OBE attributes should be taken into account. To enhance P-RCR, besides the number of facilities and population density, PBE may be a key factor. Furthermore, one-size-fits-all criteria for accessibility might not be appropriate in different rural communities, for the effects of accessibility on P-RCR may be uneven among regions. Additionally, greater consideration needs to be given to the influences of PA on Soc and Eco at both the individual and community levels (e.g., happiness, trust, satisfaction with job and income) when any BE changes occur within rural reconstruction.

Based on our findings, the following recommendations are offered for rural community development and P-RCR enhancement in China or other countries or regions facing rural issues similar to those in China:

1. Improvements to the rural built environment, such as new rural reconstruction and rural settlement remediation, should not focus only on infrastructure development while ignoring people's perceptions and evaluations of their surrounding environment.
2. Top-down planning activities initiated by the government should develop more detailed and targeted planning schemes for rural service accessibility and village mergers, which will be helpful for increasing P-RCR in different regions.
3. The development and implementation of built environment policies should consider rural people's emotional ties with their communities, including both the pros and cons of these emotional ties for P-RCR.

6. Conclusions

To explore BE's effects on P-RCR, this study proposes a framework holistically depicting the BE-P-RCR relationship and tested this framework using SEM with a sample of 7528 rural respondents from eastern, central and western China. Our findings include the following: (1) Both OBE and PBE can significantly affect three fundamental dimensions of P-RCR; (2) apart from community-level Eco in western regions, PBE consistently and positively influenced Soc and Eco but negatively influenced individual-level Env despite regional disparities; OBE's impacts on three dimensions of P-RCR were varied among regions; (3) PA and PBE were mediators in the BE-P-RCR relationship in certain regions. Based on these findings, we argue that the multi-effects of BE on P-RCR should be taken into account in RCR research and practice, especially regarding Soc and Eco.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of Peking University Institutional Review Board (IRB00001052-14010, every July).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found here: [http://www.isss.pku.edu.cn/cfps/ (accessed on 21 June 2022)].

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

Appendix A

Table A1. Composite reliability (CR) and average variance extracted (AVE) for latent variables with multiple indicators.

Regions	CR and AVE	PBE [1]	Individual-Level Soc [2]	Individual-Level Eco [3]	Covariate [4]
Eastern	CR	0.715	0.740	0.772	0.730
	AVE	0.456	0.490	0.533	0.474
Central	CR	0.724	0.702	0.776	0.722
	AVE	0.468	0.446	0.539	0.464
Western	CR	0.644	0.631	0.759	0.692
	AVE	0.380	0.367	0.514	0.428

[1] PBE = perceived built environment; [2] Soc = social dimension of proactive aspect of rural community resilience; [3] Eco = economic dimension of proactive aspect of rural community resilience; [4] Covariate = self-reported socioeconomic status.

Table A2. Discriminant validity for latent variables with multiple indicators.

Variables	PBE [1]	Individual-Level Soc [2]	Individual-Level Eco [3]	Covariate [4]
		Eastern Regions		
PBE [1]	**0.675**			
Individual-level Soc [2]	0.285	**0.700**		
Individual-level Eco [3]	0.465	0.296	**0.730**	
Covariate [4]	0.166	0.510	0.257	**0.688**
		Central Regions		
PBE [1]	**0.684**			
Individual-level Soc [2]	0.252	**0.668**		
Individual-level Eco [3]	0.496	0.261	**0.734**	
Covariate [4]	0.226	0.596	0.248	**0.681**
		Western Regions		
PBE [1]	**0.616**			
Individual-level Soc [2]	0.163	**0.606**		
Individual-level Eco [3]	0.460	0.246	**0.717**	
Covariate [4]	0.146	0.568	0.229	**0.654**

The square roots of AVE values are shown in bold font. [1] PBE = perceived built environment; [2] Soc = social dimension of proactive aspect of rural community resilience; [3] Eco = economic dimension of proactive aspect of rural community resilience; [4] Covariate = self-reported socioeconomic status.

Table A3. Specific model fits of each model.

Models *	CMIN/DF	CFI	RMSEA	SRMR
		Eastern Regions		
Model 1	3.556	0.979	0.031	0.0247
Model 2	3.564	0.979	0.031	0.0247
Model 3	2.236	0.990	0.021	0.0140
Model 4	2.236	0.990	0.021	0.0141
		Central Regions		
Model 1	3.411	0.974	0.034	0.0260
Model 2	3.083	0.978	0.031	0.0247
Model 3	3.711	0.973	0.036	0.0222
Model 4	3.633	0.974	0.035	0.0220

Table A3. *Cont.*

Models *	CMIN/DF	CFI	RMSEA	SRMR
		Western Regions		
Model 1	4.584	0.961	0.037	0.0279
Model 2	4.677	0.960	0.037	0.0284
Model 3	4.106	0.965	0.034	0.0207
Model 4	4.269	0.964	0.035	0.0215

* Model 1 refers to individual-level model with population density as the exogenous variable; Model 2 refers to individual-level model with accessibility as the exogenous variable; Model 3 refers to community-level model with population density as the exogenous variable; Model 4 refers to community-level model with accessibility as the exogenous variable. CMIN/DF = Chi-square/degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

References

1. Li, Y.; Westlund, H.; Liu, Y. Why some rural areas decline while some others not: An overview of rural evolution in the world. *J. Rural Stud.* **2019**, *68*, 135–143. [CrossRef]
2. McManus, P.; Walmsley, J.; Argent, N.; Baum, S.; Bourke, L.; Martin, J.; Pritchard, B.; Sorensen, T. Rural Community and Rural Resilience: What is important to farmers in keeping their country towns alive? *J. Rural Stud.* **2012**, *28*, 20–29. [CrossRef]
3. Jerolleman, A. Challenges of Post-Disaster Recovery in Rural Areas. In *Louisiana's Response to Extreme Weather*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 285–310.
4. Scott, M. Resilience: A Conceptual Lens for Rural Studies? *Geogr. Compass* **2013**, *7*, 597–610. [CrossRef]
5. Markantoni, M.; Steiner, A.A.; Meador, J.E. Can community interventions change resilience? Fostering perceptions of individual and community resilience in rural places. *Community Dev.* **2019**, *50*, 238–255. [CrossRef]
6. Skerratt, S. Enhancing the analysis of rural community resilience: Evidence from community land ownership. *J. Rural Stud.* **2013**, *31*, 36–46. [CrossRef]
7. Imperiale, A.J.; Vanclay, F. Experiencing local community resilience in action: Learning from post-disaster communities. *J. Rural Stud.* **2016**, *47*, 204–219. [CrossRef]
8. Fischer, A.; McKee, A. A question of capacities? Community resilience and empowerment between assets, abilities and relationships. *J. Rural Stud.* **2017**, *54*, 187–197. [CrossRef]
9. Cutter, S.L.; Barnes, L.; Berry, M.; Burton, C.; Evans, E.; Tate, E.; Webb, J. A place-based model for understanding community resilience to natural disasters. *Glob. Environ. Change* **2008**, *18*, 598–606. [CrossRef]
10. Magis, K. Community Resilience: An Indicator of Social Sustainability. *Soc. Nat. Resour.* **2010**, *23*, 401–416. [CrossRef]
11. Maguire, B.; Cartwright, S. *Assessing a Community's Capacity to Manage Change: A Resilience Approach to Social Assessment*; Australian Government Bureau of Rural Sciences: Canberra, Australia, 2008.
12. Kulig, J.C. Community resiliency: The potential for community health nursing theory development. *Public Health Nurs.* **2000**, *17*, 374–385. [CrossRef] [PubMed]
13. Steiner, A.; Markantoni, M. Unpacking Community Resilience through Capacity for Change. *Community Dev. J.* **2013**, *49*, 407–425. [CrossRef]
14. Roberts, E.; Anderson, B.A.; Skerratt, S.; Farrington, J. A review of the rural-digital policy agenda from a community resilience perspective. *J. Rural Stud.* **2017**, *54*, 372–385. [CrossRef]
15. Mackay, M.; Petersen, K. *Rural Community Resilience: Research Stocktake and Annotated Bibliography*; Faculty of Environment, Society and Design, Lincoln University: Christchurch, New Zealand, 2015.
16. Wang, S.; Tang, W.; Qi, D.; Li, J.; Wang, E.; Lin, Z.; Duffield, C. Understanding the Role of Built Environment Resilience to Natural Disasters: Lessons Learned from the Wenchuan Earthquake. *J. Perform. Constr. Facil.* **2017**, *31*, 04017058. [CrossRef]
17. Frank, L.D.; Engelke, P. Multiple Impacts of the Built Environment on Public Health: Walkable Places and the Exposure to Air Pollution. *Int. Reg. Sci. Rev.* **2005**, *28*, 193–216. [CrossRef]
18. Handy, S.L.; Boarnet, M.G.; Ewing, R.; Killingsworth, R.E. How the built environment affects physical activity: Views from urban planning. *Am. J. Prev. Med.* **2002**, *23* (Suppl. 1), 64–73. [CrossRef]
19. McAllister, T.P. Community Resilience: The Role of the Built Environment. In *Multi-Hazard Approaches to Civil Infrastructure Engineering*; Gardoni, P., LaFave, J.M., Eds.; Springer: Cham, Switzerland, 2016; pp. 533–548.
20. Cutter, S.; Ash, K.; Emrich, C. Urban–Rural Differences in Disaster Resilience. *Ann. Am. Assoc. Geogr.* **2016**, *106*, 1236–1252. [CrossRef]
21. Zhu, H.; Ji, P.; Chen, Z.; Jiang, Z. Rural Resilience and Its Influencing Factors in Zhejiang Province From the Perspective of Heterogeneity. *Econ. Geogr.* **2021**, *41*, 160–166+222.
22. Payne, P.; Kaye-Blake, W.; Kelsey, A.; Brown, M.; Niles, M. Measuring rural community resilience: Case studies in New Zealand and Vermont, USA. *Ecol. Soc.* **2021**, *26*. [CrossRef]
23. Wilson, G.A.; Schermer, M.; Stotten, R. The resilience and vulnerability of remote mountain communities: The case of Vent, Austrian Alps. *Land Use Policy* **2018**, *71*, 372–383. [CrossRef]

24. Steiner, A.; Atterton, J. Exploring the contribution of rural enterprises to local resilience. *J. Rural Stud.* **2015**, *40*, 30–45. [CrossRef]
25. Harris, C.C.; McLaughlin, W.; Brown, G.; Becker, D. *Rural Communities in the Inland Northwest: An Assessment of Small Communities in the Interior and Upper Columbia River Basins*; General Technical Report PNW; USDA Forest Service: Washington, DC, USA, 2000; pp. 1–120.
26. Farmer, J.; Prior, M.; Taylor, J. A theory of how rural health services contribute to community sustainability. *Soc. Sci. Med.* **2012**, *75*, 1903–1911. [CrossRef]
27. Prior, M.; Farmer, J.; Godden, D.J.; Taylor, J. More than health: The added value of health services in remote Scotland and Australia. *Health Place* **2010**, *16*, 1136–1144. [CrossRef]
28. Buikstra, E.; Ross, H.; King, C.A.; Baker, P.G.; Hegney, D.; McLachlan, K.; Rogers-Clark, C. The components of resilience—Perceptions of an Australian rural community. *J. Community Psychol.* **2010**, *38*, 975–991. [CrossRef]
29. Huang, J.; Liu, Y. Environmental Pollution in Rural China and Its Driving Forces. *Chin. J. Manag.* **2010**, *7*, 1725–1729.
30. Wilson, G.A. *Community Resilience and Environmental Transitions*; Routledge: New York, NY, USA, 2012; pp. 1–251.
31. Skjaeveland, O.; Garling, T. Effects of Interactional Space on Neighbouring. *J. Environ. Psychol.* **1997**, *17*, 181–198. [CrossRef]
32. Perkins, D.D.; Long, D.A. Neighborhood Sense of Community and Social Capital. In *Psychological Sense of Community: Research, Applications, and Implications*; Fisher, A.T., Sonn, C.C., Bishop, B.J., Eds.; Springer: Boston, MA, USA, 2002; pp. 291–318.
33. Wilson, G.A.; Hu, Z.; Rahman, S. Community resilience in rural China: The case of Hu Village, Sichuan Province. *J. Rural Stud.* **2018**, *60*, 130–140. [CrossRef]
34. Liu, Z.; Liu, S.; Jin, H.; Qi, W. Rural population change in China: Spatial differences, driving forces and policy implications. *J. Rural Stud.* **2017**, *51*, 189–197. [CrossRef]
35. National Bureau of Statistics. Available online: https://data.stats.gov.cn/easyquery.htm?cn=C01 (accessed on 15 November 2022).
36. Ye, J. Stayers in China's "hollowed-out" villages: A counter narrative on massive rural–urban migration. *Popul. Space Place* **2018**, *24*, e2128. [CrossRef]
37. Liu, Y.; Zang, Y.; Yang, Y. China's rural revitalization and development: Theory, technology and management. *J. Geogr. Sci.* **2020**, *30*, 1923–1942. [CrossRef]
38. Zhang, R.; Yuan, Y.; Li, H.; Hu, X. Improving the framework for analyzing community resilience to understand rural revitalization pathways in China. *J. Rural Stud.* **2022**, *94*, 287–294. [CrossRef]
39. Yang, B.; Feldman, M.W.; Li, S. The status of perceived community resilience in transitional rural society: An empirical study from central China. *J. Rural Stud.* **2020**, *80*, 427–438. [CrossRef]
40. Lu, Y.; Qian, J. Towards a material approach in rural geography: Architectural experiments in China's rural renaissance and reconstruction movements. *Geoforum* **2020**, *116*, 119–129. [CrossRef]
41. Tian, Y.; Kong, X.; Liu, Y.; Wang, H. Restructuring rural settlements based on an analysis of inter-village social connections: A case in Hubei Province, Central China. *Habitat Int.* **2016**, *57*, 121–131. [CrossRef]
42. Kong, X.; Liu, D.; Tian, Y.; Liu, Y. Multi-objective spatial reconstruction of rural settlements considering intervillage social connections. *J. Rural Stud.* **2021**, *84*, 254–264. [CrossRef]
43. Marans, R.W. Quality of Urban Life Studies: An Overview and Implications for Environment-Behaviour Research. *Procedia—Soc. Behav. Sci.* **2012**, *35*, 9–22. [CrossRef]
44. Guo, Y.; Liu, Y.; Lu, S.; Chan, O.F.; Chui, C.H.K.; Lum, T.Y.S. Objective and perceived built environment, sense of community, and mental wellbeing in older adults in Hong Kong: A multilevel structural equation study. *Landsc. Urban Plan.* **2021**, *209*, 104058. [CrossRef]
45. Lewicka, M. Place attachment: How far have we come in the last 40 years? *J. Environ. Psychol.* **2011**, *31*, 207–230. [CrossRef]
46. Chaskin, R.J. Resilience, Community, and Resilient Communities: Conditioning Contexts and Collective Action. *Child Care Pract.* **2008**, *14*, 65–74. [CrossRef]
47. Wilson, G. Multifunctional 'Quality' and Rural Community Resilience. *Trans. Inst. Br. Geogr.* **2010**, *35*, 364–381. [CrossRef]
48. Yang, T.; Chen, H.; Liu, D.; Zhang, H.; Shi, Q. Spatiotemporal change of rural community resilience in loess hilly-gully region and influencing factors:A case study of Gaoqu Township in Mizhi County, Shannxi Province. *Prog. Geogr.* **2021**, *40*, 245–256. [CrossRef]
49. Wood, L.; Shannon, T.; Bulsara, M.; Pikora, T.; McCormack, G.; Giles-Corti, B. The anatomy of the safe and social suburb: An exploratory study of the built environment, social capital and residents' perceptions of safety. *Health Place* **2008**, *14*, 15–31. [CrossRef] [PubMed]
50. Renalds, A.; Smith, T.H.; Hale, P.J. A Systematic Review of Built Environment and Health. *Fam. Community Health* **2010**, *33*, 68–78. [CrossRef]
51. Zhu, S.; Zhang, S.; Tao, W.; Wu, D.; Xie, X.; Yue, P. Identification and Analysis of the Factors Influencing Farmers' Choices to Replant Crops in the SLCP Program. *China Popul. Resour. Environ.* **2005**, *15*, 112–116.
52. Gifford, R. Environmental Psychology Matters. *Annu. Rev. Psychol.* **2014**, *65*, 541–579. [CrossRef]
53. Guo, Y.; Zhang, J.; Zhang, Y. Influencing factors and mechanism of community resilience in tourism destinations. *Geogr. Res.* **2018**, *37*, 133–144.
54. Zwiers, S.; Markantoni, M.; Strijker, D. The role of change- and stability-oriented place attachment in rural community resilience: A case study in south-west Scotland. *Community Dev. J.* **2016**, *53*, 281–300. [CrossRef]

55. Bunkus, R.; Soliev, I.; Theesfeld, I. Density of resident farmers and rural inhabitants' relationship to agriculture: Operationalizing complex social interactions with a structural equation model. *Agric. Hum. Values* **2020**, *37*, 47–63. [CrossRef]
56. Christiaanse, S.; Haartsen, T. The influence of symbolic and emotional meanings of rural facilities on reactions to closure: The case of the village supermarket. *J. Rural Stud.* **2017**, *54*, 326–336. [CrossRef]
57. Peng, J.; Yan, S.; Strijker, D.; Wu, Q.; Chen, W.; Ma, Z. The influence of place identity on perceptions of landscape change: Exploring evidence from rural land consolidation projects in Eastern China. *Land Use Policy* **2020**, *99*, 104891. [CrossRef]
58. Anton, C.E.; Lawrence, C. Home is where the heart is: The effect of place of residence on place attachment and community participation. *J. Environ. Psychol.* **2014**, *40*, 451–461. [CrossRef]
59. Xie, Y.; Hu, J. An Introduction to the China Family Panel Studies (CFPS). *Chin. Sociol. Rev.* **2014**, *47*, 3–29.
60. Zheng, L.; Shepherd, D.; Batuo, M.E. Variations in the determinants of regional development disparities in rural China. *J. Rural Stud.* **2021**, *82*, 29–36. [CrossRef]
61. Gao, J.; Liu, Y.; Chen, J.; Cai, Y. Demystifying the geography of income inequality in rural China: A transitional framework. *J. Rural Stud.* **2022**, *93*, 398–407. [CrossRef]
62. Ao, Y.; Chen, C.; Yang, D.; Wang, Y. Relationship between Rural Built Environment and Household Vehicle Ownership: An Empirical Analysis in Rural Sichuan, China. *Sustainability* **2018**, *10*, 1566. [CrossRef]
63. Mazumdar, S.; Learnihan, V.; Cochrane, T.; Davey, R. The Built Environment and Social Capital: A Systematic Review. *Environ. Behav.* **2018**, *50*, 119–158. [CrossRef]
64. Sun, B.; Yan, H.; Zhang, T. Impact of community built environment on residents' health: A case study on individual overweight. *Acta Geogr. Sin.* **2016**, *71*, 1721–1730.
65. Seguin, R.A.; Lo, B.K.; Sriram, U.; Connor, L.M.; Totta, A. Development and testing of a community audit tool to assess rural built environments: Inventories for Community Health Assessment in Rural Towns. *Prev. Med. Rep.* **2017**, *7*, 169–175. [CrossRef] [PubMed]
66. Araya, R.; Dunstan, F.; Playle, R.; Thomas, H.; Palmer, S.; Lewis, G. Perceptions of social capital and the built environment and mental health. *Soc. Sci. Med.* **2006**, *62*, 3072–3083. [CrossRef] [PubMed]
67. Shen, Y.; Jia, J. An Empirical Study on Happiness, Income Gap and Social Capital. *J. Public Manag.* **2016**, *13*, 100–110+158.
68. Inglehart, R. Public Support for Environmental Protection: Objective Problems and Subjective Values in 43 Societies. *PS Political Sci. Amp Politics* **1995**, *28*, 57–72. [CrossRef]
69. Dash, G.; Paul, J. CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technol. Forecast. Soc. Change* **2021**, *173*, 121092. [CrossRef]
70. Bagozzi, R.P.; Yi, Y. On the Evaluation of Structural Equation Models. *J. Acad. Mark. Sci.* **1988**, *16*, 74–94. [CrossRef]
71. Chin, W.W. Issues and Opinion on Structural Equation Modeling. *MIS Q.* **1998**, *22*, vii–xvi.
72. Lei, P.; Feng, Z. Age-friendly neighbourhoods and depression among older people in China: Evidence from China Family Panel Studies. *J. Affect. Disord.* **2021**, *286*, 187–196. [CrossRef] [PubMed]
73. Kline, R.B. *Principles and Practice of Structural Equation Modeling*, 4th ed.; Guilford Press: New York, NY, USA, 2016; pp. 1–534.

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Article

Spatiotemporal Analysis of the Coupling Relationship between Habitat Quality and Urbanization in the Lower Yellow River

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Abstract: Natural habitats are damaged by human interference to varying degrees during the urbanization process, which can impede a region's high-quality development. In this study, we examined the spatial–temporal evolution characteristics of habitat quality and urbanization in the Lower Yellow River from 2000 to 2020 using the integrated valuation of ecosystem services and tradeoffs (InVEST) model and the comprehensive indicator method. We also evaluated the coupling relationship between the habitat quality and urbanization using the coupling coordination degree model. The findings indicate the following aspects: (1) Between 2000 and 2020, the Lower Yellow River's habitat quality was typically mediocre, with a steady declining trend. The majority of cities displayed a trend toward declining habitat quality. (2) Both the urbanization subsystem and the urbanization level in 34 cities have demonstrated a consistent growth tendency. The urbanization level is most affected by economic urbanization among the subsystems. (3) The coupling coordination degree have revealed an ongoing trend of growth. In most cities, the relationship between habitat quality and urbanization has been evolving toward coordination. The results of this study have some reference value for ameliorating the habitat quality of the Lower Yellow River and solving the coupling coordination relationship between habitat quality and urbanization.

Keywords: habitat quality; InVEST; urbanization; coupling coordination; Lower Yellow River

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1. Introduction

The ability of a habitat to supply biological communities with stable conditions is referred to as habitat quality (HQ) [1,2]. On one hand, the background circumstances of local natural resources affect the HQ. On the other hand, the HQ also depends on the intensity of outside disturbances [3]. Human intervention during the urbanization process has significantly altered natural environments. It is believed that human activity during the urbanization process directly threatens the quality of the local habitats. Severe environmental degradation has occurred in such habitats [4,5]. In an earlier study, the HQ was typically evaluated using the indicator assessment method, which built a system of indicators using data from field surveys. To measure the HQ of Chinese provinces, Fu [6] chose 12 indicators, such as soil erosion, land salinization, and solid waste contamination. However, the laborious processes of field sampling and field surveys make it challenging to apply the indicator assessment method to large-scale HQ assessments [7]. Model evaluation has increasingly grown in importance as a research method for HQ due to the maturity of technical instruments such as remote sensing systems and the quick development of HQ assessment models [8,9]. For long-term HQ monitoring, the model assessment method has a number of advantages over the integrated indicator evaluation method [10]. The habitat suitability index (HSI) model [11], social values for ecosystem services (SolVES) model [12,13], and InVEST model [14,15] are examples of common models. The InVEST model assesses biodiversity based on the quantity of the habitat exposed to external threats, which it deems to be the primary factor contributing to the degradation of HQ [16,17]. In comparison to other models, the InVEST model has better evaluation accuracy and is more convenient for data acquisition. As a result, the InVEST model is increasingly being used in dynamic habitat quality evaluations [18].

Urbanization is a concept with multiple implications. Numerous topics are covered, including populations, economies, social security, culture, and health care [19,20]. The understanding of urbanization varies among academics from various disciplines, which has a significant impact on how urbanization levels are quantified [21–24]. The comprehensive index method may quantify the urbanization level more thoroughly than other methods of evaluation. One of the most important factors in determining the urbanization level using the comprehensive indicator method is the selection of indicators. In terms of the construction of the indicator system, the study of building the urbanization indicator system from the four aspects of space, population, economy, and society has a significant impact [25]. Urbanized systems and natural ecosystems interact in a complex way. In order to systematically analyze the coupling and coordination relationship between urbanization and habitats, we chose the comprehensive indicator method to evaluate the transformation of the urbanization level in the Lower Yellow River.

The impact of urbanization on ecological environments is one of the important issues in the study of human–land relationships. Earlier studies focused more on the impacts of urbanization on single environmental factors such as air and water [26]. These environmental factors are usually closely related to human health. The natural ecosystem is a complex system which includes soil, water, organisms, and other environmental elements [27]. Since the negative impacts of intense human activities on the authenticity and stability of natural ecosystems have been widely recognized, the interaction between urbanization and natural ecosystems has gradually become the focus of scholars. In recent years, scholars have analyzed the relationship between urbanization and ecological environments from the perspectives of ecosystem services [28] and landscape fragmentation [29–31], but the research on the coupling relationship between HQ and urbanization is insufficient. The quality of a habitat is determined by the natural background condition of habitat and the intensity of external threats represented by human activities. The quantitative study of the coupling relationship between HQ and urbanization plays an important role in coordinating the human–land relationship and is worthy of further study.

The Yellow River Basin is an important biological barrier in China, and it is vital to coordinate basin protection and development issues in order to ensure long-term national stability [32]. The ecological preservation and sustainable development of the Yellow River Basin have recently emerged as crucial national strategies. The Yellow River Basin's ecological conservation is a hot topic of research right now [33]. Studies on the relationship between the ecological environment and urbanization in the Yellow River Basin have primarily concentrated on the basin as a whole or on arid and semi-arid regions such as Shaanxi and Ningxia [34–36]. There haven't been many studies on the relationship between HQ and urbanization in the Lower Yellow River. The Lower Yellow River has higher resident population density and gross regional product in the Yellow River Basin. The Lower Yellow River has become more essential for its ability to sustain regional economic growth and habitat protection [37]. The interactive coupling link between HQ and urbanization development in the Lower Yellow River must be quantitatively studied. Understanding the characteristics of the coupling coordination involving HQ and urbanization is strategically important for promoting HQ and high-quality economic growth in the Lower Yellow River. This is also a key issue for coordinating the interactions between people and the land and fostering sustainable development.

Based on this, the two primary scientific questions addressed in this study are as follows: (1) How did the coupling relationship between the natural habitat and urbanization evolve in the Lower Yellow River from 2000 to 2020? (2) How do the coupling relationships between different urbanization subsystems and the ecological environment differ? In order to tackle these scientific questions, our study uses the InVEST model to evaluate the HQ of the Lower Yellow River from 2000 to 2020, generates urbanization indicators to describe the regional urbanization level using socioeconomic data, and uses the coupling and coordination degree model (CCDM) to reveal the relationship between HQ and the urbanization level. More particularly, our research aims to (1) describe the spatial and temporal distribution of the habitat quality in the Lower Yellow River from 2000 to 2020; (2) assess the urbanization level of urban agglomerations in the Lower Yellow River from population, economics, social security, and space perspectives; and (3) disclose the spatiotemporal evolution of the coupling coordination relationship between HQ and urbanization in the Lower Yellow River.

2. Data Material Sources and Research Methods

2.1. Definition of the Study Area

Geographically speaking, the Lower Yellow River refers to the stretch of the river that runs through the provinces of Shandong and Henan from Taohuayu to the estuary. Meanwhile, the integrity of the administrative unit should be preserved as much as is feasible in the coupling research of the ecological environment and urbanization. In order to do this, we adhered to the maxim of "taking the natural watershed of the Yellow River as the core scope and protecting the integrity of the administrative unit in every feasible way" [38]. We defined the Lower Yellow River's geographic scope as 34 cities in the provinces of Henan and Shandong (Figure 1).

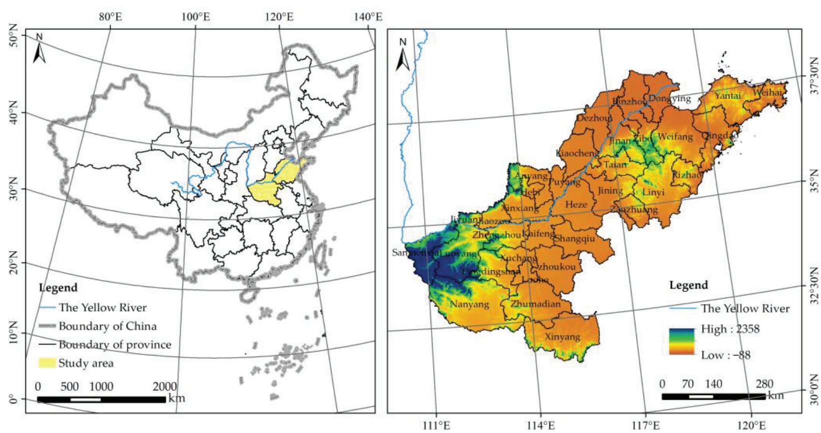

Figure 1. Location of the study area.

2.2. Data Sources and Processing

The five epochs of land use data of the Lower Yellow River were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/), accessed on 1 September 2022. With the exception of marshes, we combined the six secondary land use classifications as unused land (the primary land use classification) based on the original categorization system. The socioeconomic data needed for the construction of the urbanization index system were obtained from the Shandong Province Statistical Yearbook, the Henan Province Statistical Yearbook, and the China Urban Statistical Yearbook.

2.3. Methods

2.3.1. Evaluation of Habitat Quality

We calculated the habitat quality (HQ) index based on the InVEST model. The HQ is based on the degree to which each land use type is compatible with the habitat, manner, and radius of the threat source's influence and the susceptibility of the land class to the danger source [39]. The formula is shown below as follows:

$$Q_{xj} = H_j \left[1 - \left(\frac{D_{xj}}{D_{xj} + k} \right) \right] \quad (1)$$

where Q_{xj} represents the habitat quality index of raster cell x of land use type j, and H_j is the habitat suitability of land use type j. Here, D_{xj} is the habitat degradation index of raster cell x of land use type j, and it is calculated using Equation (2); k is a semi-saturated parameter whose value is equal to half of the maximum value of the habitat degradation index:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Yr} \left(\frac{w_r}{\sum\limits_{r=1}^{R} w_r} \right) r_y i_{rxy} \beta_x S_{jr} \quad (2)$$

where R is the number of threat sources, y represents a grid cell in the threat source layer r, Y_r is the total number of grid cells of the threat source r, w_r is the weight of threat source r, S_{jr} is the sensitivity of land use type j to threat source r, and β_x is the degree of legal protection. Here, r_y is an auxiliary value used to determine the position of the threat source raster in the layer. In the threat source layer, if the raster y belongs to the threat source, $r_y = 1$, otherwise $r_y = 0$. As shown in the equation below, i_{rxy} is calculated in two ways, as a linear decline and exponential decline:

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\max}} \right) \text{ if linear} \quad (3)$$

$$i_{rxy} = \exp\left(-2.99 \left(\frac{d_{xy}}{d_{r\max}} \right) \right) \text{ if exponential} \quad (4)$$

where d_{xy} represents the distance between raster x and y; $d_{r\max}$ represents the maximum influence distance of threat source r.

From the above equations, we can conclude that identifying the threat sources and threat parameters is crucial for the efficient operation of the InVEST model. The Lower Yellow River is an important grain-producing area in China. This region includes the urban agglomerations of Zhongyuan and the Shandong peninsula. In this situation, the major threats to the environment are cropped land and construction land because they are directly tied to human activities. The unutilized land's natural background state is poor, posing a danger to the surrounding habitat. Given the features of the study area, relevant studies, and experts' opinions, we chose paddy field, dry land, urban construction land, rural residential land, and other land use types as threat sources. Tables 1 and 2 show the model input parameters, whose values are derived from the InVEST model guidebook, scholars' research [40–42], and experts' opinions.

Table 1. Maximum impact distances, weights, and spatial recession types of threat sources.

Threat Source (r)	Maximum Threat Distance ($d_{r\max}$)/km	Weight (w_r)	Decay
Paddy field	1	0.5	linear
Dry land	1	0.5	linear
Urban construction land	8	1	exponential
Rural residential land	4	0.7	exponential
Other construction land	9	0.9	exponential
Other unutilized land	1	0.3	linear

Table 2. Habitat suitability of land use types and their sensitivity to threat sources.

Land Type (j)	Habitat Suitability (H_j)	Sensitivity (S_{jr})					
		Paddy Field	Dry Land	Urban Construction Land	Rural Residential Land	Other Construction Land	Other Unutilized Land
Paddy field	0.4	0	0.7	0.3	0	0	0.7
Dry land	0.3	0	0.6	0.2	0	0	0.6
Forest land	0.9	0.6	0.9	0.5	0.6	0.6	0.85
Scrub woodland	0.8	0.5	0.85	0.45	0.5	0.5	0.75
Sparse woodland	0.75	0.5	0.85	0.45	0.5	0.5	0.75
Other woodland	0.65	0.45	0.85	0.4	0.45	0.45	0.7
High-coverage grassland	0.7	0.55	0.9	0.5	0.55	0.55	0.85
Medium-coverage grassland	0.6	0.5	0.85	0.45	0.5	0.5	0.75
Low-coverage grassland	0.55	0.45	0.8	0.4	0.45	0.45	0.75
River	0.9	0.6	0.9	0.5	0.6	0.6	0.85
Lake	1	0.6	0.9	0.5	0.6	0.6	0.85
Reservoir	0.7	0.55	0.8	0.45	0.55	0.55	0.75
Mudflat	0.5	0.4	0.75	0.4	0.4	0.4	0.7
Beach	0.5	0.4	0.75	0.4	0.4	0.4	0.7
Swamp	0.55	0.45	0.8	0.4	0.45	0.45	0.7
Sea	0.85	0.6	0.6	0.85	0.7	0.9	0.5
Other unutilized land	0.15	0.35	0.35	0.55	0.4	0.55	0

2.3.2. Evaluation of Urbanization

Considering the data accessibility and comparability, we selected 17 indicators from the population, economic, social security, and space categories. The urbanization evaluation index system is shown in Figure 2. We utilized the linear weighted sum approach to evaluate the urbanization levels. The calculation formula is shown below:

$$U_i = \sum_{j=1}^{n} w_j \times U_{ij} \tag{5}$$

Here, w_j stands for the indicator j's weight, and U_{ij} for the indicator j's normalized value in city i. Each indicator's weights were calculated using the entropy weight approach.

2.3.3. Coupling Coordination Degree Model

The coupling coordination degree model, which contains the coupling degree C, the comprehensive evaluation index T, and the coupling coordination degree D, is able to quantify the degree of coherence in the system's development [43]. However, it is difficult to objectively reflect the level of synergy between systems by relying on the coupling degree alone, so T and D are defined to reflect the degree of system contribution to coordination [44]. In order to analyze the status of HQ and urbanization in the coupling coordination link, a synchronous development index E is constructed to explain the synchronous or lagging state of the two processes:

$$C = 2\sqrt{\frac{U_1 U_2}{(U_1 + U_2)^2}} \tag{6}$$

$$T = aU_1 + bU_2 \tag{7}$$

$$D = \sqrt{CT} \tag{8}$$

$$E = U_1 / U_2 \tag{9}$$

where U_1 and U_2 denote the HQ and urbanization level, respectively; a and b are coefficients to be determined; $a + b = 1$, a, b are used to characterize the importance of the HQ and urbanization level. Referring to the studies by Ma et al. [45] and Tang et al. [46], we considered the habitat quality system as equally important as the urbanization system, so we set a, b = 0.5. The values of C, D are between 0 and 1. The type of coupling coordination was divided as shown in Figure 3.

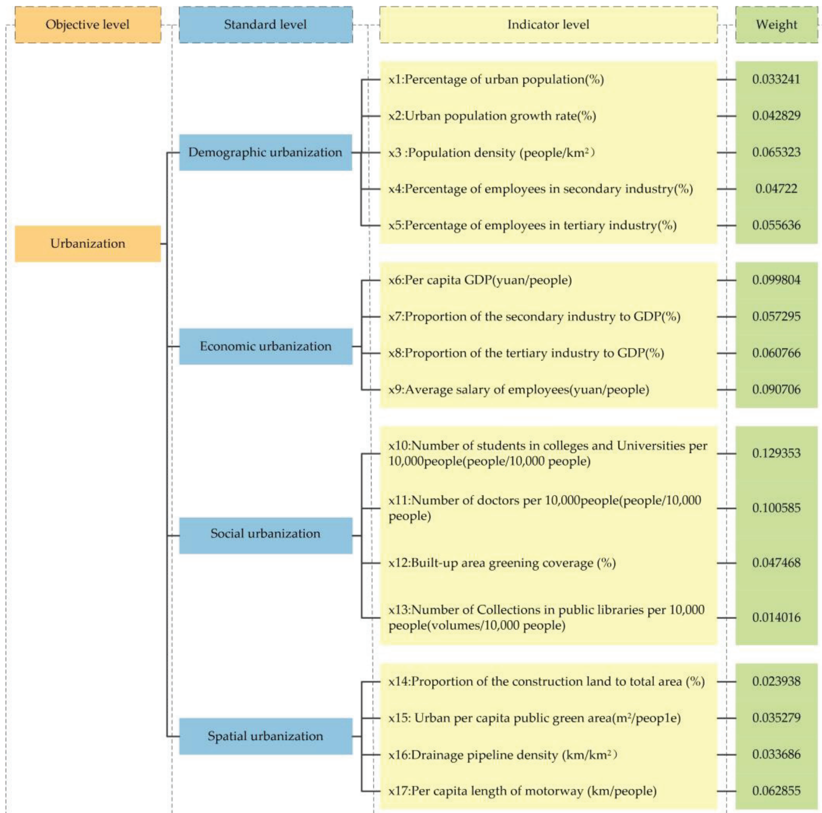

Figure 2. The Lower Yellow River's urbanization evaluation index system.

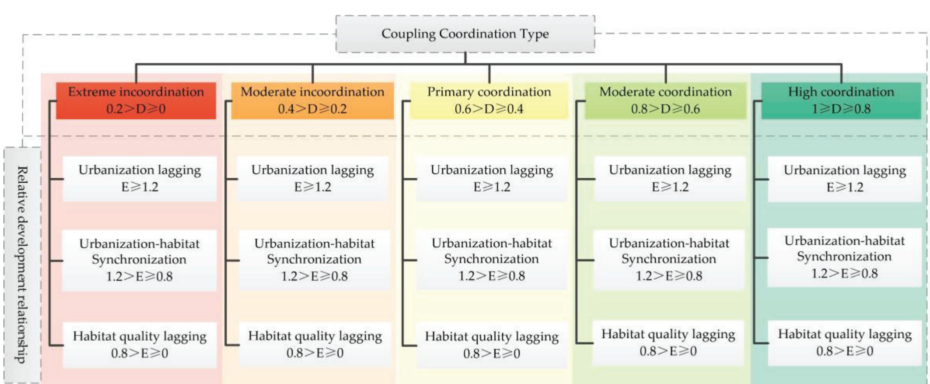

Figure 3. Coupling coordination types of urbanization and HQ.

3. Results

3.1. Variations in Habitat Quality through Time and Space along the Lower Yellow River

Using the InVEST model, we evaluated the Lower Yellow River's HQ status in the years 2000, 2005, 2010, 2015, and 2020. We divided the HQ into five categories: low (0.0–0.02), relatively low (0.2–0.4), medium (0.4–0.6), relatively high (0.6–0.8), and high (0.8–1). The findings indicated that the Lower Yellow River's HQ was generally in poor condition and has been declining steadily from 2000 to 2020, with mean values of 0.368, 0.366, 0.365, 0.364, and 0.357, respectively. The HQ values of several cities in the research area varied dramatically between 2000 and 2020, ranging from 0.239 to 0.621. Sanmenxia consistently maintained the highest level of HQ, followed by Luoyang and Jiyuan at various points in time. The HQ values of Nanyang, Xinyang, Yantai, Pingdingshan, and Zibo were all higher than the study area average, while more than 67% of the cities were lower to varying degrees (Figure 4).

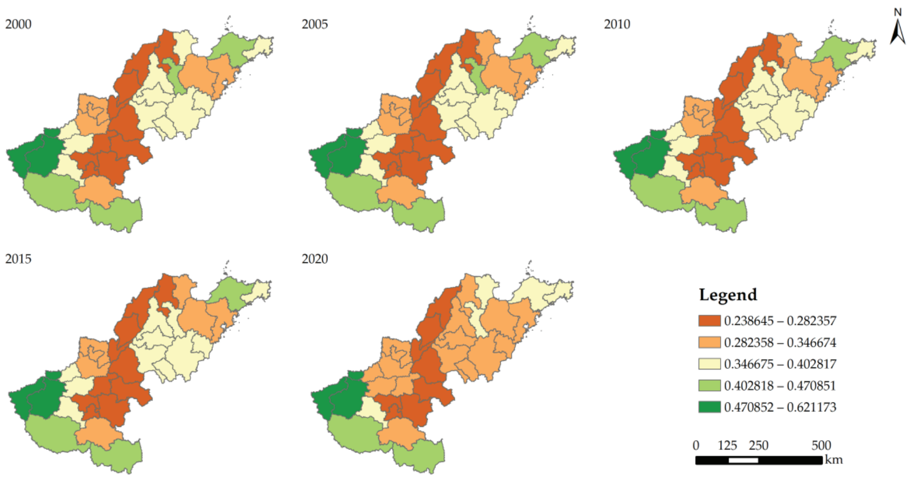

Figure 4. Habitat quality of each city in the Lower Yellow River from 2000 to 2020.

In terms of the spatial distribution, the HQ in the study region had a pattern of poor HQ in the center and high HQ around it (Figure 5). The research region's HQ grades are primarily rather low, with more than 60% of the land falling into this category, which is mostly spread in the low-altitude plains. About 13% of the region is low-grade, which includes construction land and some cultivated land that is scattered. Approximately 17% of the areas are of relatively high and high grades; these areas primarily include wetlands near rivers, lakes, and seashores, as well as forest and grassland areas at higher altitudes.

Regarding temporal variations in HQ, more than 19% of the regions displayed a decline in the HQ grade, almost 15% exhibited an increase in the HQ grade, and roughly 66% were unaltered. The Lower Yellow River showed a significant change in HQ between 2000 and 2020, which was mostly reflected in the trend of the cities with poorer HQ. The number of cities with reduced HQ increased from 27 to 33 and subsequently declined to 24 during the study period. The HQ of Kaifeng, Zhumadian, Xinyang, Binzhou, Dongying, Weifang, Jiyuan, and Nanyang improved with time, while the HQ of the other cities in the research area declined to varying degrees.

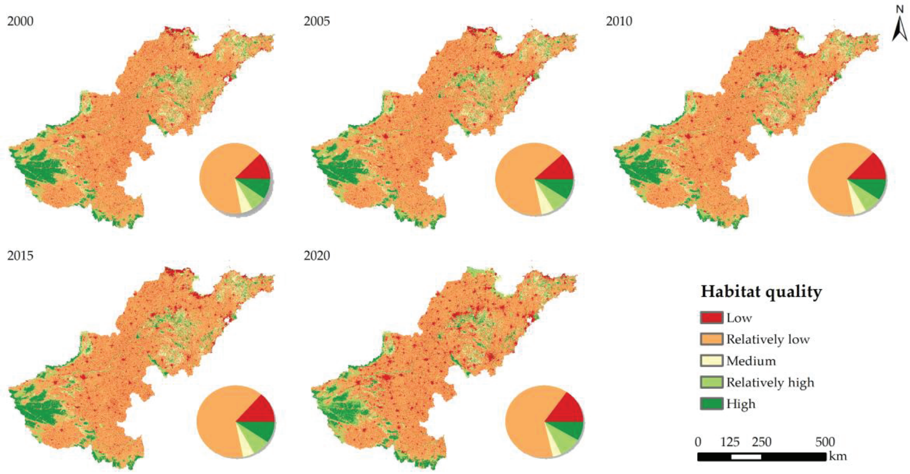

Figure 5. Spatial distribution of habitat quality along the Lower Yellow River from 2000 to 2020.

3.2. Variations in Urbanization through Time and Space along the Lower Yellow River

Between 2000 and 2020, the urbanization levels of 34 cities in the Lower Yellow River progressively grew, as did regional disparities in the urbanization levels between cities. During the study period, the urbanization levels of Xinyang, Zhumadian, Zhouko, Nanyang, Shangqiu, and Heze were consistently lower than the study area's average, while those of Jinan, Qingdao, Zhengzhou, Weihai, Yantai, and Dongying were consistently higher than the average (Figure 6). The urbanization levels in the Lower Yellow River region ranged from 0.084 to 0.307 between 2000 and 2005, and the urbanization growth was rather sluggish. The urbanization levels of Jinan, Qingdao, Weihai, and other cities dramatically grew between 2005 and 2010, widening the disparity in regional urbanization levels. The overall urbanization level of the Lower Yellow River significantly increased from 2010 to 2020, spurred by Jinan, Qingdao, Zhengzhou, and other cities, and the regional urbanization has evolved quickly, with an urbanization level between 0.312 and 0.636.

The examination of the four urbanization subsystems revealed that although each subsystem's urbanization level in the Lower Yellow River varied considerably, they all displayed a consistent upward tendency (Figure 6). The level of economic urbanization, which is substantially larger than that of the other three subsystems, is the factor that most affects the amount of urbanization along the Lower Yellow River. In comparison to other cities in the research area, Jinan, Qingdao, Yantai, Dongying, Zhengzhou, and Luoyang have obviously higher degrees of economic urbanization, whereas Liaocheng, Heze, Dezhou, and Linyi have lower levels—falling below the regional average in all periods.

In terms of social urbanization, this is the fastest growing and most regionally diversified subsystem. The social urbanization is more advanced in Jinan, Zhengzhou, and Weihai, followed by Jinan, Weihai, and Zhengzhou, but it is consistently less advanced in Zhoukou, Zhumadia, Nanyang, and Heze. The spatial urbanization increased more quickly between 2000 and 2010 and less rapidly between 2010 and 2020. Higher spatial urbanization levels can be seen in Qingdao, Weihai, Kaifeng, and Zhengzou, followed by Rizhao, Binzhou, and Luohe, while Sanmenxia, Xinyang, and Nanyang have lower levels. In comparison to the other subsystems, the increase in demographic urbanization was quite small. The rate of demographic urbanization rose by only 13% between 2000 and 2020, whereas the rate of urbanization for the other three subsystems was more than twice as high in 2020 as it was in 2000. Zhoukou, Shangqiu and Heze have comparatively low levels of demographic urbanization, whereas Zhengzhou, Jinan, and Weihai have quite high levels.

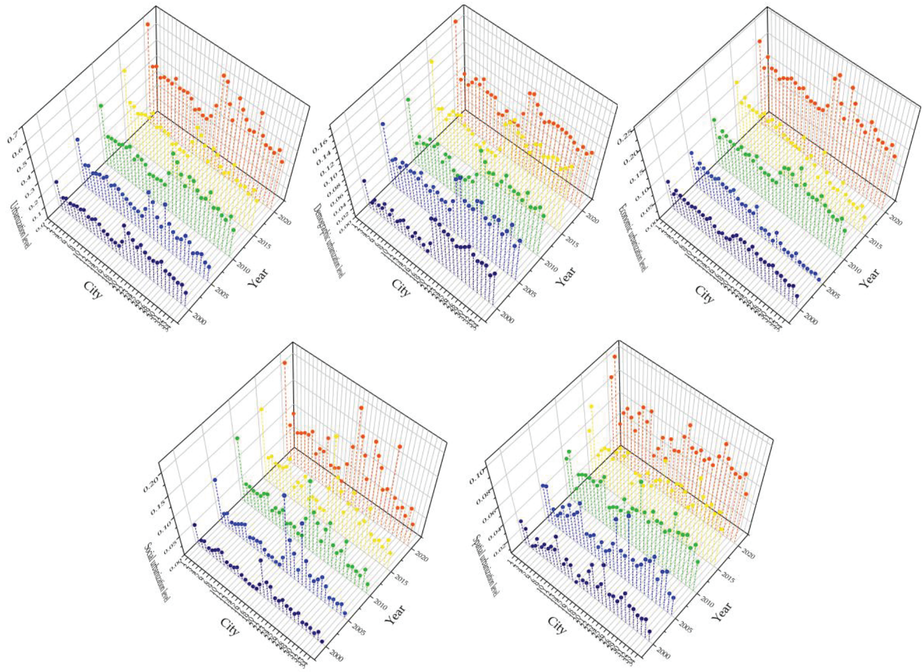

Figure 6. Urbanization levels and subsystem urbanization levels of each city in the Lower Yellow River from 2000 to 2020: (1) Zhengzhou; (2) Kaifeng; (3) Luoyang; (4) Pingdingshan; (5) Anyang; (6) Hebi; (7) Xinxiang; (8) Jiaozuo; (9) Puyang; (10) Xuchang; (11) Luohe; (12) Sanmenxia; (13) Nanyang; (14) Shangqiu; (15) Xinyang; (16) Zhoukou; (17) Zhumadian; (18) Jiyuan; (19) Jinan; (20) Qingdao; (21) Zibo; (22) Zaozhuang; (23) Dongying; (24) Yantai; (25) Weifang; (26) Jining; (27) Taian; (28) Weihai; (29) Rizhao; (30) Linyi; (31) Dezhou; (32) Liaocheng; (33) Binzhou; (34) Heze.

3.3. Coupling Coordination Relationship between Urbanization and Habitat Quality in the Lower Yellow River

The coupling coordination degree (CCD) between the HQ and urbanization level exhibited a consistent upward trend from 2000 to 2020, and the variation in CCD values between cities was striking. Only a few cities showed a decline in the coupling coordination relationship involving HQ and urbanization according to Figure 7, which shows that the majority of cities are moving in a coordinated manner. The vast majority of cities had a CCD below 0.6 in 2000, which is a relatively low value. Moderate coordination and high coordination levels were not included in the coupling coordination category. There were 17 cities with primary coordination, 14 with moderate incoordination, and 3 with extreme incoordination. The number of cities with extreme incoordination decreased to zero between 2000 and 2005, whereas the number of cities with moderate incoordination decreased and cities with moderate coordination increased from zero to seven. From 2005 to 2015, the number of cities with moderate incoordination and primary coordination dropped. The number of cities with moderate coordination increased. The level of CCD in the study area further improved between 2015 and 2020, whereas it declined in some cities. The number of cities with primary coordination and moderate incoordination declined, and the number of cities with high coordination increased from 0 to 3. However, the degree of coupling coordination in Liaocheng decreased from moderate incoordination to extreme incoordination.

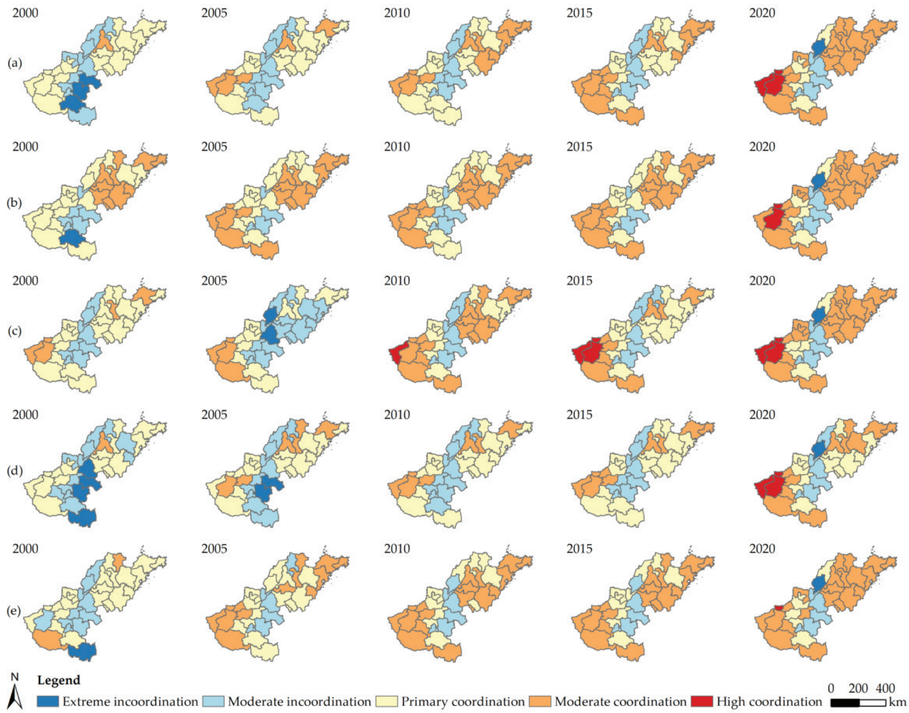

Figure 7. Coupling and coordination types of urbanization levels and subsystem urbanization levels with HQ for each city in the Lower Yellow River from 2000 to 2020: (**a**) urbanization level; (**b**) demographic urbanization level; (**c**) economic urbanization level; (**d**) social urbanization level; (**e**) spatial urbanization level.

In terms of the CCD between the HQ and the four subsystems of urbanization, the CCD of the cities in the Lower Yellow River typically displayed a rising tendency. In the coupling coordination relationship between the four urbanization subsystems and HQ, the social urbanization CCD increased the fastest, the CCD values of the economic and demographic urbanization were relatively high, and the CCD of the spatial urbanization exhibited the least regional variation. The coupling and coordination interactions between various urbanization subsystems and HQ differ significantly, yet in the same city, the relationships between the four urbanization subsystems and HQ are largely positive. In a city, if the CCD of the demographic urbanization level with HQ is relatively high, the other three urbanization subsystems with HQ are also likely to have a high CCD. There were four cities, however, where the CCD between the urbanization subsystems and HQ did not follow the above pattern. For the demographic urbanization and spatial urbanization, Luoyang had a low CCD, whereas the economic urbanization and social urbanization had a high CCD. Dezhou, Binzhou, and Heze had a relatively high CCD for demographic urbanization but a low CCD for other urbanization subsystems. Among the remaining cities, Zhengzhou, Sanmenxia, Jinan, and Weihai all had extraordinarily high CCD values for subsystem urbanizations, whereas Luohe, Shangqiu, Zhoukou, and Liaocheng all had relatively low CCD values for subsystem urbanizations.

Using Equation (7), we divided the coupling coordination characteristics between HQ and urbanization in the Lower Yellow River into three categories: urbanization lagging, urbanization–HQ synchronization, and HQ lagging. From 2000 to 2020, Luohe, Puyang, Liaocheng, Heze, Dezhou, and Binzhou all belonged to HQ lagging, whereas Sanmenxia, Nanyang, Xinyang, Luoyang, and Jiyuan all belonged to urbanization lagging. The abundance of resources in these cities has a significant impact on this. Figure 8 shows that the number of cities with lagging urbanization has steadily declined, while the number of cities with lagging HQ has steadily increased. The following section provides a description of the type of transformation process during this time.

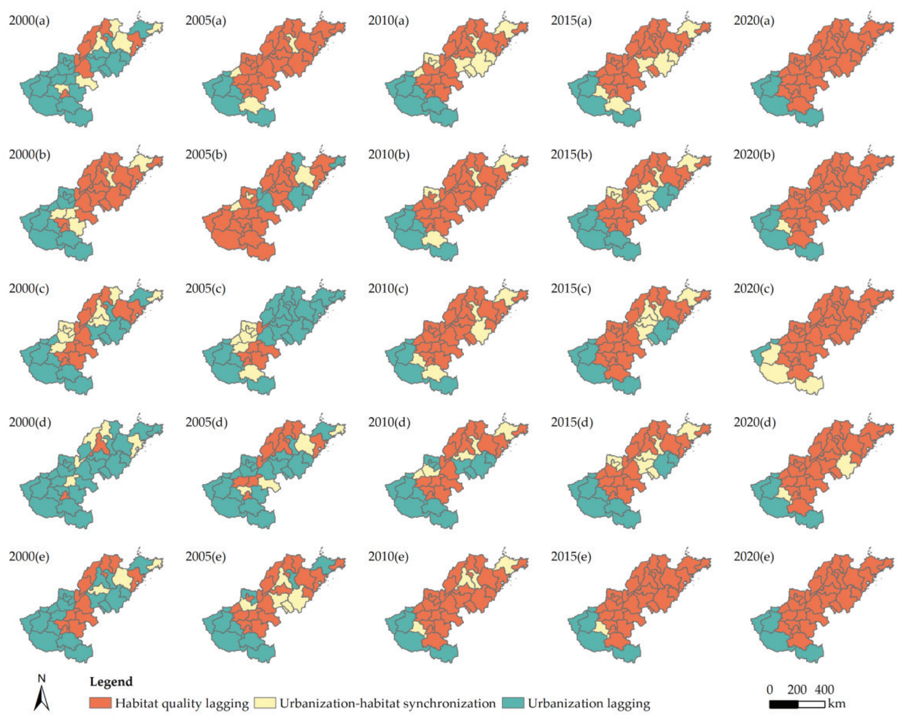

Figure 8. Relative development relationships of the urbanization level and subsystem urbanization level with HQ for each city along the Lower Yellow River between 2000 and 2020: (**a**) urbanization level; (**b**) demographic urbanization level; (**c**) economic urbanization level; (**d**) social urbanization level; (**e**) spatial urbanization level.

In 2000, there were 24 cities in the research region that belonged to the urbanization lagging category, accounting for more than 70% of all cities. The environment received little effect from anthropogenic activities throughout this time, and the habitat's condition was fairly positive. The Lower Yellow River's urbanization level is relatively low, and improving inhabitants' living conditions and stimulating quick economic growth remain the primary goals of urbanization development. Between 2000 and 2005, 50% of all cities underwent a type shift, primarily moving from urbanization–HQ synchronization and urbanization lagging to HQ lagging. From 2005 to 2010, a transition from urbanization lagging to urbanization–HQ synchronization mostly occurred, with around 33% of the total number of cities experiencing this shift. During this timeframe, the study area's level of urbanization continuously increased, the gap between urbanization and HQ gradually shrank, and the number of cities with urbanization–HQ synchronization greatly increased. However, as the urbanization levels rose quickly, a possible risk of urban growth affecting HQ slowly became apparent. Between 2010 and 2020, the majority of cities underwent a type change, changing from urbanization–HQ synchronization to HQ lagging. Over the course of the study period, fewer cities experienced a type shift, and the coupling coordination relationship between urbanization and HQ gradually stabilized.

4. Discussion

In this study, the mean value of the HQ in the Lower Yellow River fell from 0.368 to 0.357 between 2000 and 2020, with a definite downward trend. Among the grades of HQ in the Lower Yellow River, the low-grade areas increased, while the high-grade areas decreased. This may be attributed to the increase in the area of threatening sources represented by building land and the decrease in the area of land use types with higher ecological value, which is consistent with the conclusions found by Zhou et al. [47] and Lin et al. [48]. Therefore, in order to promote the long-term optimization of the ecological environment, governments and pertinent departments at all levels should adhere to the principles of environment-first and eco-friendly development, judiciously manage the growth of built-up areas, and stop the inefficient and unequal distribution of construction land from eroding ecological land [49].

It is worth noting that the overall habitat quality in the Lower Yellow River showed a downward trend, but the area changes in the regions of a relatively high grade and medium grade did not follow this rule. Compared with the area changes of other grades, the relatively high-grade area increased significantly while the medium-grade area decreased significantly from 2015 to 2020. From the change in quantity of each grade, the increase in relatively high-grade areas came mainly from medium-grade areas. This shift may be related to environmental governance in areas of medium grade. This phenomenon shows that ecological restoration in areas of medium habitat quality is one of the most effective ways to improve the overall habitat quality in the region. In order to achieve the goal of improving habitat quality, we should vigorously promote the "urban and rural greening" action and focus on environmental governance in areas with moderate habitat quality [50]. In such areas, the government should promote the development of regional habitat quality in a positive direction by expanding public green spaces, creating urban green parks, and buffering shelterbelts.

In terms of the CCD between HQ and urbanization, cities in the middle of the Lower Yellow River usually fall into the moderate incoordination and extreme incoordination categories. Their level of urbanization is low. Additionally, these cities' HQ is mediocre in comparison to their urbanization. Cities with lagging HQ, such as those in the center Lower Yellow River, should identify the unsolved habitat issues as soon as possible and rectify the negative impacts of urbanization on the ecosystem. Next, they should address the subjective and objective problems that prevent high-quality urbanization and provide favorable socioeconomic conditions for habitat improvements. The remaining cities essentially fall into two categories, moderate coordination and high coordination, with minimal variance in terms of urbanization and HQ. These cities are further classified as having lagging urbanization and lagging HQ based on the relative states of the two systems. Cities that are part of the HQ lagging category should be aware of any potential HQ problems brought on by urbanization. For sustainable urban development, the government must provide an eco-friendly platform [51,52]. In light of their unique circumstances, cities with different relative development relationships between HQ and urbanization should create their urban development strategies.

In terms of the coupling relationship between the four subsystems and HQ, the CCD of the economic urbanization and demographic urbanization is higher. Yun [53] evaluated the coupling coordination between the ecological environment and urbanization in the Yellow River Basin and found that the coupling coordination index of the demographic urbanization was lower than that of the other three urbanization subsystems. Yun's conclusion is somewhat different from the results of this study, where we highlighted the evolution of the coupling coordination relationship between HQ and urbanization in regions with high levels of demographic and economic urbanization. The coupling coordination relationship between the demographic subsystem and HQ in the Lower Yellow River Basin is very different from that in the Yellow River Basin. This important difference also indicates that the study of the coupling relationship between HQ and urbanization in the Lower Yellow River is of great significance for revealing the coupling relationship between urbanization and HQ in densely populated and economically developed areas.

This study looked at the spatial and temporal evolution of HQ and urbanization and their interactions, which can operate as a factual support for the high-quality development of socioeconomic activities and the environment in the Lower Yellow River. Additionally, this study could serve as a reliable source for determining metrics for HQ evaluations and for investigating the connections between HQ and urbanization in comparable places. However, our study still has several limitations. To begin with, the range of indicators available is limited due to the accuracy of publicly available urbanization-related data. In further research, we will try to obtain more indicators to enrich the urbanization indicator system. Second, the InVEST model is one of the most critical tools for habitat quality assessments and has been broadly applied in large-scale and meso-scale habitat quality studies. However, the InVEST model still has the limitations, in that it ignores the habitat quality variation among the same habitats and cannot fully reflect the actual habitat quality conditions. Finally, our study did not include the driving factors. Along with our upcoming research, we will attempt to delve deeper into the drivers of the relationship between HQ and urbanization in the Lower Yellow River.

5. Conclusions

We first characterized the spatial and temporal variations in HQ and urbanization levels using the InVEST model and the comprehensive indicator method, and then we applied the CCDM to tackle their interaction. From 2000 to 2020, the studies revealed an overall poor state of HQ along the Lower Yellow River, with a continuous downward tendency. More than 60% of the study areas had a low HQ grade. The pattern of HQ in the Lower Yellow River was poor in the middle and high around the edges. Significant disparities existed in the HQ of various cities, and while most cities displayed a trend toward declining HQ, the number of cities that did so gradually declined.

The 34 cities' urbanization levels, as well as the urbanization levels of each subsystem, showed a stable growth tendency in terms of temporal variability in urbanization levels. Between 2000 and 2020, Jinan, Qingdao, and Zhengzhou showed higher urbanization levels, while Xinyang, Nanyang, and Heze showed lower urbanization levels. Economic urbanization has the greatest impact on the Lower Yellow River's urbanization level, while social urbanization is the fastest expanding subsystem with the greatest regional disparity.

The CCD of the Lower Yellow River showed a consistent upward tendency between 2000 to 2020. In most cities, the relationship between HQ and urbanization moved in the direction of coordination, while only a few cities saw a decline in the coupling coordination relationship. The spatial distribution of the CCD is characterized by high values in the east and west and low values in the middle, meaning that the eastern part of Henan Province and the western part of Shandong Province have high CCD values, while the junction of these two provinces has low values of CCD. The number of cities with moderate coordination has increased significantly, while the number of cities with moderate incoordination and extreme incoordination has decreased. The number of cities with lagging urbanization has decreased, while the number of cities with lagging HQ has increased. On the whole, the evolution of the coupling coordination relationship between HQ and urbanization is positive. However, the HQ in the Lower Yellow River has gradually lagged behind urbanization, which is a potential threat to the coupling coordination between regional HQ and urbanization. This phenomenon deserves close attention. The coupling coordination levels between the four urbanization subsystems and HQ differ significantly. The CCD levels of demographic and economic urbanization are particularly high among the subsystems. Our research is critical for improving the habitat quality and coordinating the relationship between the habitat quality and urbanization in the Lower Yellow River, and it can serve as a scientific reference for government agencies' ecological regulations.

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writing—review and editing, F.K.; funding acquisition, M.H. All authors have read and agreed to the published version of the manuscript.

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References

1. Johnson, M.D. Measuring Habitat Quality: A Review. *Condor* **2007**, *109*, 489–504. [CrossRef]
2. Zhang, H.; Zhang, C.; Hu, T.; Zhang, M.; Ren, X.; Hou, L. Exploration of roadway factors and habitat quality using InVEST. *Transp. Res. Part D Transp. Environ.* **2020**, *87*, 102551. [CrossRef]
3. Gao, Y.; Ma, L.; Liu, J.; Zhuang, Z.; Huang, Q.; Li, M. Constructing Ecological Networks Based on Habitat Quality Assessment: A Case Study of Changzhou, China. *Sci. Rep.* **2017**, *7*, 46073. [CrossRef]
4. Zhang, Y.; Chen, R.; Wang, Y. Tendency of land reclamation in coastal areas of Shanghai from 1998 to 2015. *Land Use Policy* **2020**, *91*, 104370. [CrossRef]
5. Horcajada-Sanchez, F.; Escribano-Avila, G.; Lara-Romero, C.; Virgos, E.; Barja, I. The effect of livestock on the physiological condition of roe deer (*Capreolus capreolus*) is modulated by habitat quality. *Sci. Rep.* **2019**, *9*, 15953. [CrossRef]
6. Fu, B. The evaluation of eco-environmental qualities in China. *China Popul. Resour. Environ.* **1992**, *02*, 48–54.
7. Zhang, X.; Liao, L.; Xu, Z.; Zhang, J.; Chi, M.; Lan, S.; Gan, Q. Interactive Effects on Habitat Quality Using InVEST and GeoDetector Models in Wenzhou, China. *Land* **2022**, *11*, 630. [CrossRef]
8. Berta Aneseyee, A.; Noszczyk, T.; Soromessa, T.; Elias, E. The InVEST Habitat Quality Model Associated with Land Use/Cover Changes: A Qualitative Case Study of the Winike Watershed in the Omo-Gibe Basin, Southwest Ethiopia. *Remote Sens.* **2020**, *12*, 1103. [CrossRef]
9. Li, M.; Zhou, Y.; Xiao, P.; Tian, Y.; Huang, H.; Xiao, L. Evolution of Habitat Quality and Its Topographic Gradient Effect in Northwest Hubei Province from 2000 to 2020 Based on the InVEST Model. *Land* **2021**, *10*, 857. [CrossRef]
10. Wu, J.; Li, X.; Luo, Y.; Zhang, D. Spatiotemporal effects of urban sprawl on habitat quality in the Pearl River Delta from 1990 to 2018. *Sci. Rep.* **2021**, *11*, 13981. [CrossRef]
11. Chen, T.-Y.; Hwang, G.-W.; Mayfield, A.B.; Chen, C.-P.; Lin, H.-J. The development of habitat suitability models for fiddler crabs residing in subtropical tidal flats. *Ocean Coast. Manag.* **2019**, *182*, 104931. [CrossRef]
12. Zhang, Z.; Zhang, H.; Feng, J.; Wang, Y.; Liu, K. Evaluation of Social Values for Ecosystem Services in Urban Riverfront Space Based on the SolVES Model: A Case Study of the Fenghe River, Xi'an, China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 2765. [CrossRef] [PubMed]
13. Sherrouse, B.C.; Semmens, D.J.; Ancona, Z.H. Social Values for Ecosystem Services (SolVES): Open-source spatial modeling of cultural services. *Environ. Model. Softw.* **2022**, *148*, 105259. [CrossRef]
14. Wu, J.; Luo, J.; Zhang, H.; Qin, S.; Yu, M. Projections of land use change and habitat quality assessment by coupling climate change and development patterns. *Sci. Total Environ.* **2022**, *847*, 157491. [CrossRef]
15. Sun, X.; Jiang, Z.; Liu, F.; Zhang, D. Monitoring spatio-temporal dynamics of habitat quality in Nansihu Lake basin, eastern China, from 1980 to 2015. *Ecol. Indic.* **2019**, *102*, 716–723. [CrossRef]
16. Lin, Y.-P.; Lin, W.-C.; Wang, Y.-C.; Lien, W.-Y.; Huang, T.; Hsu, C.-C.; Schmeller, D.S.; Crossman, N.D. Systematically designating conservation areas for protecting habitat quality and multiple ecosystem services. *Environ. Model. Softw.* **2017**, *90*, 126–146. [CrossRef]
17. Wei, H.; Xiong, L.; Tang, G.; Strobl, J.; Xue, K. Spatial–temporal variation of land use and land cover change in the glacial affected area of the Tianshan Mountains. *CATENA* **2021**, *202*, 105256. [CrossRef]
18. Kunwar, R.M.; Evans, A.; Mainali, J.; Ansari, A.S.; Rimal, B.; Bussmann, R.W. Change in forest and vegetation cover influencing distribution and uses of plants in the Kailash Sacred Landscape, Nepal. *Environ. Dev. Sustain.* **2018**, *22*, 1397–1412. [CrossRef]
19. Wang, H.; He, Q.; Liu, X.; Zhuang, Y.; Hong, S. Global urbanization research from 1991 to 2009: A systematic research review. *Landsc. Urban Plan.* **2012**, *104*, 299–309. [CrossRef]
20. Liu, X.; Wang, Y.; Li, Y.; Wu, J. Quantifying the Spatio-Temporal Process of Township Urbanization: A Large-Scale Data-Driven Approach. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 389. [CrossRef]
21. Zhang, D.; Xu, J.; Zhang, Y.; Wang, J.; He, S.; Zhou, X. Study on sustainable urbanization literature based on Web of Science, scopus, and China national knowledge infrastructure: A scientometric analysis in CiteSpace. *J. Clean. Prod.* **2020**, *264*, 121537. [CrossRef]

22. Zhang, Q.-R.; Li, Y.; Liu, J.-S.; Chen, Y.-D.; Chai, L.-H. A dynamic co-word network-related approach on the evolution of China's urbanization research. *Scientometrics* **2017**, *111*, 1623–1642. [CrossRef]
23. Jiao, H.; Zhang, X.; Yang, C.; Cao, X. The characteristics of spatial expansion and driving forces of land urbanization in counties in central China: A case study of Feixi county in Hefei city. *PLoS ONE* **2021**, *16*, e0252331. [CrossRef]
24. Yu, M.; Guo, S.; Guan, Y.; Cai, D.; Zhang, C.; Fraedrich, K.; Liao, Z.; Zhang, X.; Tian, Z. Spatiotemporal heterogeneity analysis of Yangtze River delta urban agglomeration: Evidence from nighttime light data (2001–2019). *Remote Sens.* **2021**, *13*, 1235. [CrossRef]
25. Chu, N.; Zhang, P.; Wu, X. Spatiotemporal evolution characteristics of urbanization and its coupling coordination degree in Russia—Perspectives from the population, economy, society, and eco-environment. *Environ. Sci. Pollut. Res.* **2022**, *29*, 61334–61351. [CrossRef] [PubMed]
26. Duha, J.; Shandas, V.; Chang, H.; George, L.A. Rates of urbanisation and the resiliency of air and water quality. *Sci. Total Environ.* **2008**, *400*, 238–256. [CrossRef] [PubMed]
27. Liu, H.; Fang, C.; Li, Y. The Coupled Human and Natural Cube: A conceptual framework for analyzing urbanization and eco-environment interactions. *Acta Geogr. Sin.* **2019**, *74*, 1489–1507.
28. Xiao, R.; Lin, M.; Fei, X.; Li, Y.; Zhang, Z.; Meng, Q. Exploring the interactive coercing relationship between urbanization and ecosystem service value in the Shanghai–Hangzhou Bay Metropolitan Region. *J. Clean. Prod.* **2020**, *253*, 119803. [CrossRef]
29. Zhu, C.; Zhang, X.; Zhou, M.; He, S.; Gan, M.; Yang, L.; Wang, K. Impacts of urbanization and landscape pattern on habitat quality using OLS and GWR models in Hangzhou, China. *Ecol. Indic.* **2020**, *117*, 106654. [CrossRef]
30. Yohannes, H.; Soromessa, T.; Argaw, M.; Dewan, A. Spatio-temporal changes in habitat quality and linkage with landscape characteristics in the Beressa watershed, Blue Nile basin of Ethiopian highlands. *J. Environ. Manag.* **2021**, *281*, 111885. [CrossRef]
31. Yushang, c.; Yang, G.; Zhen, X.; Yuzhu, Z.; Xize, Y. Spatiotemporal evolution and spatial correlation of habitat quality and landscape pattern over Beijing-Tianjin-Hebei region. *China Environ. Sci.* **2021**, *41*, 848–859.
32. Xiaonan, W.; Wei, S. Transformation efficiency of resource-based cities in the Yellow River Basin and its influencing factors. *Prog. Geogr.* **2020**, *39*, 1643–1655.
33. Zhang, X.; Lyu, C.; Fan, X.; Bi, R.; Xia, L.; Xu, C.; Sun, B.; Li, T.; Jiang, C. Spatiotemporal Variation and Influence Factors of Habitat Quality in Loess Hilly and Gully Area of Yellow River Basin: A Case Study of Liulin County, China. *Land* **2022**, *11*, 127. [CrossRef]
34. Li, L.; Xu, W.; Zheng, J. A Study on Spatial Interactive Effects Between Urbanization Process and Ecological Efficiency in the Yellow River Basin. *Econ. Surv.* **2022**, *39*, 25–34.
35. He, H.; Wang, Z.; Dong, J.; Wang, J.; Zou, J. Synergy and trade-off between vegetation change and urbanization development in the YellowRiver Basin of Shaanxi Province based on satellite remote sensing data. *Acta Ecol. Sin.* **2022**, *42*, 3536–3545.
36. Zhao, J.; Zhao, H. Coupling coordination analysis of urbanization and eco-environment in Ningxia based onDMSP-OLS and MODIS data. *Bull. Surv. Mapp.* **2021**, *535*, 9.
37. Li, Y.; Dan, X. Spatiotemporal change of urban green development efficiency in the Yellow River Basin and influencing factors. *Resour. Sci.* **2020**, *42*, 2274–2284.
38. Keyun, Z.; Ying, Z. The Evolution of Regional Economic Disparity in the Yellow River Basin at Different Spatial Scales. *Econ. Geogr.* **2020**, *40*, 1–11.
39. Tang, F.; Fu, M.; Wang, L.; Zhang, P. Land-use change in Changli County, China: Predicting its spatio-temporal evolution in habitat quality. *Ecol. Indic.* **2020**, *117*, 106719. [CrossRef]
40. Li, Y.; Duo, L.; Zhang, M.; Yang, J.; Guo, X. Habitat quality assessment of mining cities based on InVEST model—A case study of Yanshan County, Jiangxi Province. *Int. J. Coal Sci. Technol.* **2022**, *9*, 28. [CrossRef]
41. Hu, B.; Kang, F.; Han, H.; Cheng, X.; Li, Z. Exploring drivers of ecosystem services variation from a geospatial perspective: Insights from China's Shanxi Province. *Ecol. Indic.* **2021**, *131*, 108188. [CrossRef]
42. Li, X.; Liu, Z.; Li, S.; Li, Y. Multi-Scenario Simulation Analysis of Land Use Impacts on Habitat Quality in Tianjin Based on the PLUS Model Coupled with the InVEST Model. *Sustainability* **2022**, *14*, 6923. [CrossRef]
43. Tian, Y.; Huang, P.; Zhao, X. Spatial analysis, coupling coordination, and efficiency evaluation of green innovation: A case study of the Yangtze River Economic Belt. *PLoS ONE* **2020**, *15*, 243459. [CrossRef]
44. Wang, D.; Jiang, D.; Fu, J.; Lin, G.; Zhang, J. Comprehensive Assessment of Production–Living–Ecological Space Based on the Coupling Coordination Degree Model. *Sustainability* **2020**, *12*, 2009. [CrossRef]
45. Ma, M.; Tang, J. Interactive coercive relationship and spatio-temporal coupling coordination degree between tourism urbanization and eco-environment: A case study in Western China. *Ecol. Indic.* **2022**, *142*, 109149. [CrossRef]
46. Tang, F.; Wang, L.; Guo, Y.; Fu, M.; Huang, N.; Duan, W.; Luo, M.; Zhang, J.; Li, W.; Song, W. Spatio-temporal variation and coupling coordination relationship between urbanisation and habitat quality in the Grand Canal, China. *Land Use Policy* **2022**, *117*, 106119. [CrossRef]
47. Liang, Z.; Jianjun, T.; Xingke, L.; Xuewei, D.; Haowei, M. Effects of urban expansion on habitat quality in densely populated areas on the Loess Pla-teau: A case study of Lanzhou, Xi'an-Xianyang and Taiyuan, China. *Chin. J. Appl. Ecol.* **2021**, *32*, 261–270.
48. Lin, C.; Chong, H.; Qingsheng, L.; Gaohuan, L. Changes of coastal zone landscape spatial patterns and ecological quality in Liaoning Province from 2000 to 2010. *Resour. Sci.* **2015**, *37*, 1962–1972.
49. Tang, Y.; Gao, C.; Wu, X. Urban Ecological Corridor Network Construction: An Integration of the Least Cost Path Model and the InVEST Model. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 33. [CrossRef]

50. Zhang, T.; Gao, Y.; Li, C.; Xie, Z.; Chang, Y.; Zhang, B. How Human Activity Has Changed the Regional Habitat Quality in an Eco-Economic Zone: Evidence from Poyang Lake Eco-Economic Zone, China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 6253. [CrossRef]
51. Wu, L.; Sun, C.; Fan, F. Estimating the Characteristic Spatiotemporal Variation in Habitat Quality Using the InVEST Model—A Case Study from Guangdong–Hong Kong–Macao Greater Bay Area. *Remote Sens.* **2021**, *13*, 1008. [CrossRef]
52. Fan, X.; Gu, X.; Yu, H.; Long, A.; Tiando, D.S.; Ou, S.; Li, J.; Rong, Y.; Tang, G.; Zheng, Y.; et al. The Spatial and Temporal Evolution and Drivers of Habitat Quality in the Hung River Valley. *Land* **2021**, *10*, 1369. [CrossRef]
53. Yun, X. Coupling Coordination Measurement and Interactive Coercing Verification Between Urbanization and Eco-Environment in the Yellow River Basin. *Econ. Probl.* **2022**, *516*, 86–95.

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Constructing a Flood-Adaptive Ecological Security Pattern from the Perspective of Ecological Resilience: A Case Study of the Main Urban Area in Wuhan

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Abstract: The frequent occurrence of floods in urban areas caused by climate change challenges urban resilience. This research aims to construct an ecological security pattern (ESP) that is adaptive to floods to enhance urban resilience in the hope that it will help cities cope with floods better. In this research, the main urban area of Wuhan (WUH) represents the study area. The lakes were selected as the ecological sources and the Soil Conservation Service-Curve Number (SCS-CN) model was used to calculate the runoff volume corresponding to each land type and, based on this, assign resistance values to the land types; as such, the land type surface is referred to as the runoff resistance surface, and the runoff resistance surface is then modified by ecosystem service capabilities. The Minimum Cumulative Resistance (MCR) model was used to extract the connecting corridors between the sources. This research plan includes 18 ecological sources, 10 key ecological corridors, and 22 potential ecological corridors, with a total length of about 344.21 km. Finally, it provides a *two-axis* and three-core urban ecological resilience optimization strategy for decision makers and a new approach for controlling floods in urban areas from the perspective of ecological resilience.

Keywords: SCS-CN model; flood adaptation; ecological security pattern; resilient city

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1. Introduction

Due to climate change and urbanization, floods in urban areas are occurring more frequently. Climate change also causes extreme rainfall [1,2], while urbanization increases impervious underlying surfaces, causing waterlogging [3–5]. The traditional flood control and drainage measures promote the construction of traditional gray infrastructure, such as drainage pipes and flood control revetments. Although these facilities are flood-resistant, their static defense cannot fully adapt to the increasing flood risks and cannot automatically recover after damage occurs. Therefore, gray infrastructure is not sustainable. In other words, cities should develop more effective ecological methods to prevent floods [6].

As a comprehensive urban development concept, a *resilient city* is characterized by its flexibility, adaptability, and transformative ability [7]. Likewise, it provides theoretical support for solving current flood-related problems in cities. Many cities have introduced resilient retrofit programs, such as New York [8], Melbourne [9], Rotterdam [10], etc. In China, a sponge city represents a comprehensive solution for various water-related problems, such as water shortage, water pollution, and floods [11]. Researchers conducted extensive studies on the planning and design [12,13] and index control [14], including the unit area, runoff coefficient, expected rainfall, etc. There has also been significant exploration of the system construction [15] of sponge cities, but researchers have also conducted case studies [16] on some pilot areas in sponge cities, including the synergy between green and gray infrastructure [17,18], flood control capability [19], contamination risks [20], etc. Some studies also optimize the layout of sponge cities in terms of the rainfall runoff, pollutant discharge, minimization of construction and operation costs, and maximization of environmental benefits [21]. A sponge city improves the storage capacity of the underlying surface, regulates the infiltration, interception, storage, purification, reuse, and discharge of rainwater, and enhances flood resilience of the city through disaster reduction. However, sponge cities have exposed many deficiencies in the process of their construction and use. These deficiencies are the ecological risks to soil and groundwater caused by the decomposition of the Sponge City filler during rainfall, cumulative effect of pollutants, ecological pressure and economic burden caused by the clogging of the filling and the recycling of the waste fill, weak ecological service capability, uneven distribution, and lack of integrity [6]. This means that cities should be made more resilient from an ecological perspective.

While some studies [22–24] have systematically evaluated the urban resilience of Wuhan city and proposed detailed guidance schemes for policy makers, this study will be conducted from the perspective of spatial analysis and ecological planning. The resilient city theory holds that urban ecosystems with complex structures resist disturbances from outside the city better. The ecological security pattern (ESP) is a spatial configuration scheme that combines the ecological or human elements in the region through a combination of points, lines, and surfaces [25], and is a complex network structure with a holistic and multi-patch [26] connectivity designed to adapt to floods, complement the sponge city, and enhance urban ecological resilience. Most traditional research on ecological security patterns follows a single ecological protection perspective [27–29] or combines human activities [30,31], natural geographical elements (such as slope and elevation) [32,33], habitat protection [34], economy [35,36], etc. However, the study of the interaction between flooding and ecological security patterns is not well understood. Some studies [26] have also proposed ecological improvement measures for the central area of Wuhan from the perspective of spatial analysis, but their results cannot effectively guide the construction of ecological corridors within the urban area.

This research takes the main urban area of Wuhan (WUH) as the study area in order to enhance the ecological resilience of the city and study the flood adaptability of the urban ESP. The lakes are protected as ecological sources, the blueways and greenways are combined with each other as ecological corridors which look like river parks, and ecological corridors are planned to connect the waters of the lakes to each other to form a holistic and resilient ecological network. In this, the blueways can quickly divert runoff during heavy rainfall and the interconnected lakes have greater storage capacity, which can increase the threshold of precipitation needed for creating urban flooding. In addition, to differentiate from the traditional gray infrastructure, the study incorporates ecosystem service functions to ensure that the ESP provides ecological services to the city even during non-flooding periods. This study also introduces a gravity model to guide the priority of corridor construction and field investigations to find a target paradigm for corridor construction, which hopefully will help relevant authorities to take better relevant measures. The main urban area of WUH is key for rainwater management and control. Research into the ESP that is adaptive to floods can provide theoretical and methodological support for WUH and other cities to improve their ecological resilience.

2. Study Area

The main urban area of WUH is affiliated with Wuhan City in the Hubei Province. It covers an area of 450 km^2 [37] and is located at the intersection of the Yangtze and Hanjiang Rivers. Wuhan has many lakes, namely the East Lake, Yanxi Lake, South Lake, Moon Lake, MoShui Lake, Nantaizi Lake, Wanjia Lake, etc. Due to its location in the alluvial plain in the middle reaches of the Yangtze River, the soils in the study area are dominated by paddy and chao soil [38] under the influence of groundwater movement and farming activities, both of which are characterized by a clay-like texture and poor permeability. Wuhan's climate is humid and subtropical, characterized by monsoons, with an annual average temperature of 17.4 °C, a mean monthly maximum temperature of 30.8 °C, an annual average rainfall of 129 days, and an annual average rainfall of 1317.5 mm (the 2009–2019 average) [39].

In 2021 [40], the average precipitation in May to October during the flood season was 998.2 mm, accounting for 74.3% of the annual precipitation; the average precipitation from mid-June to July was 329.5 mm, accounting for 24.5% of the annual precipitation; the month with the most precipitation was August, with 310.0 mm; the least precipitative month was December, with 8.7 mm. There are 574 million m^3 of surface water resources in the main city of Wuhan, with 791.2 billion m^3 of transit water.

In addition to the Yangtze River and Han River, there are three major water systems: the Daoshui River, the Nieshui River, and the Jushui River. There are also many tributary systems, such as the Tongshun River and the Jinshui River [41]. The river network is crisscrossed and the water system is huge. Wuhan is known as the *City of a Hundred Lakes* and the *city of wetlands*, and the lake ecosystem plays a decisive role in urban flood control. Flood control has been very effective in WUH, but there are still certain risks, mainly with three aspects: (1) there are many water systems and the pressure on flood control is high; (2) extreme weather is increasing, so the risk of severe floods is still present; (3) waterlogging is frequent. In addition, urban construction has encroached upon many lake ecosystems [42], which increased Wuhan's vulnerability to severe floods. According to *People's Daily* [43], the lakes in Wuhan have shrunk by 106 km^2 in the past three decades. These shrinking lakes continue to weaken the ecological service capacity, threatening regional ecological security and greatly weakening urban ecological resilience. The location and land use types of the study area are shown in Figure 1.

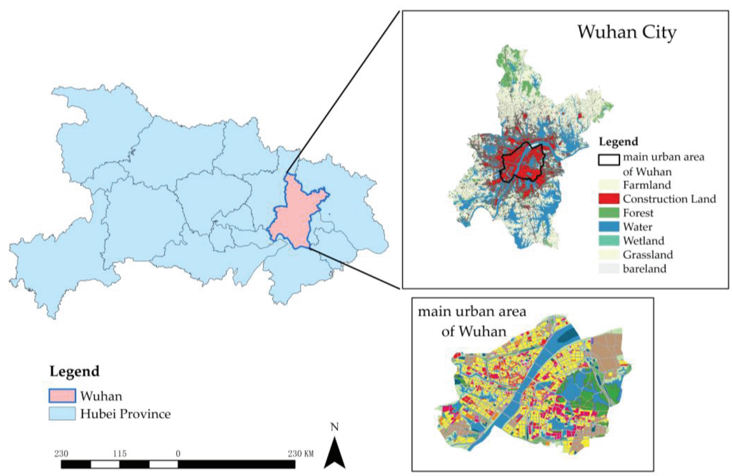

Figure 1. Map of the main urban area in Wuhan.

In the map above, the Hubei Province is in south-central China. The location of the main urban area of Wuhan within the city is shown in the upper right part of the box.

3. Methodology and Data Sources

3.1. Data Sources

The daily data of precipitation come from Hubei Meteorological Administration, the elevation data (DEM) with 30 M accuracy from the Chinese Academy of Sciences Geospatial Data Cloud (http://www.gscloud.cn/search, accessed on 18 November 2021), and the land use data in the main urban area of Wuhan come from the Wuhan Bureau of Natural Resources and Planning (ghttp://zrzyhgh.wuhan.gov.cn/zwgk_18/fdzdgk/ghjh/zzqgh/202001/t20200107_602858.shtml, accessed on 20 November 2021), Wuhan soil data with 30 M accuracy comes from the Harmonized World Soil Database (https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/, accessed on 10 December 2021), the spatial distribution data of waterlogging points are from the Wuhan Municipal Water Affairs Authority (http://swj.wuhan.gov.cn/tzdt/jcss/202005/t20200511_1309387.html, accessed on 25 December 2021), the net primary productivity (NPP) data of vegetation in the main urban area of Wuhan with 30 M accuracy comes from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 10 March 2022), the data of points of interest (POI) in the main urban area of Wuhan are from Baidu Map Open Platform (https://lbsyun.baidu.com/, accessed on 25 December 2021), and the rest of the meteorological data in Wuhan comes from the "*Wuhan Statistical Yearbook*" (2010–2020) (http://tjj.wuhan.gov.cn/tjfw/tjnj/, accessed on 18 November 2021).

3.2. The Methodological Framework

Sources are patches that influence the stability, integrity, and functionality of ESP and are the basis of ESP. In this research, lakes in the main urban area of WUH were selected as ecological sources. The Soil Conservation Service-Curve Number (SCS-CN) model is used to calculate the surface runoff volume of each category after a rainstorm, which is spatially expressed in ArcGIS and transferred to a raster map after assigning resistance values, called the runoff resistance surface. Likewise, the water connotation function and the recreation and leisure function are rasterized and assigned resistance values, which are called water connotation resistance surface and recreation and leisure resistance surface. The raster calculator tool of ArcGIS is used to superimpose the three resistance surfaces to get the comprehensive resistance surface (the quantitative expression of the degree of difficulty of moving matter and energy through a certain surface). Ecological corridors were constructed using the Minimum Cumulative Resistance (MCR) model. Furthermore, the location of ecological corridors was optimized based on the runoff path (Figure S1) and the waterlogging points (Figure S2) issued by the Wuhan Municipal Water Affairs Authority. Finally, the gravity model was used to prioritize the construction of the ecological corridor. The specific experimental flow is shown in Figure 2.

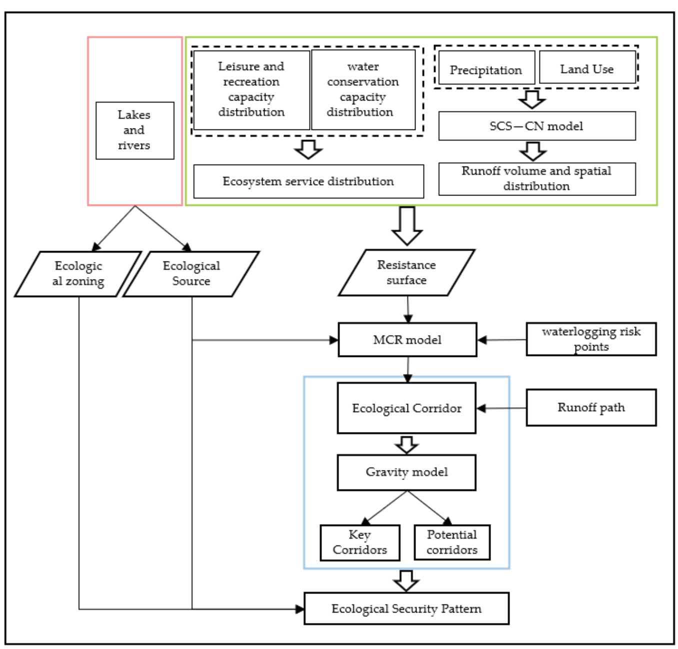

Figure 2. The methodological framework of the study.

3.3. Runoff Calculation Based on the SCS-CN Model

The variety of land types have their own impervious areas and unique substrate properties, which determine their different runoff-generating capacities in the face of rainfall processes. In this research, the SCS-CN model [44] was used to calculate the runoff volume generated by different land types after heavy rain, and then the values of the runoff volume were connected with the vector land type distribution map in ArcGIS to derive the spatial distribution of runoff volume corresponding to different land types. The SCS-CN model is a simple model with a clear physical concept and few required parameters [45]. The regular formula for the SCS-CN model is [46]:

$$\frac{F}{S} = \frac{Q}{P - I_a} \tag{1}$$

where P represents the total precipitation (mm), and I_a the initial abstraction (mm), including the initial loss of ground filling, interception, surface water storage, and infiltration. F is the loss after the generation of surface runoff, i.e., the actual cumulative infiltration (mm) (excluding I_a); Q is the direct runoff (mm); S is the possible retention amount (mm).

The water balance equation is as follows [47]:

$$P = I_a + F + Q \tag{2}$$

Combining Equation (1) with Equation (2), eliminating F, we obtain Equation (3) [48]. It should be noted that runoff cannot be generated when the initial loss is satisfied.

$$\begin{cases} Q = \frac{(P - I_a)^2}{P + S - I_a},\ P \geq 1 \\ Q = 0,\ P < 1 \end{cases} \tag{3}$$

Equation (3) is the equation for calculating the yield flow of the SCS-CN model. Since I_a data were not obtained, the parameter initial loss rate λ was used to establish a linear relationship between I_a and S [49]:

$$I_a = \lambda S \tag{4}$$

where λ usually has the standard value of 0.2 [44]. If the value of λ is 0.2, the yield calculation formula of the surface runoff of the SCS-CN model is [49]:

$$\begin{cases} Q = \frac{(P - 0.2S)^2}{P + 0.8S},\ P \geq 0.2S \\ Q = 0,\ P < 0.2S \end{cases} \tag{5}$$

The S value in all of the above equations is usually calculated from the equation with the CN value parameter [49]:

$$S = 25,400/\text{CN} - 254(\text{international system of units}) \tag{6}$$

In the formula, CN is a dimensionless constant reflecting the antecedent soil moisture condition (AMC) in the basin, and CN values are influenced by multiple factors such as land types, vegetation, and soil texture [46]. Since the United States and China have different land types, the original CN values could not be used directly in this study, and the optimization and adaptation methods of the model are not focused on here. This study also concluded that, in urban areas, CN values are more likely to be influenced by land types, so this research used the CN value of Suzhou City [50], which has similar land types, soil textures, and climatic and hydrological conditions to Wuhan City, as a reference to correct the CN value. According to the soil texture and the model standards, soil is divided into four categories: A, B, C, and D (Table 1) [46]. The content of clay is relatively high in Wuhan, making it a part of category C. Therefore, the CN value under category C was selected. AMC was divided into three types: AMC-I (dry), AMC-II (general), and AMC-III (wet), according to precipitation in the previous five days. Based on historical records of rainfall in Wuhan, this research selected the rainfall value of the past ten years starting from 6 July 2016, which marked a 12 h long rainfall of 179.3 mm in a single day. The precipitation in the first five days was moderate, so AMC-II conditions were selected to simulate the runoff in the study area.

Table 1. SCS model soil hydrology group classification criteria.

Soil Hydrology Group	Soil Texture	Minimum Permeability (mm/h)
A	Thick sand, thick loess, and agglomerated silt	7.26–11.43
B	Thin loess, sandy loam	3.81–7.26
C	Clay loam, thin sandy loam, low organic matter or high clay soil	1.27–3.81
D	Soils that swell significantly after absorbing water, plastic soils, some saline soils	0–1.27

Since the generation of flood risk does not depend entirely on the runoff volume (runoff depth) but also on the distribution area of each land type in the study area, in order to investigate the contribution of different land types to the volume of rainwater retained on the surface of the study area, this study used ArcGIS to count the distribution area of different land types in the study area and calculate the volume of runoff corresponding to different land types. In this study, the total runoff volume was used as a proxy for the runoff volume.

3.4. Water Conservation Capability Assessment

Water conservation capacity is the ability of an ecosystem to regulate water flow and the water cycle [51]. The overflow of sediments in the Yangtze River and the urban expansion of Wuhan have affected lakes and wetlands, weakening their water conservation capacity. Water conservation services function by enhancing soil infiltration and moderating surface runoff [52] to improve the ecosystem service capacity of the ESP while correcting the resistance distribution of runoff. This research used the water conservation capacity to modify the simulation results of the SCS-CN model. The ecosystem water conservation service capability index [53] was selected for the evaluation index of water conservation. The formula is as follows [53]:

$$WR = NPP_{mean} \times F_{sic} \times F_{pre} \times (1 - F_{slo}) \tag{7}$$

where WR is the ecosystem water conservation service capacity index; NPP_{mean} is the annual average net primary productivity of the ecosystem; F_{sic} is the soil infiltration capacity factor; F_{pre} is the annual average precipitation; F_{slo} is the slope value. All four values were normalized. Finally, the four factors were calculated by overlaying them using ArcGIS's raster calculator tool.

3.5. Leisure and Recreation Capability Assessment

In addition to flood control and ecological functions, leisure and recreational functions are also important features that distinguish ESP from traditional gray infrastructure. The deeply buried pipeline has a single function and does not provide an additional service during non-flooding periods, while the ecological corridor combining the blueway and greenway not only has better flood resistance during flooding periods, but also provides leisure and recreational services for urban residents during non-flooding periods. The accessibility of ecological space and cultural services in residential areas is important for promoting the physical and mental wellbeing of residents [54]. This study uses a crawler tool called easypoi to crawl the point data coded as parks, scenic spots, and green spaces in the *Baidu map open platform*, generate vector point data, and import them into ArcGIS. With the Kernel Density tool in ArcGIS, the density of the POI data of the ecological space and cultural services in the main urban area of Wuhan was calculated and used as the basis for evaluating the accessibility of the ecological space.

3.6. The MCR Model

In order to find the corridor development and construction mode with the lowest impact and the best drainage effect, it was necessary to extract the lowest cost path between the various sources. Based on the MCR model, this research used ArcGIS to extract the lowest cost path between each ecological source:

$$MCR = \int_{min} \sum (D_{ij} \times R_i) \tag{8}$$

where D_{ij} refers to the field distance from lake j to the environmental unit i in the region; R_i refers to the resistance coefficient of environmental unit I; R_i represents the ease of passage of matter and energy [55].

3.7. DEM-Based Runoff Path Analysis

Runoff paths are the locations of the most likely stream channels in the study area extracted from DEM data using ArcGIS hydrologic analysis, and are contiguous segments of a number of continuous low elevation locations where rainfall is more likely to collect in the study area during rainfall. The hydrological analysis tool was used to extract the stream channels and compare the maps to remove the existing streams to obtain the potential stream channels in the study area. These potential channels can be used as a basis for guiding the construction of artificial rivers. According to the spatial distribution of runoff paths, the optimization of the urban ESP enhances the infiltration capacity of ecological corridors and maximizes ecological benefits, which is in line with the requirements of urban elastic transformation.

3.8. Gravity Model

The development and construction of ecological corridors are usually carried out in stages. In order to provide guidance on timing the construction of corridors, the gravity model was used to calculate the strength of the interaction between ecological sources. The data were then used to judge the relative importance of each corridor. The formula is as follows [56]:

$$G_{ij} = \frac{N_i N_j}{{D_{ij}}^2} = \frac{\left[\frac{1}{P_i} \times ln(S_i)\right]\left[\frac{1}{P_j} \times ln(S_j)\right]}{\left(\frac{L_{ij}}{L_{max}}\right)^2} = \frac{L_{max}^2 lnS_i lnS_j}{L_{ij}^2 P_i P_j} \tag{9}$$

where G_{ij} is the interaction force between sources i and j; N_i and N_j are the weighting values of sources i and j, respectively; D_{ij} is the normalized value of the minimum cumulative resistance between sources i and j; P_i and P_j are the resistance values (extracted from the raster layer attribute table of the ecological corridor) of sources i and j; S_i and S_j are the areas of sources i and j; L_{ij} is the minimum cumulative resistance value between sources i and j; L_{max} refers to the maximum cumulative resistance of all the corridors in the study area.

3.9. ESP Construction Principles

3.9.1. Selection of Ecological Sources

The ecological source is the source of species dispersal, the place where rainwater collects, and the cornerstone of urban resilience. It should have the following characteristics: ① a higher ecosystem service value; ② a larger water volume; ③ a larger land area. A higher ecosystem service value can ensure a stable provision of ecological services and a higher protection value [57]. A larger water volume can reduce the flood peaks and regulate and store water from floods. A larger land area can ensure the stability of the ESP.

3.9.2. Construction of Resistance Surfaces

The ESP that is adaptive to floods should integrate the three functions of flood regulation and storage and ecological and cultural services. Therefore, this research selected the spatial distribution of the runoff simulated in the SCS-CN model as the basic resistance surface. Furthermore, it used the spatial distribution of water conservation and recreation capacity to correct the resistance surface. Because the absolute value of resistance has no practical significance, and since the tendency to assign resistance is more important [58], this research chose 1–50 as the assignment interval and assigned runoff resistance values to different patches based on the degree of development impact, construction cost, and stormwater management and control goals. The difficulty of constructing and developing ecological corridors and the cost of construction were proportional to the resistance value. The lower the construction difficulty and cost, the lower the resistance value. To regulate rainwater, this research used the runoff as the basis for resistance assignment. The larger the total runoff volume was, the lower the resistance value of the corresponding land type was. The next step was to connect the resistance values to the land type and then convert to raster output. The two ecosystem service capacity values are then used as the basis for assigning resistance values. These three resistance surfaces are combined to obtain the integrated resistance surface.

3.9.3. Extraction of Ecological Corridors

Based on the MCR model, the shortest path from one source to the other was extracted as the base ecological corridor using the cost distance and cost path analysis tools of the distance analysis module in ArcGIS. Through hydrological analysis, the runoff path data were extracted from DEM. Based on the waterlogging risk points in the main urban area, the coordinates of each waterlogging road section were imported into ArcGIS. Using the waterlogging risk points as the source points, the ecological corridors between the waterlogging risk points were obtained through the MCR model. The ecological corridor between the runoff path and each waterlogging risk point was used to optimize base ecological corridors.

4. Results

4.1. Corresponding Runoff Analysis by Land Type

ArcGIS was used to vectorize the land use planning map of the main urban area of Wuhan (Figure 3) and count the area corresponding to each land type. The total runoff volume corresponding to each land type is shown in Table 2 and its distribution is shown in Figure 4.

Table 2. Total runoff volume corresponding to each land type.

Land Use Types	CN Value	S (mm)	Q (mm)	Area (m^2)	Total Runoff Volume (m^3)
Protect green space	72	98.78	196.55	507,492.75	99,745.64
Logistics and warehousing	91	25.12	431.80	2,100,792.94	907,117.32
Administrative office space	82	55.76	297.80	3,813,765.88	1,135,734.66
Other green spaces	67	125.10	157.98	37,262,863.73	5,886,628.39
Production green space	75	84.67	223.09	16,904,581.75	3,771,311.36
Park green space	66	130.85	151.00	54,656,304.71	8,253,315.63
Entertainment and sports land	90	28.22	414.07	9,021,995.04	3,735,721.10
Municipal utilities	90	28.22	414.07	20,276,203.44	8,395,730.74
Commercial and business facility	92	22.09	450.41	20,041,809.81	9,027,042.93
Education and research	91	25.12	431.80	26,388,219.08	11,394,369.34
Residential	77	75.87	242.46	122,887,264.91	29,794,771.57
Industrial manufacturing	91	25.12	431.80	62,441,887.42	26,962,256.36
Waters	98	5.18	584.91	115,447,026.19	67,525,774.34
Road	98	5.18	584.91	177,813,282.11	104,004,234.32

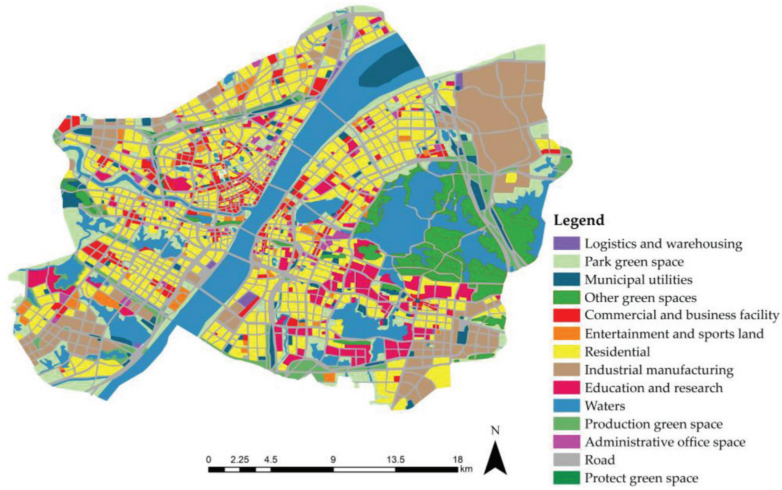

Figure 3. Distribution of land types on vector map.

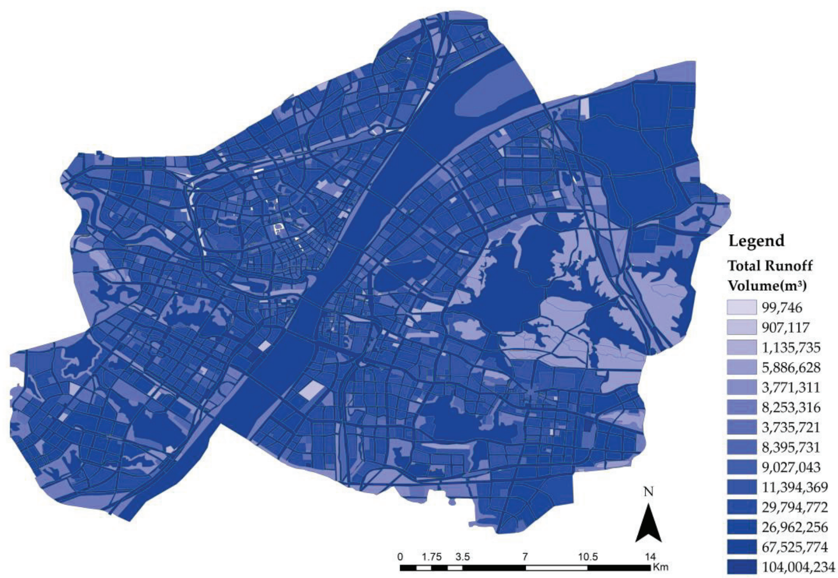

Figure 4. Spatial distribution of total runoff volume.

According to Figure 4, bodies of water, roads, industrial land, and residential areas are the most likely to collect rainwater. In particular, roads had the largest CN value and area, generating the most surface runoff. This suggests that stormwater management and road control should be priorities. The main reason for the great influx of industrial real-estate is the area's considerable size. The area also has a rigid underlying surface with a high CN value, resulting in a high capacity for rainwater retention. Residential areas and educational land generated more surface runoff as they accounted for a quarter of the total study area.

4.2. Distribution Characteristics of Two Ecosystem Services

The spatial distribution of the two ecosystem services showed a complementary trend (Figures 5 and 6). In terms of their water conservation capacity, high value areas were mainly distributed in ① the East Lake–Yanxi Lake area, Hanyang Ecological Zone (an area with a well-developed internal structure and a complete ecological function that can exist on its own.), ② the Zhujia River–Fu River area, ③ the Wuchang Institute of Technology–Hubei University of Technology, and ④ the East of Hanyang Ecological Zone, while the low value area was located in the Hankou and Wuchang Ecological Zones. When it comes to their leisure and recreation capacity, the high value areas were mainly concentrated in ⑤ the South of Hankou Ecological Zone, ⑥ the Wuhan Garden Expo Park, ⑦ the Moon Lake–Moshui Lake area, ⑧ the intersection between the Yangtze and the Hanjiang Rivers, and ⑨ the East Lake Scenic Area. In terms of the accessibility of ecological spaces and cultural services, residents of urban centers have an advantage over those in the urban periphery.

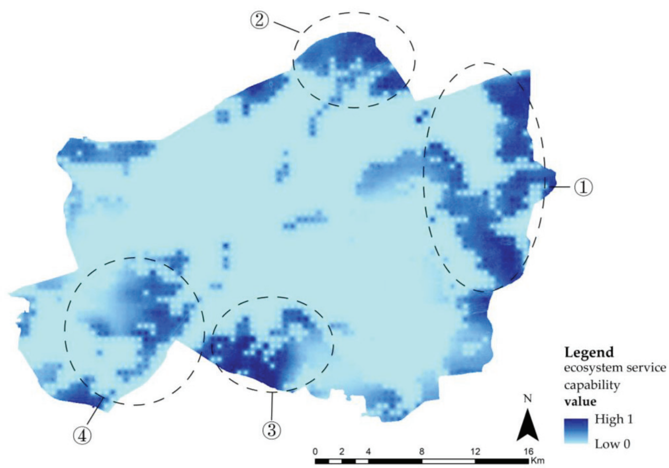

Figure 5. Distribution of the water conservation capacity.

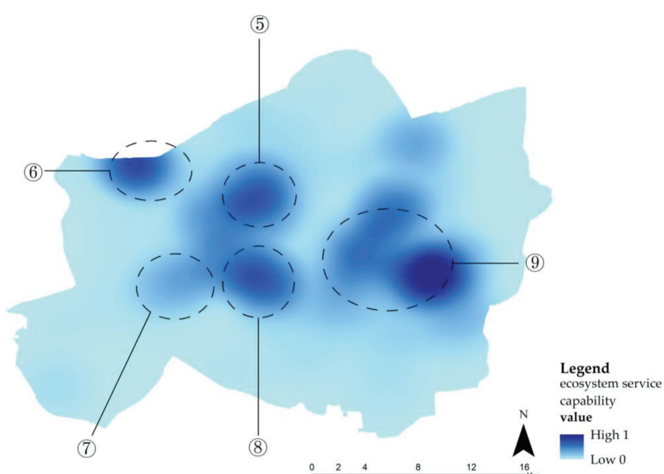

Figure 6. Distribution of the leisure and recreation capacity.

4.3. Construction of a Flood-Adaptive ESP

4.3.1. Distribution of Ecological Sources

According to the geographical and hydrological characteristics of Wuhan and its urban land type, 18 lakes in the main urban area were selected as ecological sources (Figure 7). It was found that the total area of the ecological sources is 29.54 km^2, accounting for 6.56% of the study area. As for mountainous and woodland areas, both were excluded from this paper because of their small size and weak flood storage capacity.

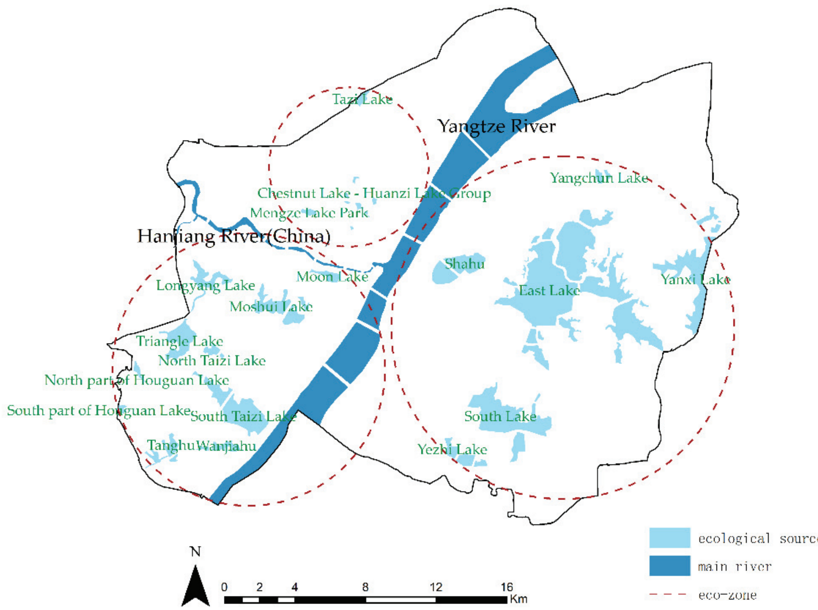

Figure 7. Distribution of ecological sources.

4.3.2. Construction of the Resistance Surface

The distribution of runoff resistance values is shown in Figure 8c. Low resistance values were mainly concentrated on roads and bodies of water. Compared to residential, commercial, and financial land types, the construction and development of roads and bodies of water had the advantages of a lower development impact and low costs.

The values of water conservation and leisure and recreation capacity are negatively correlated with the resistance values. The distribution of the resistance values for leisure and recreation and water conservation are shown in Figure 8a and b, respectively. The three raster resistance surfaces a, b, and c were overlaid using the Raster Calculator tool in ArcGIS. The comprehensive resistance is shown in Figure 8d. After the correction, the comprehensive resistance was found to be low in the center and high in the surrounding area. The low value was mainly distributed in ① the Yiyuan Community–Chezhanlufuren Community and ② the Changfeng sub-district–Garden Expo Park sub-district in the Hankou Ecological Zone, ③ Parrot sub-district–Wulidun sub-district and ④ Xianzheng Street Community in the Hanyang Ecological Zone, ⑤ the Xinhe sub-district–Jiyuqiao sub-district–Zhonghua Road sub-district, and ⑥ the East Lake–Yangchun Lake Community–Beiyangqiao Community area in the Wuchang Ecological Zone.

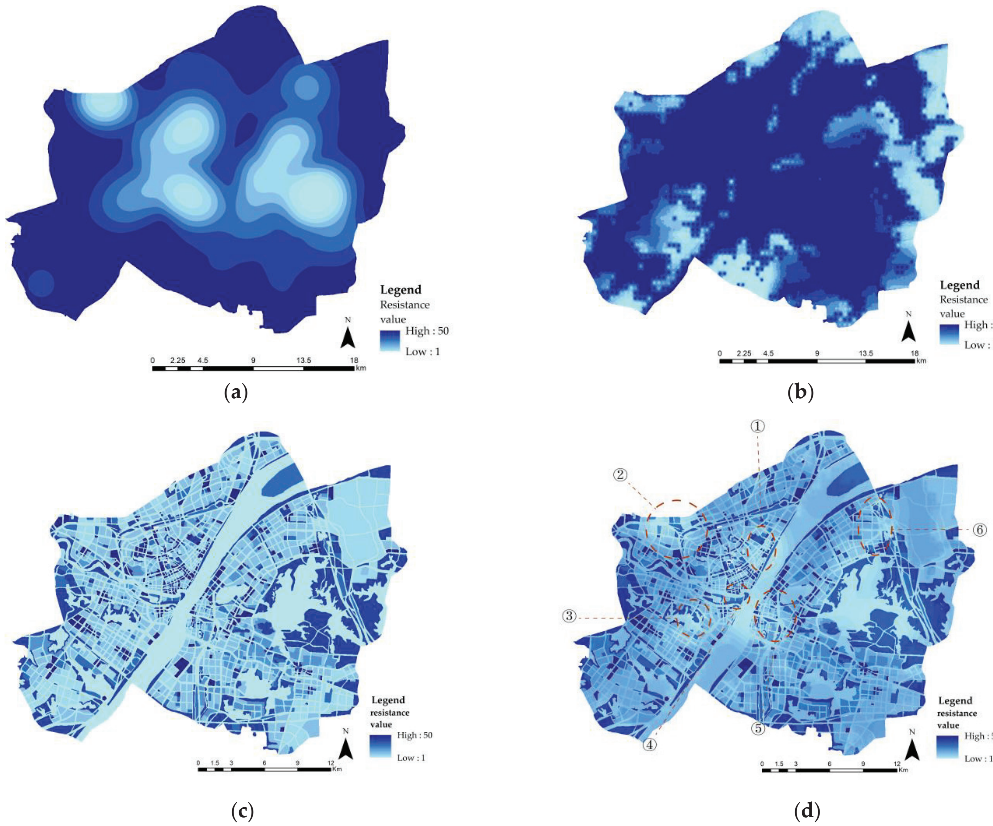

Figure 8. Resistance distribution: (**a**) leisure and Recreational resistance distribution, (**b**) Water conservation resistance distribution, (**c**) Runoff resistance distribution and (**d**) Comprehensive resistance distribution.

4.3.3. Identification and Optimization of Corridors

The distribution of ecological corridors is shown in Figure 9.

As shown in Figure 9, there are 19 ecological sources (As shown by the bolded numbers) and 32 ecological corridors (As shown by the circled numbers) in the study area, 9 of which are in the Hankou Ecological Zone; they are generally scattered and long. Of these nine corridors, Corridors No. 6 and 9 meet on the west side of Wuhan No. 17 Middle School. In total, 16 ecological corridors were found in the Hanyang Ecological Zone, accounting for half of the total of ecological corridors in the study area. Their distribution is concentrated, and the corridors are generally short, of which Corridors No. 10, 6, and 9 intersect on the west side of Wuhan No. 17 Middle School. Seven ecological corridors were found in the Wuchang Ecological Zone, roughly showing the spatial distribution pattern of *three verticals and three horizontals*, of which Corridors No. 26 and 30 are connected to the north side of Hubei Shuiguohu High School. Corridors No. 29 and 28 meet at Shouyi Park, while Corridors No. 29 and 32 meet south of the Wuchang Institute of Technology. The specific distribution of these 32 corridors is shown in Table S1.

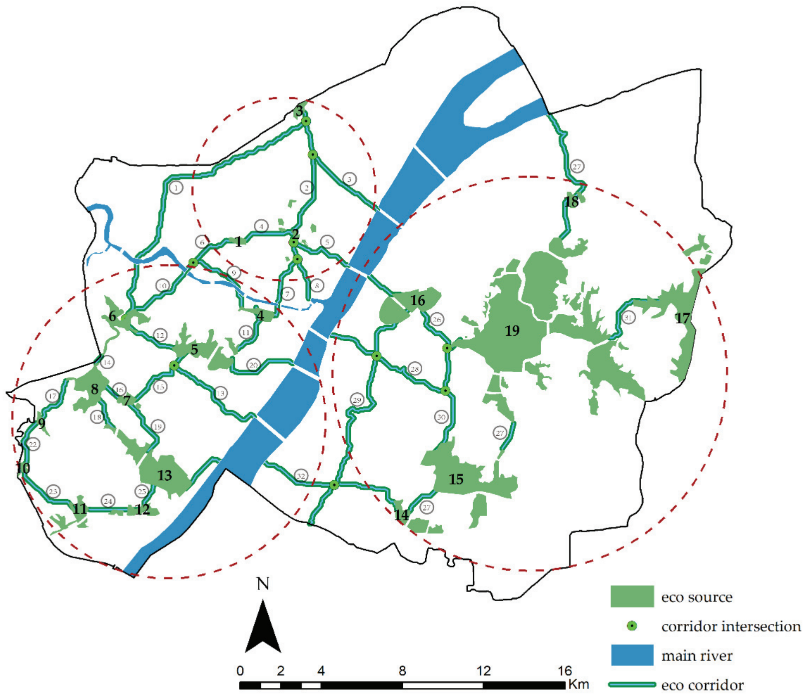

Figure 9. Distribution of ecological corridors.

According to Figure 9, the ecological corridors in the Wuchang Ecological Zone have the most extensive connectivity range. Although there are fewer communication channels between the ecological sources, the source area is relatively large. Furthermore, the ecological corridors in the Hanyang Ecological Zone are small in scale but strong in connectivity, and the corridors are compact and short. The ecological source area of the Hankou Ecological Zone is small and scattered, resulting in long corridors. Therefore, the width of the corridors should be increased to enhance their anti-interference ability and ensure that the ecological corridors function properly.

4.4. Identification of Construction Priorities

Based on the gravity model, this research constructed a matrix of interactions between ecological sources (Table S2) to identify the strength of the interaction between ecological sources and select key ecological corridors (Figure 10).

The key corridors identified by the gravity model should become priorities for construction so as to reduce the impact of corridor development and improve the efficiency of corridor construction. From Figure 9 and Table S2, it can be seen that the strength of the connection between source 2 (Chestnut Lake–Huanzi Lake Group) and 5 (Moon Lake) was weak. However, Corridor 7, as a key link between the north and south of the Hanjiang River, was critical for the overall connectivity of the study area and should be given priority. The strength of the connection between source 11 (Tang Lake) and 13 (South Taizi Lake) was also weak. Corridors No. 24 and 25 were important passages connecting Tanghu Lake and the Hanyang Ecological Zone. They were used as key corridors for construction, which can improve the ecological service capacity of the southern part of the Hanyang Ecological Zone. Overall, the strength of the connection between the sources weakened from west to east and from south to north. In particular, the strength of the connection between Tazi Lake and other sources in the northwest was the weakest.

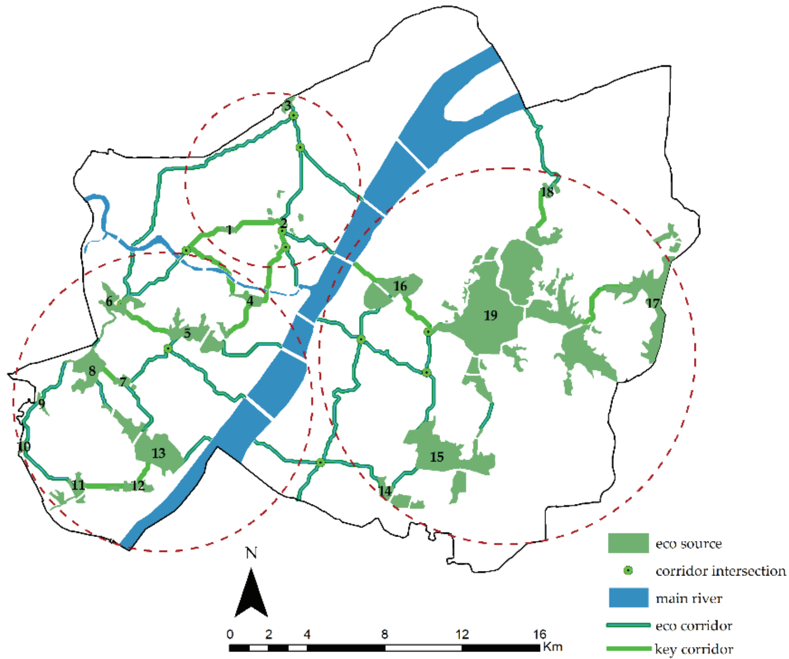

Figure 10. Distribution of key corridors.

By ArcGIS statistics, the total cumulative length of the 32 ecological corridors in the main urban area of Wuhan is 344.21 km. In total, 10 key corridors with a total length of 63.56 km were mainly distributed around the East Lake and the Hanyang Ecological Zone. There were 22 potential corridors with a total length of 280.65 km located north of the Hanjiang River and south of Wuchang District. By planning ecological corridors to connect to important ecological sources north and south of the main urban area and adding the ecological resources of the Yangtze River to the overall cycle of the ESP, the whole study area can respond to the floods in a more dynamic, proactive, and resilient manner.

5. Discussion

5.1. Comparison of Current Status

In the past decade or so, the Wuhan municipal government has proposed a plan to improve the ecology of the region, called *Six Lakes Linkage* [59], which would connect some of the rivers and lakes through canals. Therefore, this paper compares the results of the study with the current situation and investigates the merits and shortcomings of the plan.

Firstly, comparison of real-time satellite maps shows that corridors already exist between the four ecological sources (source 5, 6, 7, and 8). Four existing corridors were found in the right location as the research results, namely, Corridors No. 12, 13, 14, and 15. There were two corridors with partially identical results, i.e., the North Prince Lake–Haitang section of Corridor No. 19 and the East Lake–Shahu section of Corridor No. 26.

Secondly, two existing corridors were mislocated. In particular, Corridor No. 2 was mislocated and not long enough. Due to the construction difficulty, the Begonia Road–South Taizi Lake section of Corridor No. 19 cut a corner and took a straight route, abandoning the closer route along Jiangcheng Avenue and opting for one block farther along Wisteria Road. There was already a corridor (East Lake Harbor) connecting the Yangtze River to Yangchun and East Lake. However, the curved shape of East Lake Harbor led to an excessively long corridor in the East Lake–Yangchun Lake section compared to Corridor No. 27 in the research results. Excessively long and mislocated corridors can impede the transfer of ecological materials and energy between source places and weaken the ecological service capacity of ecological corridors. The existing zigzag corridors make it difficult to absorb and discharge stormwater and tend to cause stormwater accumulation, which is not conducive to the prevention of floods in urban areas.

Lastly, the lack of connecting corridors between the remaining source sites affects the flow of ecological materials and energy. Likewise, it does not facilitate the discharge and dissipation of stormwater during the flood season, weakening the resilience of the main urban area.

5.2. Exploration of the Development Model

The largest number of ecological corridors was found in the Hanyang Ecological Zone, which is the product of *the Hanyang District Six Lakes Linkage Project* [59] ongoing since 2005 that was originally developed to curb the deterioration of lakes' water quality with the natural water power of the Yangtze River. The construction method incorporated parallel blueways and greenways, that is, it included artificial river channels and supplemented them with greenways on either side. Firstly, the interconnected lakes can increase the overall storage capacity by increasing water storage space, thus offering an advantage in dealing with floods. Constructing greenways can also provide a path for stormwater transfer. Likewise, the flexible underlaying surface can increase the infiltration of stormwater during the transfer process and reduce the water amount. During the construction of ecological corridors, the lakes were seen as ecological sources able to curb the damage from urban construction activities. Corresponding plants in the areas were selected to control runoff pollution in response to the local runoff pollution characteristics of the study area.

The ESP that is adaptive to floods aims to build a resilient city and connect the major lakes in the main urban area of WUH through ecological corridors to form a regional and systematic ecological network. This network can, in turn, improve the ecological resilience of the main urban area. Through the flood-adaptive design of the ESP, the threshold of precipitation from floods is increased, while the speed of flood dissipation and transfer is enhanced, giving rise to a city resilient to floods.

5.3. Methodology Advantage

Compared to traditional gray infrastructure with a single function and no integrity, an ESP adaptive to floods is more holistic, diverse, economical, environmentally friendly, and less impactful.

Although traditional gray infrastructure is taller and more solid, it loses its single function [60] during non-flooding periods. The hard surface of the infrastructure is neither aesthetically pleasing nor safe, as well. The ESP that is adaptive to floods can not only cope with floods in urban areas but can also provide recreational and ecological services for urban residents during the non-flooding period.

Furthermore, traditional gray infrastructure negatively impacts the environment [61,62]. Hard levee separates lake and river ecosystems from other ecosystems, blocking the normal exchange of ecological materials and energy and increasing the risk of ecological fragility. The construction of traditional gray infrastructure, such as levees, not only occupies more of the lake's natural space, but also deprives the lake of its hydrophilic vitality. However, the ESP that is adaptive to floods adopts a "sparse" approach to enhance ecosystem service capacity of rivers and lakes while also minimizing the impact of floods. In addition, the natural force of the river can be used to improve the water quality of the urban lakes by connecting them to natural water systems, such as the Yangtze and Han Rivers.

In terms of the construction impact, the construction of ecological corridors does not have to happen overnight. The corridors can be built first as key ones and then as potential ones. This step-by-step construction has less impact on the corridors' functionality and can greatly reduce construction investment. This research developed two specific ways of construction: ① it adopted the culvert connection, i.e., maintaining the elevation of the roadbed and digging under the road to form the culvert. This specific method was used in road construction of Mudu Ancient Town in Wuzhong District, Suzhou. The advantage is that the construction cost is low, while the disadvantages are that the corridor cannot realize the functions of leisure and recreation, runoff pollution control, and cultural education, and the public perception is also greatly reduced; ② this research also used an artificial river with a road bridge above it, so that the part under the bridge becomes a park and the bridge becomes a road. This example refers to the effect of the Wuhan City Hanyang District–South Third Ring Road–Wetland Park–Meizi Interchange. However, its disadvantages are high construction costs, long lead time, and management difficulties.

In terms of economic impact, ESP has lower construction and maintenance costs and adds ecological and cultural value [63]. On the other hand, traditional gray infrastructure is not only costly, but also puts a certain amount of pressure on local finances for maintenance.

Compared to sponge cities, an ESP that is adaptive to floods is holistic and dynamic, complements the static defense of sponge cities, and relieves their storage pressure. Taking advantage of the natural hydraulics of the Yangtze and Hanjiang Rivers supplemented by plants can make up for the deficiencies of the sponge city in controlling runoff pollution [20]. An ESP that is adaptive to floods is also more advantageous in terms of cultural and educational services and public perception. The combination of a flood-adaptive ESP and sponge city can effectively improve a city's resilience.

Based on the existing green space and river system in the main urban area of WUH, it was found that the existing blueways were limited in path selection by straight lines or original old river channels. The ESP that is adaptive to floods proposed in this research used the SCS-CN model to visualize and express the retention of surface water volume during floods. Because stormwater management should be given priority, corridor paths were extracted based on cost and distance using the MCR model. In traditional ESP studies [64,65], descriptions of the ecological corridor locations are not specific enough, causing difficulties in locating them precisely during construction. In this research, the specific locations of corridors were narrowed down to the street level. The suggestions about construction were made by comparing existing plans, so the research results are more practical, which is beneficial to governments for precise policy making and reducing decision-making costs.

6. Conclusions

This paper analyzed the spatial distribution of stormwater runoff under extreme precipitation and constructed an ESP that is adaptive to floods.

The SCS-CN model guided flood control objectives and derived the surface volume and spatial distribution of the runoff. The volume and spatial distribution were subsequently used to develop ecological corridors. The surface runoff path and the distribution of waterlogging points were used to optimize the corridor locations.

This research identified 19 ecological sources, 3 ecological zones, 32 ecological corridors, 10 key corridors, and 22 potential corridors using the gravity model. The Wuchang Ecological Zone exhibited a *three vertical and three horizontal* spatial distribution patterns with East Lake as the core. Furthermore, the Hankou Ecological Zone had a dispersed distribution pattern with Chestnut Lake–Huanzi Lake Group as the center. Lastly, the Hanyang Ecological Zone showed a clustered distribution. The research finally proposed a *two-axis and three-core* urban ecological resilience optimization strategy for decision makers, consisting of three ecological zones and two rivers.

In conclusion, enhancing urban ecological resilience can help cities cope with severe floods and can provide new methods and approaches for rainfall and flood control in Wuhan. Likewise, it can provide ideas for maintaining the ecological service capacity of lakes, realizing urban resilience, and ensuring regional ecological security.

The shortcomings of this research are as follows. (1) Hydrological heterogeneity within the same land type was not studied due to data limitations. Therefore, landscape design for controlling runoff pollution needs further research. (2) This research proposed the location of the corridors, but did not clarify their width, so subsequent studies should supplement this aspect to serve urban construction better. (3) Since there are few examples of how to construct flood-adaptive ESPs, it was difficult to quantify their functionality; thus, future studies need to address this problem. These questions are to be addressed in a follow-up study.

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References

1. Yu, W.; Huang, Y.; Shao, M. Research on characteristics of extreme weather disasters and fluctuations trend on Lancang river basin. *Acta Ecol. Sin* **2015**, *35*, 1378–1387.
2. Ali, H.; Mishra, V. Contrasting Response of Rainfall Extremes to Increase in Surface Air and Dewpoint Temperatures at Urban Locations in India. *Sci. Rep.* **2017**, *7*, 1228. [CrossRef] [PubMed]
3. Peng, J.; Wei, H.; Wu, W.; Liu, Y.; Wang, Y. Storm flood disaster risk assessment in urban area based on the simulation of land use scenarios: A case of Maozhou Watershed in Shenzhen City. *Acta Ecol. Sin* **2018**, *38*, 3741–3755.
4. Luo, K.; Zhang, X. Increasing Urban Flood Risk in China over Recent 40 Years Induced by LUCC. *Landsc. Urban Plan* **2022**, *219*, 104317. [CrossRef]
5. Sanyal, J.; Densmore, A.L.; Carbonneau, P. Analysing the Effect of Land-Use/Cover Changes at Sub-Catchment Levels on Downstream Flood Peaks: A Semi-Distributed Modelling Approach with Sparse Data. *Catena* **2014**, *118*, 28–40. [CrossRef]
6. Li, F.; Wang, R.; Zhao, D. Urban ecological infrastructure based on ecosystem services: Status, problems and perspectives. *Acta Ecol. Sin* **2014**, *34*, 190–200.
7. Dianat, H.; Wilkinson, S.; Williams, P.; Khatibi, H. Planning the Resilient City: Investigations into Using "Causal Loop Diagram" in Combination with "UNISDR Scorecard" for Making Cities More Resilient. *Int. J. Disaster Risk Reduct.* **2021**, *65*, 102561. [CrossRef]
8. PlanNYC: A Stronger, More Resilient New York. Available online: https://toolkit.climate.gov/reports/stronger-more-resilient-new-york (accessed on 28 August 2022).
9. Ltd, B. Evaluating Options for Water Sensitive Urban Design (WSUD)—A National Guide. Available online: http://www.environment.gov.au/node/25018 (accessed on 27 August 2022).
10. The "Climate-Proofing" of Rotterdam. Available online: https://www.renewableenergyworld.com/baseload/the-climateproofing-of-rotterdam/ (accessed on 24 July 2022).
11. Köster, S. How the Sponge City Becomes a Supplementary Water Supply Infrastructure. *Water-Energy Nexus* **2021**, *4*, 35–40. [CrossRef]
12. Liu, J.; Gong, X.; Li, L.; Chen, F.; Zhang, J. Innovative Design and Construction of the Sponge City Facilities in the Chaotou Park, Talent Island, Jiangmen, China. *Sustain. Cities Soc.* **2021**, *70*, 102906. [CrossRef]
13. Zhai, J.; Ren, J.; Xi, M.; Tang, X.; Zhang, Y. Multiscale Watershed Landscape Infrastructure: Integrated System Design for Sponge City Development. *Urban For. Urban Green.* **2021**, *60*, 127060. [CrossRef]
14. Ji, M.; Bai, X. Construction of the Sponge City Regulatory Detailed Planning Index System Based on the SWMM Model. *Environ. Technol. Innov.* **2021**, *23*, 101645. [CrossRef]
15. Jiang, C.; Li, J.; Hu, Y.; Yao, Y.; Li, H. Construction of Water-Soil-Plant System for Rainfall Vertical Connection in the Concept of Sponge City: A Review. *J. Hydrol.* **2022**, *605*, 127327. [CrossRef]
16. Wang, S.; Palazzo, E. Sponge City and Social Equity: Impact Assessment of Urban Stormwater Management in Baicheng City, China. *Urban Clim.* **2021**, *37*, 100829. [CrossRef]
17. Cheng, T.; Huang, B.; Yang, Z.; Qiu, J.; Zhao, B.; Xu, Z. On the Effects of Flood Reduction for Green and Grey Sponge City Measures and Their Synergistic Relationship—Case Study in Jinan Sponge City Pilot Area. *Urban Clim.* **2022**, *42*, 101058. [CrossRef]

18. Leng, L.; Mao, X.; Jia, H.; Xu, T.; Chen, A.S.; Yin, D.; Fu, G. Performance Assessment of Coupled Green-Grey-Blue Systems for Sponge City Construction. *Sci. Total Environ.* **2020**, *728*, 138608. [CrossRef]
19. Wang, J.; Liu, J.; Wang, H.; Shao, W.; Mei, C.; Ding, X. Matching Analysis of Investment Structure and Urban Inundation Control Function of Sponge Cities in China. *J. Clean. Prod.* **2020**, *266*, 121850. [CrossRef]
20. Zhang, Z.; Li, J.; Li, Y.; Zhao, L.; Duan, X. Accumulation of Polycyclic Aromatic Hydrocarbons in the Road Green Infrastructures of Sponge City in Northwestern China: Distribution, Risk Assessments and Microbial Community Impacts. *J. Clean. Prod.* **2022**, *350*, 131494. [CrossRef]
21. She, L.; Wei, M.; You, X. Multi-Objective Layout Optimization for Sponge City by Annealing Algorithm and Its Environmental Benefits Analysis. *Sustain. Cities Soc.* **2021**, *66*, 102706. [CrossRef]
22. Zhang, M.; Peng, C.; Shu, J.; Lin, Y. Territorial Resilience of Metropolitan Regions: A Conceptual Framework, Recognition Methodologies and Planning Response—A Case Study of Wuhan Metropolitan Region. *Int. J. Environ. Res. Public Health* **2022**, *19*, 1914. [CrossRef]
23. Jia, H.; Liu, Z.; Xu, C.; Chen, Z.; Zhang, X.; Xia, J.; Yu, S.L. Adaptive Pressure-Driven Multi-Criteria Spatial Decision-Making for a Targeted Placement of Green and Grey Runoff Control Infrastructures. *Water Res.* **2022**, *212*, 118126. [CrossRef]
24. Yang, J.J.; Zhu, X. Adapting Urban Water Utilities to Climate Uncertainties: A Case Study of Wuhan, PRC. *Procedia Eng.* **2017**, *198*, 496–510. [CrossRef]
25. Liu, Y.; Meng, J.; Song, L. Progress in the research on regional ecological security patterns. *Acta Ecol. Sin* **2010**, *30*, 6980–6989.
26. Fan, F.; Wen, X.; Feng, Z.; Gao, Y.; Li, W. Optimizing Urban Ecological Space Based on the Scenario of Ecological Security Patterns: The Case of Central Wuhan, China. *Appl. Geogr.* **2022**, *138*, 102619. [CrossRef]
27. Peng, J.; Pan, Y.; Liu, Y.; Zhao, H.; Wang, Y. Linking Ecological Degradation Risk to Identify Ecological Security Patterns in a Rapidly Urbanizing Landscape. *Habitat Int.* **2018**, *71*, 110–124. [CrossRef]
28. Jiang, H.; Peng, J.; Dong, J.; Zhang, Z.; Xu, Z.; Meersmans, J. Linking Ecological Background and Demand to Identify Ecological Security Patterns across the Guangdong-Hong Kong-Macao Greater Bay Area in China. *Landscape Ecol.* **2021**, *36*, 2135–2150. [CrossRef]
29. Fu, Y.; Shi, X.; He, J.; Yuan, Y.; Qu, L. Identification and Optimization Strategy of County Ecological Security Pattern: A Case Study in the Loess Plateau, China. *Ecol. Indic.* **2020**, *112*, 106030. [CrossRef]
30. Wu, J.; Luo, K.; Ma, H.; Wang, Z. Ecological security and restoration pattern of Pearl River Delta, based on ecosystem service and gravity model. *Acta Ecol. Sin.* **2020**, *40*, 8417–8429.
31. Wang, X.; Chen, T.; Feng, Z.; Wu, K.; Lin, Q. Construction of ecological security pattern based on boundary analysis: A case study on Jiangsu Province. *Acta Ecol. Sin.* **2020**, *40*, 3375–3384.
32. Zheng, Q.; Shen, M.; Zhong, L. Construction of ecological security pattern in Pudacuo National Park. *Acta Ecol. Sin.* **2021**, *41*, 874–885.
33. Zhang, L.; Yue, W.; Chen, Y. Construction of urban ecological security pattern based on of patch composite characteristics: A case study of Hangzhou. *Acta Ecol. Sin.* **2021**, *41*, 4632–4640.
34. Ribeiro, M.P.; de Mello, K.; Valente, R.A. How Can Forest Fragments Support Protected Areas Connectivity in an Urban Landscape in Brazil? *Urban For. Urban Green.* **2022**, *74*, 127683. [CrossRef]
35. Dai, L.; Liu, Y.; Luo, X. Integrating the MCR and DOI Models to Construct an Ecological Security Network for the Urban Agglomeration around Poyang Lake, China. *Sci. Total Environ.* **2021**, *754*, 141868. [CrossRef] [PubMed]
36. Serret, H.; Raymond, R.; Foltête, J.-C.; Clergeau, P.; Simon, L.; Machon, N. Potential Contributions of Green Spaces at Business Sites to the Ecological Network in an Urban Agglomeration: The Case of the Ile-de-France Region, France. *Landsc. Urban Plan.* **2014**, *131*, 27–35. [CrossRef]
37. Wuhan City Master Plan 2010–2020. Available online: http://zrzyhgh.wuhan.gov.cn/zwgk_18/fdzdgk/ghjh/zzqgh/202001/t20200107_602858.shtml (accessed on 8 December 2022).
38. Editor, Encyclopedia of China Chao Soil. Available online: http://www.baiven.com/baike/221/243523.html (accessed on 30 November 2022).
39. Wuhan Statistical Yearbook. Available online: http://tjj.wuhan.gov.cn/tjfw/tjnj/ (accessed on 8 December 2022).
40. Wuhan Water Resources Bulletin. Available online: http://swj.wuhan.gov.cn/szy/202204/t20220411_1953495.html (accessed on 1 December 2022).
41. Wuhan: The Thoroughfare of the Nine Provinces. Available online: http://slt.hubei.gov.cn/slyw/slwh/slls/201912/t20191213_1761919.shtml (accessed on 19 December 2022).
42. Chen, K.; Qi, M.; Wang, X.; Huang, G. Study of urban lake landscape ecological security pattern evolution in Wuhan, 1995—2015. *Acta Ecol. Sin.* **2019**, *39*, 1725–1734.
43. Nearly 90 Lakes in Wuhan Have Disappeared in the Past 50 Years, and Officials Have Introduced Measures to Strictly Control the Lakes. Available online: http://www.xinhuanet.com/politics/2015-01/19/c_127399182.htm (accessed on 29 August 2022).
44. Service, U.S. *SCS National Engineering Handbook, Section 4-Hydrology*; Government Printing: Washington, DC, USA, 1971.
45. Prokešová, R.; Horáčková, Š.; Snopková, Z. Surface Runoff Response to Long-Term Land Use Changes: Spatial Rearrangement of Runoff-Generating Areas Reveals a Shift in Flash Flood Drivers. *Sci. Total Environ.* **2022**, *815*, 151591. [CrossRef] [PubMed]
46. Yuan, Z. *Watershed Hydrological Model*, 1st ed.; Water Resources and Electric PowerPress: Beijing, China, 1990; ISBN 7-120-01021-2.
47. Verma, S.; Singh, P.K.; Mishra, S.K.; Singh, V.P.; Singh, V.; Singh, A. Activation Soil Moisture Accounting (ASMA) for Runoff Estimation Using Soil Conservation Service Curve Number (SCS-CN) Method. *J. Hydrol.* **2020**, *589*, 125114. [CrossRef]

48. Lee, B.; Kullman, S.W.; Yost, E.E.; Meyer, M.T.; Worley-Davis, L.; Williams, C.M.; Reckhow, K.H. Predicting Characteristics of Rainfall Driven Estrogen Runoff and Transport from Swine AFO Spray Fields. *Sci. Total Environ.* **2015**, *532*, 571–580. [CrossRef]
49. Shadeed, S. Application of GIS-Based SCS-CN Method in West Bank Catchments, Palestine. *Water Sci. Eng.* **2010**, *3*, 13.
50. Cai, X. The Research of the Coupling Degree of the Green Space System of Suzhou Industrial Park and the Urban Surface Runoff. Master's Thesis, Soochow University, Suzhou, China, 2018.
51. Wang, K.; Feng, Y.; Qiu, C.; Wang, X.; Ma, J.; Zhang, Y. Spatial and Temporal Evolution and Drivers of Ecosystem Services in Beijing. Tianjin and the Beijing-Tianjin Ring Urban Agglomeration. *Acta Ecol. Sin.* **2022**, *42*, 7871–7883. [CrossRef]
52. Guzman, C.D.; Hoyos-Villada, F.; Da Silva, M.; Zimale, F.A.; Chirinda, N.; Botero, C.; Morales Vargas, A.; Rivera, B.; Moreno, P.; Steenhuis, T.S. Variability of Soil Surface Characteristics in a Mountainous Watershed in Valle del Cauca, Colombia: Implications for Runoff, Erosion, and Conservation. *J. Hydrol.* **2019**, *576*, 273–286. [CrossRef]
53. Liang, C.; Zeng, J.; Shen, Z.; Wang, Q. Spatial pattern analysis and management of urban ecosystem services under rapid urbanization:A case study of Xiamen. *Acta Ecol. Sin.* **2021**, *41*, 4379–4392.
54. Tu, X.; Huang, G.; Wu, J. Review of the relationship between urban greenspace accessibility and human well-being. *Acta Ecol. Sin.* **2019**, *39*, 421–431.
55. He, J.; Pan, Y.; Liu, D. Analysis of the wetland ecological pattern in Wuhan City from the perspective of ecological network. *Acta Ecol. Sin.* **2020**, *40*, 3590–3601.
56. Li, S.; Zhao, Y.; Xiao, W.; Yue, W.; Wu, T. Optimizing Ecological Security Pattern in the Coal Resource-Based City: A Case Study in Shuozhou City, China. *Ecol. Indic.* **2021**, *130*, 108026. [CrossRef]
57. Wang, X.; Wan, R.; Pan, P. Construction and adjustment of ecological security pattern based on MSPA-MCR Model in Taihu Lake Basin. *Acta Ecol. Sin.* **2022**, *42*, 1968–1980.
58. Chen, C.; Wu, S.; Douglas, M.C.; Lv, M.; Wen, Z.; Jiang, Y.; Chen, J. Effects of changing cost values on landscape connectivity simulation. *Acta Ecol. Sin.* **2015**, *35*, 7367–7376.
59. Yearbook of 40 Years of Reform and Opening Up in Wuhan. Available online: http://58.48.136.171:81/book/dfz/bookread/id/783/category_id/232146.html%20 (accessed on 27 August 2022).
60. Chen, W.; Wang, W.; Huang, G.; Wang, Z.; Lai, C.; Yang, Z. The Capacity of Grey Infrastructure in Urban Flood Management: A Comprehensive Analysis of Grey Infrastructure and the Green-Grey Approach. *Int. J. Disaster Risk Reduct.* **2021**, *54*, 102045. [CrossRef]
61. Morris, R.L.; Konlechner, T.M.; Ghisalberti, M.; Swearer, S.E. From Grey to Green: Efficacy of Eco-Engineering Solutions for Nature-Based Coastal Defence. *Global Chang. Biol.* **2018**, *24*, 1827–1842. [CrossRef]
62. Yao, Y.; Li, J.; lv, P.; Li, N.; Jiang, C. Optimizing the Layout of Coupled Grey-Green Stormwater Infrastructure with Multi-Objective Oriented Decision Making. *J. Clean. Prod.* **2022**, *367*, 133061. [CrossRef]
63. Xu, C.; Liu, Z.; Chen, Z.; Zhu, Y.; Yin, D.; Leng, L.; Jia, H.; Zhang, X.; Xia, J.; Fu, G. Environmental and Economic Benefit Comparison between Coupled Grey-Green Infrastructure System and Traditional Grey One through a Life Cycle Perspective. *Resour. Conserv. Recycl.* **2021**, *174*, 105804. [CrossRef]
64. Li, Z.-T.; Li, M.; Xia, B.-C. Spatio-Temporal Dynamics of Ecological Security Pattern of the Pearl River Delta Urban Agglomeration Based on LUCC Simulation. *Ecol. Indic.* **2020**, *114*, 106319. [CrossRef]
65. Yu, J.; Tang, B.; Chen, Y.; Zhang, L.; Nie, Y.; deng, W. Landscape ecological risk assessment and ecological security pattern construction in landscape resource-based city: A case study of Zhangjiajie City. *Acta Ecol. Sin* **2022**, *42*, 1290–1299.

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The Impact of Urban Construction Land Change on Carbon Emissions—A Case Study of Wuhan City

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Abstract: Urban construction land (UCL) change is a significant cause of changes in urban carbon emissions. However, as the extent of this effect is currently unclear, cities cannot easily formulate reasonable carbon reduction policies in terms of land use. Taking the city of Wuhan, China, as an example, this paper combines data on land use and carbon emissions from 1995 to 2019 and uses spatial analysis, curve estimation, and correlation evaluation to explore the direct and indirect effects of the UCL changes on carbon emissions. The results show that: (1) Between 1995 and 2019, the UCL area in Wuhan increased by 193.44%, and carbon emissions increased by 78.63%; moreover, both changes showed a gradually increasing spatial correlation, and the quantitative relationship could be better fitted with a composite function model; (2) The UCL change had mainly an indirect impact on carbon emissions via factors such as population and energy use intensity per unit of carbon emissions; (3) The maximum value of carbon emissions inside a unit area decreased during the study period, with an average annual decrease of about 2.02%. Therefore, the city of Wuhan can promote the achievement of its carbon emissions reduction targets by improving the existing land use policies, for example, by dividing the city into multiple functional zones.

Keywords: UCL; carbon emissions; spatial and temporal variation; Wuhan

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1. Introduction

Large amounts of carbon emissions can lead to global meteorological changes, which can cause serious natural disasters [1,2]. In Climate Change and Land, the IPCC (Intergovernmental Panel on Climate Change) pointed out the interactive relationship between land-use change and climate change and that reasonable land-use management policies can help achieve the carbon emissions reduction targets of the Paris Agreement [3]. Some scholars have demonstrated that land-use change significantly impacts carbon emissions and meteorological changes [4–6]. Land-use change affects not only the carbon stock of soil but also carbon emissions from human activities by changing the linkages between socioeconomic and natural systems [7–9]. Land-use change is also the second cause of the increase in carbon emissions from fossil energy combustion [10–12]. Therefore, it is necessary to clarify the extent of the impact of land-use change on carbon emissions to support the formulation of rational land-use policies and carbon emissions reduction measures.

Current research on the relationship between land-use change and carbon emissions has focused on the following hot topics:

(1) Determining the role of land-use change on carbon emissions. Houghton et al. [13] explored the relationship between land-use change and carbon emissions by taking Asia as the research object; they found that forestry activities and land-use change in South and Southeast Asia released 43.5 Pg of carbon into the atmosphere during the period 1850–1995. By reconstructing Land-Use and Land-Cover Change (LUCC) data, Pacala et al. [14] found that carbon emissions from terrestrial ecosystems in the United States from 1700 to 1945

were about 27 ± 6 Pg. Ge [15] took China as a case study and used the "thin record model" to measure carbon emissions due to land-use change in the previous 300 years. Later studies focused on the effect of small-scale land-use change on carbon emissions. Ren et al. [16] took Dongliao County, China, as the research object and used land-use change data from 1980 to 2018 to study the effect of land-use change on the carbon stock of the ecosystem.

(2) Land-use carbon emissions accounting methods and standards. In 1980, Houghton [17] proposed and refined a thin-notation model based on an annual time-series bookkeeping model with extensive survey and empirical data, which laid the foundations for numerous subsequent studies proposing models to estimate carbon emissions. Ge [15] used a model estimation method to measure the changes in carbon emissions due to land-use change in China over the previous 300 years; Fang et al. [18] studied the forest vegetation carbon pool in China and its spatial and temporal variation by using the resource inventory data of the Senjin system and associated statistical records in China in the past 50 years. Zhao et al. [19] used remote-sensing statistics and Gross Primary Productivity (GPP) data to build a model to estimate carbon emissions changes in the United States. Although these three methods are widely used for carbon emission calculation, due to the complexity and variability of the underlying data, classification system, research methods, and empirical parameters, accounting results can vary greatly for the same research object. Therefore, it is extremely important to employ a reasonable carbon emissions accounting standard [20]. The National Greenhouse Gas Inventory Program (NGGIP), a thematic working group under the IPCC, has established a database of greenhouse gas emission factors, which is regularly updated and provides a basis for carbon emission accounting in various countries and regions [21]. Fang et al. [22], Zheng et al. [23], Lai [21], Zhang et al. [24], and Ye et al. [25] estimated the carbon sinks of various land types in China using agricultural statistics, remote sensing images, ground observation data, and previous research results, and obtained carbon emission factors for forest land, cropland, unused land, watershed, and grassland, which provided a basis for later scholars to use the factor measure to calculate the carbon emissions of different regions of China.

(3) The mechanism of land-use change on carbon emissions. Xia et al. [26] used ecological network analysis to explore the ecological relationship between different land-use changes and proposed a land-carbon correlation rate to describe the impact of land-use changes on carbon balance. Yuan et al. [27] explored the relationship between urbanization and land-use change in three representative models by simulating land use in 13 cities in the Beijing–Tianjin–Hebei urban agglomeration, China and using environmental Kuznets curves; they found that land-use patterns at different levels of urbanization have other effects on carbon emissions. Rounsevell [28] analyzed the impact of land-use change on carbon emissions in the UK, finding that socioeconomic and technological changes may be the most important drivers of land-use change, which in turn determines carbon emissions changes. The above-mentioned studies have initially revealed the role of land use on carbon emissions; however, they mainly focused on analyzing the impact of land-use changes on carbon emissions in provincial areas. As such, they have the following shortcomings: (1) They lack an analysis of the impact of land-use changes on carbon emissions within cities from a spatial perspective and fail to reveal the extent of the influence of land-use changes on carbon emissions in a comprehensive way by establishing quantitative models; (2) They lack an urban-scale exploration of carbon emissions from land use, and the existing carbon emission assessments at the city level are limited to the estimation of energy consumption [29–31], which is not helpful for urban land use and carbon reduction development, and does not allow to provide more precise guidance.

In recent years, with the implementation of the national strategy of the "Yangtze River Economic Belt", the industrialization and urbanization level of the city of Wuhan, which is located in the middle reaches of the Yangtze River, has been rapidly advancing, and the UCL area has been rapidly increasing. The population size, technology development level, and energy use have changed accordingly, affecting urban carbon emissions and posing a remarkable risk to the city's sustainable development. Therefore, the issue of optimizing the layout of land use and coordinating the relationship between land use and carbon emissions has become urgent for the city of Wuhan. In this study, we quantitatively evaluated the spatial and temporal variation characteristics between the UCL area and carbon emissions in Wuhan and determined the spatial connection between UCL change and carbon emissions change through spatial correlation analysis; then, we quantified the degree of impact of the UCL change on carbon emissions using curve estimation, and analyzed the relationship between carbon emissions influences, identified by Kaya's constant equation, and changes in UCL using grey correlation; finally, we established the direct and indirect relationship between the change in UCL area and the change in carbon emissions in Wuhan city during the study period. The results of this study can provide suggestions for cities to formulate rational land use policies and promote sustainable urban development.

2. Materials and Methods

2.1. Materials

2.1.1. Study Area

Wuhan is located between 29°58′–31°22′ N latitude and 113°41′–115°05′ E longitude, at the confluence of the Yangtze River and the Han River. This area is characterized by several lakes and a well-developed water system; the landscape is low and flat in the central part, hilly in the northern and southern parts, and low mountainous in the north (Figure 1).

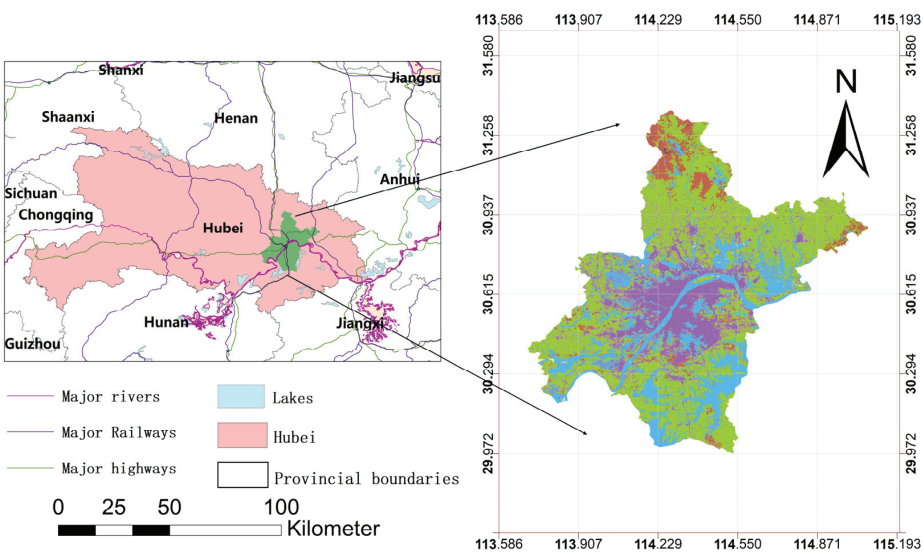

Figure 1. Wuhan city location map. (**a**) Location of Wuhan; (**b**) longitude and latitude of Wuhan.

With the implementation of the Outline of the Yangtze River Economic Belt Development Plan in September 2016, Wuhan has become the main city for the development of the Yangtze River Economic Belt. Therefore, its ability to achieve efficient and low-carbon land use in rapid development is of tremendous importance for the future construction of an ecologically prioritized, green, coordinated, and sustainable society; moreover, Wuhan will also play a leading position in the low-carbon improvement of neighboring cities.

2.1.2. Data Collection

The main data sources employed in this study are shown in Table 1.

Table 1. Data Source.

Name of Data	Source of Data
The land-use data	European Space Agency (ESA) (https://viewer.esa-worldcover.org/worldcover/ (accessed on 9 November 2022))
Socioeconomic and energy consumption data	The Wuhan Statistical Yearbook (http://tjj.wuhan.gov.cn/tjfw/tjnj/ (accessed on 9 November 2022))
Carbon Emission factors of energy source	The 2006 IPCC Guidelines for National Greenhouse Gas Inventories. (https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html (accessed on accessed on 9 November 2022)) [32]
Carbon emission factors of land types	Research achievements of Li [21], Fang et al. [22], Zheng [23], Zhang et al. [24], Ye et al. [25].

2.2. Methods

2.2.1. Calculation of Carbon Emissions

The coefficient measurement method was used to calculate carbon emissions. This method is easy to implement, has robust convincing power, and is widely used to calculate carbon emissions [26,27]. The calculation formula employed is as follows:

$$C = \sum_{i=1}^{6} C_i = \sum_{i=1}^{6} A_i \times S_i, \tag{1}$$

where C represents the total carbon emissions; C_i represents the carbon emissions for each land category; A_i represents the carbon emission factor for each land category; and S_i represents the utilized area for each land category. i was assigned a value from 1 to 6 to indicate Cropland, Water, Forestland, Grassland, Unused land, and UCL, respectively.

The human activities in UCL vary from city to city; hence, using a fixed carbon emission factor was impossible. However, as UCL mainly hosts social production activities, in this study, the method of Xiao et al. [33] was adopted, which expresses UCL carbon emissions (C_6) in terms of carbon emissions generated through energy consumption as follows:

$$C_6 = \sum B_t \times Q_t, \tag{2}$$

where B_t represents the carbon emission factor of each energy source; and Q_t represents the quantity of use of each energy source.

The carbon emission coefficients of Forestland, Unused land, Water, Grassland, and Cropland in Wuhan and the carbon emission coefficients of major energy sources are shown in Table 2.

Table 2. Carbon emission coefficients for each type of land use and each major energy source.

Land Use Type	Carbon Emission Factor (t/km^2)	Energy	Carbon Emission Factor (t/tce)	Energy	Carbon Emission Factor (t/tce)
Cropland	49.7 [23]	Coal	0.7559 [32]	Kerosene	0.5714 [32]
Forestland	−64.4 [22]	FC	0.7559 [32]	RDG	0.4602 [32]
Grassland	−2.4 [25]	Coke	0.8559 [32]	LP	0.5042 [32]
Water	−46 [24]	Crude Oil	0.5857 [32]	COG	0.3548 [32]
Unused land	−0.5 [21]	Fuel Oil	0.6185 [32]	Heat	0.26 [32]
UCL	-	Gasoline	0.5538 [32]	Electricity	2.5255 [32]
		Diesel	0.5921 [32]	BFG	0.3548 [32]

Where the carbon emission factor of the land class is less than zero, it means that the land class is a carbon sink class and has carbon absorption capacity; FC—Finished coal; RDG—Refinery Dry Gas; LP—Liquefied Petroleum; COG—Coke oven gas; BFG—Blast furnace gas.

2.2.2. Land-Use Changes Dynamic Attitude

Land use dynamic attitude represents the magnitude of changes in the way various land-use categories are utilized over a certain period and can be used to quantitatively measure the magnitude of land-use change [34]. In this study, we used a single land-use dynamic attitude to assess the change in land-use types in Wuhan, as follows:

$$LC_i = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%, \tag{3}$$

where LC_i represents the dynamic attitude of using single land areas; U_a and U_b represent the area of single land use sorts at the beginning and the end of the study period, respectively, and T represents the temporal interval.

2.2.3. Spatial Correlation Analysis

In this study, the spatial autocorrelation analysis was used to explore the spatial and temporal characteristics of the impact of the UCL change on carbon emissions in Wuhan. This type of analysis is articulated into global and local spatial autocorrelation analysis [35].

Global spatial autocorrelation analysis can be used to determine the average degree of correlation and spatial distribution between attributes of a region and to reflect the similarity between each unit and the neighboring units in the entire study area. The Moran's I index is often used to measure global spatial correlation. Its value is in the range $[-1, 1]$; higher values indicate a stronger correlation between the overall attributes of a region. The *Moran's I* index was calculated as follows [36]:

$$I_{pq}^{i} = \frac{Y_p^i - \overline{Y}_p}{T_p^2} \cdot \sum\nolimits_{j=1}^{n} W_{ij} \cdot \frac{Y_q^i - \overline{Y}_q}{T_q^2}, \tag{4}$$

where I_{pq}^{i} denotes the spatial correlation between the p-attribute and the q-attribute of the i-th spatial unit; Y_p^i denotes the value of the p attribute on the i-th spatial unit; $\overline{Y}_p$ denotes the mean of all spatial unit p attributes in the study area; T_p^2 denotes the variance of all spatial unit p attributes in the study area; Y_q^i denotes the value of attribute q on the i-th spatial unit; $\overline{Y}_q$ denotes the mean of all spatial unit q attributes in the study area; T_q^2 denotes the variance of all spatial unit q attributes in the study area; W_{ij} denotes the weight matrix based on the row criterion; and n denotes the number of spatial units.

Local spatial autocorrelation analysis can determine the possible spatial correlation patterns and local spatial distribution characteristics of different spatial locations. The autocorrelation of the local space can be analyzed by employing the local Moran's I index. A Local Indicators Spatial Autocorrelation (LISA) clustering map was drawn based on the Z-test ($p < 0.05$). Five types of clusters were identified: H-H clusters, where the attribute values of the observed area and its surrounding areas are high, and other clusters are similar; L-L clusters; H-L clusters; L-H clusters; and NS clusters. The formula for the local spatial Moran's I index was as follows [36]:

$$I_i = \frac{Y_i - \overline{Y}}{T_i^2} \cdot \sum\nolimits_{i=1, j \neq 1}^{n} W_{ij} \cdot \left(Y_i - \overline{Y}\right), \tag{5}$$

where Y_i denotes the attribute value of the i-th spatial unit; $\overline{Y}$ denotes the mean of the attribute values of all spatial units in the study area; T^2 denotes the variance of the attribute values of all spatial units in the study area; W_{ij} denotes the weight matrix based on the row criterion; and n denotes the number of spatial units.

2.2.4. Curve Estimation

To further quantify the influence of the UCL change on carbon emissions, scatter plots were drawn considering the UCL area as the independent variable and carbon emissions as the dependent variable. A suitable mathematical model was selected for curve estimation based on the scatter plot, and the best-fit equation was determined using the significance test. In this study, we use Linear Model (Equation (6)), Logarithmic Model (Equation (7)), Quadratic Model (Equation (8)), Three times Model (Equation (9)), Composite Model (Equation (10)), Power Model (Equation (11)). These formulas employed were as follows:

$$y = \beta_0 + \beta_1 x \quad (6)$$

$$y = \beta_0 + \beta_1 \ln x \quad (7)$$

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 \quad (8)$$

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 \quad (9)$$

$$y = \beta_0 * {\beta_1}^x \quad (10)$$

$$y = \beta_0 x^{\beta_1} \quad (11)$$

The goodness of match of the regression model was determined by using the equation fit coefficient R^2, whereby the closer the R^2 to 1, the better the model fits the change in carbon emissions and the change in UCL. Moreover, the significance test was employed to determine the validity of the regression equation, whereby the smaller the significance coefficient p, the more valid the equation is in responding to the effect of the UCL change on carbon emissions. Generally speaking, this equation is considered extremely valid when $p < 0.05$ [37].

2.2.5. Indirect Impacts of UCL Changes on Carbon Emissions

While the direct impact of UCL changes on carbon emissions was determined by assessing the qualitative and quantitative relationship between these two elements, the indirect impact was determined by assessing the relationship between UCL changes and the factors influencing carbon emissions. The carbon emissions impact factors were then determined by employing Kaya's constant equation.

Kaya's constant equation was first proposed by the Japanese scholar Yoichi Kaya [38]. This equation links the general macro factors, such as society and economy, to carbon emissions, and considers carbon emissions as the result of the combined effect of four factors: GDP per capita; energy consumption per 10,000 Yuan GDP; energy use intensity per unit of carbon emissions; and population. Due to its simple structure and robust explanatory power of the change factors, it is widely recommended by the IPCC to analyze the characteristics of carbon emissions changes and its influencing factors [39,40]. As such, it has been widely recommended by the IPCC to analyze the characteristics of carbon emissions changes and their influencing factors. The formula employed is as follows:

$$C \propto \frac{C}{E} * \frac{E}{GDP} * \frac{GDP}{P} * P, \quad (12)$$

where C is carbon emission; E is energy use; p is population number; $\frac{C}{E}$ denotes energy use intensity per unit of carbon emission; $\frac{E}{GDP}$ denotes energy use per 10,000 Yuan; $\frac{GDP}{P}$ denotes GDP per capita.

The gray correlation analysis was used to explore the relationship between UCL changes and factors influencing carbon emissions. The gray correlation analysis can measure the connection between two elements and is suitable for small samples and in cases of poor information and uncertainty. The greater the gray correlation, the closer the relationship between the two elements [41]. The formula employed is as follows:

$$\gamma_0(i) = \frac{1}{m}\sum_{k=1}^{m} \xi_i(k), \quad (13)$$

where $\xi_i(k) = \frac{\min\limits_i \min\limits_k |x_0(k) - x_i(k)| + \rho \max\limits_i \max\limits_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max\limits_i \max\limits_k |x_0(k) - x_i(k)|}$; $\gamma_0(i)$ and ξ_{ij} represent the gray correlation coefficient and the correlation degree corresponding to $x_i(k)$ and the reference sequence $x_0(k)$, respectively; ρ represents the resolution, and is generally assigned a value of $\rho = 0.5$; and $x_0(k)$ and $x_i(k)$ represent the reference series and the k-th term of the i-th variable, respectively.

3. Results

3.1. Analysis of Urban Land-Use Change and Carbon Emissions Change

3.1.1. Urban Land-Use Change Analysis

The results of the spatial analysis of land use in Wuhan from 1995–2019 are shown in Figure 2. UCL was mainly located in the central urban area of Wuhan, while in other areas, it showed a concentrated distribution with multiple land-use centers, as well as a star-shaped spreading pattern from the center to the surrounding area. The total area of UCL increased from 391.55 km^2 in 1995 to 1148.96 km^2 in 2019, with an average annual increase of 2.79%. Furthermore, the Cropland area decreased from 6382.86 km^2 in 1995 to 5573.21 km^2 in 2019, with an average annual decrease of 33.74 km^2. The water area is located in the central and southern sections of the city; its extension decreased from 1225.62 km^2 in 1995 to 1194.268 km^2 in 2019, following a fluctuating downward trend of increase–decrease–increase–decrease. Forestland is mainly located in the northwestern region and in the northeastern fringe area, while the other land types are scattered in the central and southern regions, with the total area following a trend of first decreasing and then increasing.

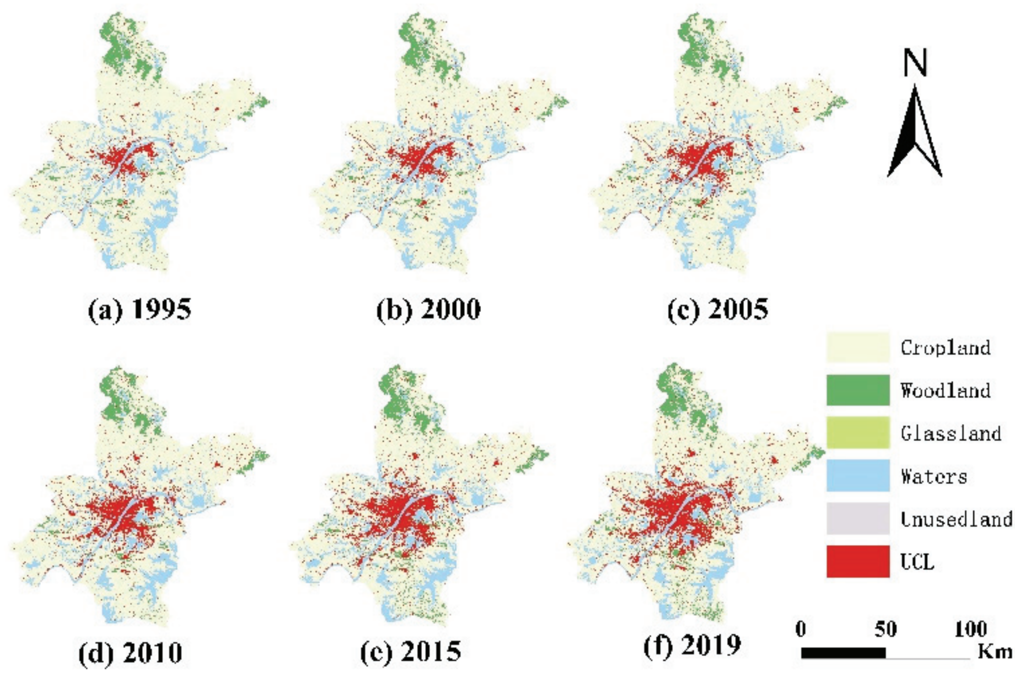

Figure 2. Land use in Wuhan, 1995–2019. (Take six points in time from 1995–2019: 1995, 2000, 2005, 2010, 2015, 2019).

In the process of UCL changes, the annual growth showed a fluctuating change of decrease-increase-decrease; the period with the highest growth was 2005–2010, with an average annual growth of 43.06 km^2, while that with the lowest growth was 2000–2005, with an average annual increase of 23.81 km^2. The period with the greatest change in land-use dynamics was 1995–2000, reaching as high as 6.91%, while the lowest change was 2015–2019, with 2.88% (Figure 3).

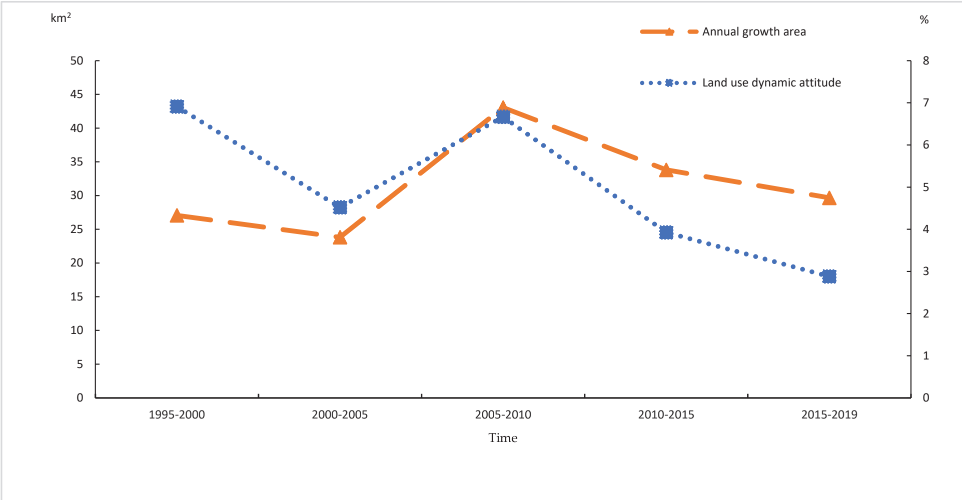

Figure 3. Area of the UCL change and UCL dynamic attitude in Wuhan, 1995–2019 (Divide the years 1995–2019 into five time periods: 1995–2000, 2000–2005, 2005–2010, 2010–2015, and 2015–2019).

During the study period, the new UCL occupied the largest amount of Cropland, i.e., about 713.97 km^2, accounting for about 94.40% of the new UCL, followed by water with 34.28 km^2, accounting for about 4.53% of the new UCL.

Looking at different study periods, the proportion of new UCL originating from Cropland varied widely, with the highest proportion in 2010–2015, accounting for 100.46% of new UCL, and the lowest in 1995–2000, at 90.24%. In addition, the period with the largest proportion of the water conversion of new UCL occurred in 2000–2005, at 8.84%. The proportion of the sum of other land types to the new UCL fluctuated, with the highest proportion of 1.53% calculated for 1995–2000. The proportion of the transformed part of each land type to the new UCL continued to change due to the scattered distribution of multiple land types within Wuhan and the principle of proximity in the expansion of the UCL (Table 3).

Table 3. Sources of new UCL in Wuhan, 1995–2019.

	Cropland	Water	Forest Land	Grassland	Wasteland	Totally
1995–2000	122.10	11.12	1.02	0.87	0.18	135.19
2000–2005	107.45	10.52	0.63	0.22	0.15	118.97
2005–2010	200.74	11.57	0.76	1.37	0.24	214.68
2010–2015	169.70	−2.70	0.5	1.38	0.04	168.92
2015–2019	114.08	3.77	0.18	0.48	0.06	118.57
1995–2019	713.97	34.28	3.09	4.32	0.67	756.33

Unit: km^2.

3.1.2. Carbon Emissions Analysis

In general, Wuhan's carbon emissions showed an upward trend, rising from 21,187,800 t in 1995 to 38,972,400 t in 2019, corresponding to an increase of 78.63% in 24 years, with an average annual increase rate of 2.45%. More in detail, carbon emissions from energy consumption on urban construction sites, which is the main source of carbon emissions in Wuhan, increased from 21,594,600 t in 1995 to 38,793,700 t in 2019, with an average annual increase rate of 2.47%. The carbon emissions coefficient of the UCL, determined as the ratio of total carbon emissions to land area, decreased continuously throughout the study period, with an average annual decrease of 2.02%. The energy consumption per 10,000 Yuan GDP in Wuhan also decreased continuously, with an average annual decrease of 10.99%; the largest decline of 64.20% was measured from 2005 to 2010, with an average annual decrease of 18.57% during that period. The decreasing trend of the energy use intensity per unit of carbon emissions, on the other hand, was confirmed, with an average annual decline of 1.42%; the highest decline was measured from 2000–2005, with an average annual decline of 2.67%, while a brief upward trend occurred from 2015–2019. However, this increase was not significant, equaling 1.39% (Table 4).

Table 4. Wuhan Carbon Emissions-Related Indices, 1995–2019.

	Total Energy Consumption Per 10,000 Yuan GDP(t of Standard Coal)	Energy Use Intensity Per Unit of Carbon Emissions	Total Carbon Emissions (10^4 t)	The Carbon Emission Factor of UCL (10^4 t/km^2)
1995	2.78	1.03	2181.78	5.515095
2000	1.43	0.95	2352.93	4.424664
2005	0.81	0.83	2705.73	4.155276
2010	0.29	0.76	3096.16	3.571424
2015	0.19	0.72	3662.59	3.537729
2019	0.17	0.73	3897.24	3.376421

During the study period, carbon emissions from the direct consumption of fossil energy have always remained above 50% of total carbon emissions (Figure 4), and the consumption of fossil energy such as coal, washed coal, coke, and crude oil has always remained above 75% of the total energy consumption. This is consistent with the fact that China is expected to continue using fossil energy in the future [42].

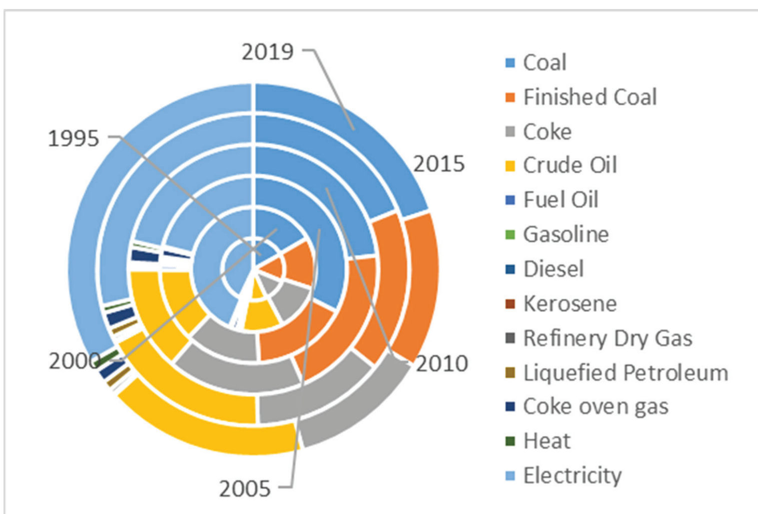

Figure 4. Energy consumption ratio in Wuhan, 1995–2019.

3.2. Spatial Correlation Analysis

ArcGIS 10.2 was used to draw a 1 km × 1 km grid map, where the city of Wuhan was divided into several spatial units according to their spatial locations, which were graded using the natural breakpoint method to obtain the distribution of carbon emissions within a unit area of Wuhan city during the study period. UCL area in the spatial cells was used as the spatial indicator of the UCL, and GeoDa was used to conduct a bivariate spatial analysis of urban land use and carbon emissions.

3.2.1. Urban Land-Use Carbon Emissions

During the study period, the average carbon emissions of each Wuhan area showed an increasing trend. The number of low carbon emissions areas decreased, and the number of other types of areas increased. Moreover, the upper limit for classifying each level of carbon emissions within a unit area also decreased (Table 5).

Table 5. Carbon emissions per unit area in Wuhan, 1995–2019.

		Low	Lower	Medium	Higher	High
1995	Upper (t)	2733.84	10,072.52	22,556.94	38,686.81	55,150.90
	Lower (t)	−64.40	2733.85	10,072.53	22,556.95	38,686.82
	Number	7795	695	238	142	146
2000	Upper (t)	2662.07	9228.44	19,773.40	32,708.65	44,246.60
	Lower (t)	−64.40	2662.08	9228.45	19,773.41	32,708.66
	Number	7491	878	294	166	181
2005	Upper (t)	2445.65	8351.33	18,243.34	30,601.90	41,552.80
	Lower (t)	−64.40	2445.66	8351.34	18,243.35	30,601.91
	Number	7124	1042	389	221	232
2010	Upper (t)	2646.76	8532.18	17,194.60	27,131.87	35,714.20
	Lower (t)	−64.40	2646.77	8532.19	17,194.61	27,131.88
	Number	6938	1005	464	286	324
2015	Upper (t)	2773.28	8634.01	17,167.13	26,952.47	35,377.47
	Lower (t)	−64.40	2773.29	8634.02	17,167.14	26,952.48
	Number	6638	1072	534	373	395
2019	Upper (t)	3024.05	9175.16	17,383.56	26,225.59	33,764.20
	Lower (t)	−64.40	3024.06	9175.17	17,383.57	26,225.60
	Number	6559	1074	561	385	437

The analysis of the spatial distribution of carbon emissions per unit area in Wuhan city indicated a gradual decrease from the central to the surrounding areas; more in detail, the overall distribution from north to south and east to west was low-medium-high-medium-low (Figure 5). The high-carbon emissions areas were mainly located in the city center, gradually expanding to the surrounding areas from a scattered to a more integrated distribution, and the area gradually increased. The carbon emissions in the central-northern areas and local northeastern areas gradually increased, while those in the southeastern and southwestern areas generally did not record a considerable change. It is noteworthy that some areas with high carbon emissions were found to have low carbon emissions, and their distribution corresponded to the distribution of water.

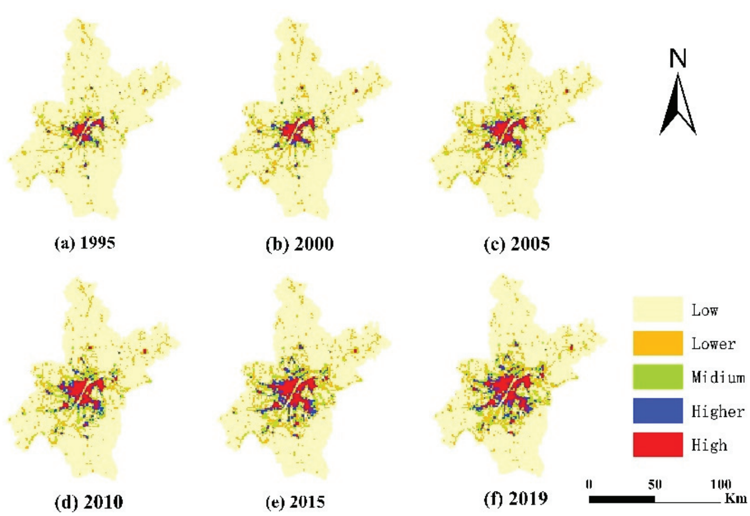

Figure 5. Spatial distribution of carbon emissions within a unit area in Wuhan, 1995–2019.

3.2.2. Global Autocorrelation

The values of Moran's I index between UCL and carbon emissions during the study period were all greater than 0 and continued to increase, passing the significance test (Table 6). This indicates an important and increasingly positive correlation between the area of urban land-use change and carbon emissions change.

Table 6. Spatial correlation between carbon emissions and UCL area in Wuhan City, 1995–2019 and the significance test results.

	1995	2000	2005	2010	2015	2019
Moran's I index	0.799	0.808	0.817	0.829	0.832	0.833
p-value	0.001	0.001	0.001	0.001	0.001	0.001
z-value	108.73	111.48	110.88	111.79	112.26	112.30

3.2.3. Local Autocorrelation

Based on the results of the local autocorrelation analysis of carbon emissions and UCL in Wuhan from 1995–2015 (Table 7), it clearly emerged that the overall spatial clustering relationship between carbon emissions and UCL varied greatly over time (Figure 6).

Table 7. Results of spatial local autocorrelation analysis between carbon emissions and UCL area in Wuhan, 1995–2019.

	1995	2000	2005	2010	2015	2019
H-H	453	538	661	915	1051	1117
H-L	2	1	1	1	0	0
L-H	22	21	29	36	40	39
L-L	1353	1398	1497	1638	1786	1875
NS	7188	7060	6830	6428	6141	5987

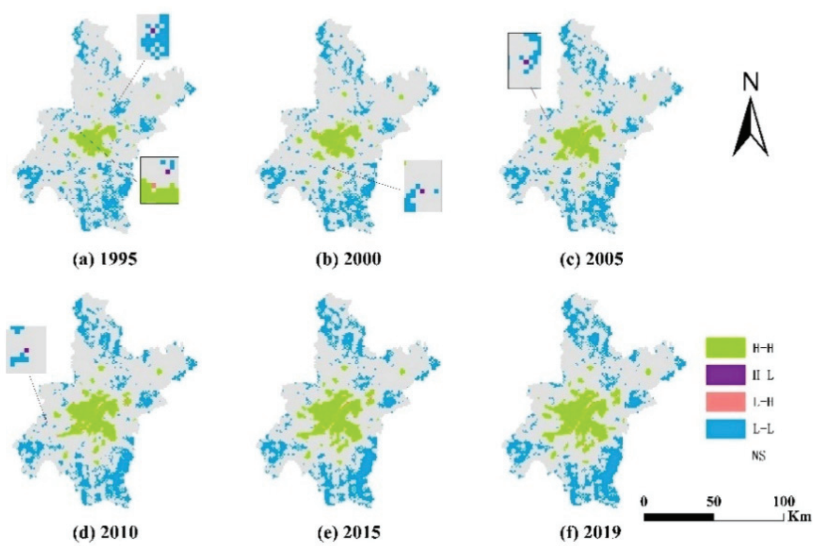

Figure 6. Spatial distribution of spatially localized autocorrelation results between carbon emissions and UCL area in Wuhan, 1995–2019.

In 1995, the spatial clusters were mainly L-L clusters, and were scattered in various areas of Wuhan; H-H clusters were mainly located in the central part of Wuhan and accounted for a small share of the whole area; in parallel, a large number of L-H clusters were distributed in-between H-H clusters, showing a linear arrangement; finally, H-L clusters were located in the inner part of the city, adjacent to L-L clusters. In 2000, the spatial clustering changed compared to 1995. These changes mainly include the increase in the number of H-H clustering areas, the gradual concentration of L-L cluster areas, and the development trend to the periphery. More in detail, the number of L-H cluster areas decreased; these were mainly located in-between H-H cluster areas, and the distribution pattern did not change much. The number of H-L cluster areas decreased; these were mainly located in the central and southern parts of the city. In 2005, some L-L cluster areas transformed into H-H cluster areas, further increasing their extension.

Moreover, the number of L-L cluster areas continued to enlarge in the peripheral areas of Wuhan; the number of L-H cluster areas increased, and was mainly distributed around the H-H cluster areas, and the number of H-L cluster areas was the same as in 2000. In 2010 and 2015, the number of H-H cluster areas increased continuously; these were mostly located in the central area of Wuhan. In 2010 and 2015, the number of H-H clusters continued to increase; these were located in the central region of Wuhan, with a small number located in the central-northern and central-southern areas. The number of L-L clusters continued to increase, gradually concentrating in the urban periphery, while the area of L-H clusters continued to increase, and the H-L clusters gradually disappeared. In 2019, the areas of concentration of the H-H clusters continued to expand outward, and their number increased compared to 2015. Moreover, the number of L-H clusters decreased by one compared to 2015 and were mainly located near the H-H cluster regions. Finally, the number of L-L cluster regions further increased, and the overall development trend changed less compared to the past.

3.3. Impact of UCL Changes on Carbon Emissions

Using UCL area and carbon emission data of Wuhan city for the period 1995–2015, a scatter plot was drawn to represent the changes in UCL and carbon emissions, considering UCL area as the independent variable (x) and carbon emissions as the dependent variable (y), as shown in Figure 7. The linear function model, the quadratic function model, the cubic function model, the composite function model, and the power function model were employed for curve estimation fitting. The obtained fitting results of each function model are shown in Table 8.

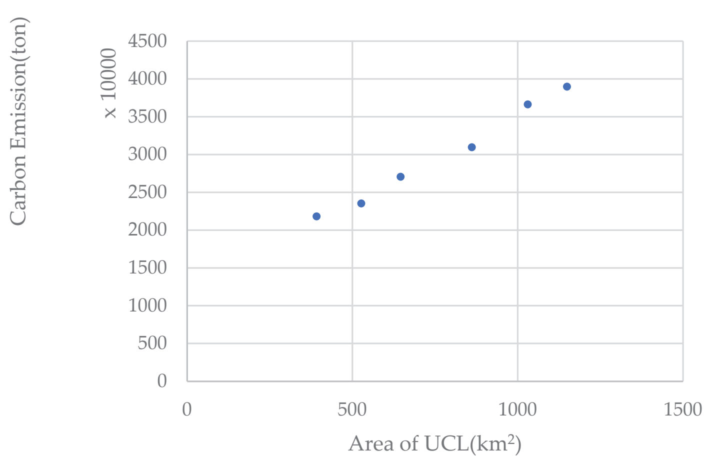

Figure 7. Changes in UCL and carbon emissions, 1995–2019.

Table 8. Summary of curve estimation models and parameter estimates.

Model	Model Summary					Parameter Estimates			
	R^2	F	df_1	df_2	Sig.	Constants	b_1	b_2	b_3
Linear	0.982	162.844	1	3	0.001	1206.105	2.306		
Logarithmic	0.937	44.455	1	3	0.007	−6921.337	1500.012		
Quadratic	0.992	130.818	2	2	0.008	1815.085	0.405	0.001	
Three times	0.993	49.190	3	1	0.104	1177.880	3.477	−0.003	2.186×10^{-6}
Composite	0.991	329.357	1	3	0.000	1570.584	1.001		
Power	0.964	80.619	1	3	0.003	87.136	0.533		

Dependent variable: Carbon emissions. Independent variable: UCL area.

As shown in Table 8, although the fit of the function models used in the study (R^2) was greater than 0.9, the fit of the quadratic function (Equation (14)) and the composite function model (Equation (15)) was higher ($R^2 > 0.99$, $p < 0.01$). The following model was thus established:

$$y = 1815.08512 + 0.4047x + 0.0013x^2 \tag{14}$$

$$y = 1570.5844 * 1.0008^x \tag{15}$$

These two models were used as alternative models, and UCL area and carbon emissions data of Wuhan in 2019 were used as test data to evaluate the prediction accuracy of these two models using the error between the predicted and the true values of the two models and to determine the final curve estimation results. The results obtained by substituting the test data into the alternative model, are presented in Table 9.

Table 9. Results of secondary and compound model tests.

	Quadratic Model	Composite Function Model
Predicted results (10^4 t)	4035.27	3987.31
Real Results (10^4 t)	3897.24	3897.24
Prediction error (10^4 t)	138.03	90.07
Error rate	3.54%	2.31%

The prediction error of the composite model was found to be low; therefore, the composite function model (Equation (15)) was used as the final curve estimation model.

4. Discussion

4.1. Impact of Spatial and Temporal Changes in UCL on Carbon Emissions

By investigating the land-use scenarios and carbon emissions in Wuhan from 1995–2019, it was found that the UCL area in Wuhan increased by 757.41 km^2 and carbon emissions rose by 17,154,600 t during the study period. This is the same as the results of Houghton [13], Pacala [14], and Ren et al. [16]. However, unlike this study, Houghton and Pacala et al. derived their results from the analysis of a large study area of terrestrial ecology in Asia and the United States, while Ren explored the effects of land-use change on carbon stocks. In this study, it is worth noting that the largest change and the largest increase in the UCL area occurred in the periods 2005–2010 and 1995–2000, respectively, while both the largest change and the largest increase in carbon emissions occurred in the period 2010–2015. Looking at the spatial distribution of carbon emissions, it was found that carbon emissions from other land types in large low-carbon emission areas increased rapidly when they were converted into UCL. High-carbon emission areas gradually spread from the urban center to the surrounding areas, and gradually connected with high-carbon emission areas in other areas to form a patch, roughly following the same direction as the expansion of UCL. In contrast, the land types in the urban fringe areas mostly played the role of carbon sinks, and their utilization changed less during urban development. Hence, it may be concluded that the carbon emissions in the fringe areas did not change considerably from 1995 to 2019.

At the same time, the present study found that, although overall carbon emissions in Wuhan were increasing, the upper limit of high-carbon emission areas identified by the natural breakpoint method was decreasing; at the same time, total energy consumption per 10,000 Yuan GDP and carbon emission intensity per unit of energy were also found to decrease. These outcomes were mostly due to the continuous enhancement of energy utilization effectiveness and the partial elimination of energy-dependent industries in the process of industrial upgrading thanks to continuous technological advances in Wuhan [43]. This indicates that reasonable carbon emission reduction policies can have an important impact on carbon emissions.

4.2. Qualitative and Quantitative Relationships between UCL Changes and Carbon Emissions

The application of the spatial autocorrelation evaluation method allowed us to find a positive spatial correlation between the changes in the UCL area and the changes in carbon emissions in Wuhan, i.e., both changes showed to follow the same spatial development trend. The finding is comparable to those of Li et al. [44], with the difference that the latter used panel records to analyze the effect of land-use change on carbon emissions in Anhui Province from a spatial perspective. In contrast, the finding that changes in the UCL area and carbon emissions were not synchronized needed to be further investigated by building a quantitative model.

The extension of H-H cluster areas increased from 1995 to 2019 in Wuhan, mainly because of the city's continuous development, such that the other land types around UCL continuously transformed into UCL. The extension of the L-H cluster area changed. The reason mainly lies in that the early development of Wuhan city relied on the convenience of water resources conditions and that the core urban area was built by the river. In that period, Wuhan city vigorously developed tourism and heavy industry, and human activities in water increased together with carbon emissions. After 2010, the development strategy of Wuhan changed; the city began to pay attention to ecological protection, and the carbon emissions in water decreased continuously, determining the spatial clustering of some areas in the form of L-H/H-H/L-H clusters. In the first part of the study period, the L-L cluster areas were scattered between the urban fringe and the H-H cluster areas and then gradually concentrated in the urban fringe. Although urban fringe areas were less affected by land-use changes, the overall average carbon emissions in these areas increased. This is mainly due to the development of the central part of the city and the promotion of the synergistic development of fringe areas, accompanied by an increase in economic activities, which in turn resulted in an increase in carbon emissions. The H-L cluster areas were not found to have high carbon emissions per unit area; this occurred mainly because these areas were composed mostly of Cropland and a small portion of UCL. As Cropland is also a source of carbon emissions, carbon emissions reduction policies for Cropland should also be considered in future development [45,46].

The results of the developed complex function model showed an overall positive relationship between the UCL area and carbon emissions. For every 1 km^2 expansion of the UCL area, carbon emission increased to reach about 1.001 times the level before expansion. This quantitative relationship proves that the increase of the UCL area increased the generation of carbon emissions.

4.3. Relationship between UCL Change and Carbon Emissions Influencing Factors

Using *Kaya*'s constant equation, carbon emissions were decomposed into four factors: energy consumption per 10,000 Yuan GDP; energy use intensity per unit of carbon emissions; GDP per capita; and population. Then, a gray correlation analysis was conducted between these four factors and the UCL area (Table 10). The results of this analysis showed that the three factors of population, energy use intensity per unit of carbon emissions, and energy consumption per 10,000 Yuan GDP were strongly correlated with the UCL area; this indicates that the changes in the UCL area had a strong interaction with these factors and, thus, affected carbon emissions. This is similar to the findings of Yuan [27] and

Rounsevell M. et al. [28]: socioeconomic, technological and other elements are considered to play an important role in the process of land-use change affecting carbon emission changes. However, unlike this study, Yuan investigated the mechanism of land-use change on carbon emission from the perspective of analyzing different urbanization levels of cities, in which more socioeconomic and technological indicators are included in the indicators of urbanization level; Rounsevell M investigated the mechanism of land-use change on carbon emission from a macro perspective, taking the UK as an example.

Table 10. Gray correlation analysis of carbon emissions and Kaya's constant decomposition factor.

Factor	Correlation
Population	0.98
Energy use intensity per unit of carbon emissions	0.93
Total energy consumption per 10,000 Yuan GDP	0.89
GDP per capita	0.68

In the future, the relationship between the UCL area and these factors should be coordinated to achieve carbon emissions reduction. The correlation between GDP per capita and the UCL area was poor. This indicates that the changes in the UCL area did not considerably influence the changes in carbon emissions through the interaction with GDP per capita; on the other hand, it also indicates that the increase in the UCL area did not necessarily improve GDP per capita, and urban development should be separated from "blind expansion".

4.4. Study Shortcomings and Future Research

The shortcomings of this study may be summarized as follows:

(1) In this study, the carbon emission coefficients of various land types in Wuhan were calculated by summarizing those derived from previous studies. However, the latter may vary according to the natural vegetation conditions, ground cover, and energy intensity of each place, which may affect the accuracy of the final results.

(2) This study only focused on the impact of spatial and temporal changes in the UCL area on carbon emissions. However, the mechanism of the effects of the UCL changes on carbon emissions is complex. It includes several factors, such as population size and economic development level, which are more or less related to the UCL policy [47]. In the future, we should explore the interaction between these factors and the changes in urban land use and assess how these elements affect carbon emissions through UCL changes from a spatial perspective.

(3) In this study, only the effect of the UCL changes on carbon emissions was analyzed, as this is the major factor affecting land-use change. The assessment of the influence of the UCL changes of other land types on carbon emissions was ignored, which affected the comprehensiveness of the study results.

5. Conclusions

Based on previous studies, this study firstly quantifies the characteristics of urban land-use changes in Wuhan city and measures the changes in carbon emissions based on them; after that, using spatial autocorrelation analysis and curve estimation, Kaya's constant equation and gray correlation analysis, the relationship between spatial and temporal changes of the UCL on carbon emissions is explored from a spatial perspective; finally, the direct and indirect effects of the UCL changes on carbon emissions are determined. The results of the study are as follows: (1) In 2019, the UCL area and carbon emissions in Wuhan were about 2.93 times and 1.79 times those in 1995. The expansion of the UCL area showed to follow a star-shaped spreading from the central area to the surrounding areas, and the areas of carbon emissions increase within the unit area showed an outward expansion in all directions. The spatial distribution and development direction of the areas of carbon emissions increase within a unit area and of the UCL change areas were roughly the same, and were found to have a positive spatial correlation that was increasing year by year. The fitting effect of the composite model on the relationship between UCL area changes and carbon emissions changes in Wuhan was more scientific and rational than other curve estimation models. The proposed model allowed us to find that the growth of the UCL entailed an increase in carbon emissions of about 1.001 times those before the expansion for every 1 km^2 of the UCL area.

(2) The correlation between UCL area and population, energy use intensity per unit of carbon emission, energy consumption per 10,000 Yuan GDP, and GDP per capita gradually decreased during the study period. More in detail, the correlation between population and energy use intensity per unit of carbon emissions was greater than 0.9, indicating that the UCL area changes will indirectly impact urban carbon emissions by affecting population and energy use intensity per unit of carbon emissions.

(3) The maximum value of carbon emissions within a unit area decreased during the study period, such that the value in 1995 was about 1.63 times that in 2019. This indicates that reasonable policies will positively affect the reduction of carbon emissions, and reasonable land-use policies will promote the achievement of carbon emissions reduction goals in Wuhan on an existing basis.

To achieve the objective of decreasing carbon emissions and promoting sustainable social development, this study suggests adopting the following measures. Firstly, suitable functional areas, such as economic development areas and carbon sink areas, should be established based on the actual situation of each district, avoiding encouraging economic growth and reducing human production activities in the carbon sink areas, as well as strengthening the construction of "satellite cities". Secondly, we should change our thinking on development, promote technological innovation, optimize and upgrade the existing UCL, improve the resource allocation rate, and promote the optimization and upgrading of existing industries and their development towards low carbonization. Finally, we should make reasonable use of the stock of the UCL, improve land-use conservation, slow down the expansion of the UCL, and give priority to the encroachment of land with weak carbon sink capacity in exchange for the protection of land with strong carbon sink capacity when expanding UCL.

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References

1. Crutzen, P.J. Geology of Mankind. *Nature* **2002**, *415*, 23. [CrossRef] [PubMed]
2. Rodríguez Martín, J.A.; Álvaro-Fuentes, J.; Gonzalo, J.; Gil, C.; Ramos-Miras, J.J.; Grau Corbí, J.M.; Boluda, R. Assessment of the Soil Organic Carbon Stock in Spain. *Geoderma* **2016**, *264*, 117–125. [CrossRef]
3. Eggleston, H.S.; Buendia, L.; Miwa, K.; Ngara, T.; Tanabe, K. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*; Institute for Global Environmental Strategies: Hayama, Japan, 2006.
4. Chuai, X.; Huang, X.; Qi, X.; Li, J.; Zuo, T.; Lu, Q.; Li, J.; Wu, C.; Zhao, R. A Preliminary Study of the Carbon Emissions Reduction Effects of Land Use Control. *Sci. Rep.* **2016**, *6*, 1–8. [CrossRef]

5. Harper, A.B.; Powell, T.; Cox, P.M.; House, J.; Huntingford, C.; Lenton, T.M.; Sitch, S.; Burke, E.; Chadburn, S.E.; Collins, W.J.; et al. Land-Use Emissions Play a Critical Role in Land-Based Mitigation for Paris Climate Targets. *Nat. Commun.* **2018**, *9*, 1–13. [CrossRef] [PubMed]
6. Houghton, R.A.; House, J.I.; Pongratz, J.; van der Werf, G.R.; DeFries, R.S.; Hansen, M.C.; Le Quéré, C.; Ramankutty, N. Carbon Emissions from Land Use and Land-Cover Change. *Biogeosciences* **2012**, *9*, 5125–5142. [CrossRef]
7. Zhao, M.; Tan, L.; Zhang, W.; Ji, M.; Liu, Y.; Yu, L. Decomposing the Influencing Factors of Industrial Carbon Emissions in Shanghai Using the LMDI Method. *Energy* **2010**, *35*, 2505–2510. [CrossRef]
8. Wang, S.; Liu, X.; Zhou, C.; Hu, J.; Ou, J. Examining the Impacts of Socioeconomic Factors, Urban Form, and Transportation Networks on CO2 Emissions in China's Megacities. *Appl. Energy* **2017**, *185*, 189–200. [CrossRef]
9. Vogt-Schilb, A.; Walsh, B.; Feng, K.; Di Capua, L.; Liu, Y.; Zuluaga, D.; Robles, M.; Hubacek, K. Author Correction: Cash Transfers for pro-Poor Carbon Taxes in Latin America and the Caribbean. *Nat. Sustain.* **2019**, *2*, 941–948. [CrossRef]
10. Canadell, J.G.; Le Quéré, C.; Raupach, M.R.; Field, C.B.; Buitenhuis, E.T.; Ciais, P.; Conway, T.J.; Gillett, N.P.; Houghton, R.A.; Marland, G. Contributions to Accelerating Atmospheric CO_2 Growth from Economic Activity, Carbon Intensity, and Efficiency of Natural Sinks. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 18866–18870. [CrossRef]
11. Hansen, M.C.; DeFries, R.S. Detecting Long-Term Global Forest Change Using Continuous Fields of Tree-Cover Maps from 8-Km Advanced Very High Resolution Radiometer (AVHRR) Data for the Years 1982–99. *Ecosystems* **2004**, *7*, 695–716. [CrossRef]
12. Stockmann, U.; Adams, M.A.; Crawford, J.W.; Field, D.J.; Henakaarchchi, N.; Jenkins, M.; Minasny, B.; McBratney, A.B.; de Remy de Courcelles, V.; Singh, K.; et al. The Knowns, Known Unknowns and Unknowns of Sequestration of Soil Organic Carbon. *Agric. Ecosyst. Environ.* **2013**, *164*, 80–99. [CrossRef]
13. Houghton, R.A. Releases of Carbon to the Atmosphere from Degradation of Forests in Tropical Asia. *Can. J. For. Res.* **1991**, *21*, 132–142. [CrossRef]
14. Pacala, S.W.; Hurtt, G.C.; Baker, D.; Peylin, P.; Houghton, R.A.; Birdsey, R.A.; Heath, L.; Sundquist, E.T.; Stallard, R.F.; Ciais, P.; et al. Consistent Land- and Atmosphere-Based U.S. Carbon Sink Estimates. *Science* **2001**, *292*, 2316–2320. [CrossRef]
15. Ge, Q.; Dai, J.; He, F.; Pan, L.; Wang, M. Land use, land cover change and carbon cycling in China over the past 300 years. *Sci. China* **2008**, *51*, 871–884. [CrossRef]
16. Ren, X.; Dong, S.; Xiao, X.; Xue, B. Land use/cover change and its impact on carbon storage in Dongliao county, Jilin Province. *J. Liaoning Univ.* **2021**, *48*, 1–11+2. [CrossRef]
17. Houghton, R.A.; Hackler, J.L. Emissions of Carbon from Forestry and Land-Use Change in Tropical Asia. *Glob. Change Biol.* **1999**, *5*, 481–492. [CrossRef]
18. Fang, J.; Piao, S.; Zhao, S. CO_2 lost sink and carbon sink in mid-high latitude terrestrial ecosystems in the Northern Hemisphere. *J. Plant Ecol.* **2000**, *6*, 817–833.
19. Zhao, T.; Brown, D.G.; Bergen, K.M. Increasing Gross Primary Production (GPP) in the Urbanizing Landscapes of Southeastern Michigan. *Photogramm. Eng. Remote Sens.* **2007**, *73*, 1159–1167. [CrossRef]
20. Xia, C. Multi-Scale Urban Carbon Metabolism and "Emission Reduction" Scenario Simulation Based on Land Use Perspective. Ph.D. Thesis, Zhejiang University, Hangzhou, China, 2019.
21. Lai, L. Study on Carbon Emission Effect of Land Use in China. Ph.D. Thesis, Nanjing University, Nanjing, China, 2010.
22. Fang, J.; Guo, Z.; Piao, S.; Chen, A. Estimation of terrestrial vegetation carbon sink in china from 1981 to 2000. *Sci. China* **2007**, *37*, 804–812.
23. Zheng, S. Study on the spatio-temporal characteristics and decoupling relationship of carbon emissions in jiangxi province based on land use. *Agric. Technol.* **2021**, *41*, 133–136. [CrossRef]
24. Zhang, W.; Tong, C.; Wu, J.; Xu, M.; Song, C. Simulation and prediction of carbon cycle in typical wetland ecosystem. *Environ. Sci.* **2007**, *28*, 1905–1911. [CrossRef]
25. Ye, H.; Pu, L. Study on the impact of land use change on carbon sequestration capacity of ecosystem in Suzhou. *China Land Sci.* **2010**, *24*, 60–64. [CrossRef]
26. Xia, C.; Chen, B. Urban Land-Carbon Nexus Based on Ecological Network Analysis. *Appl. Energy* **2020**, *276*, 115465. [CrossRef]
27. Zhou, Y.; Chen, M.; Tang, Z.; Mei, Z. Urbanization, Land Use Change, and Carbon Emissions: Quantitative Assessments for City-Level Carbon Emissions in Beijing-Tianjin-Hebei Region. *Sustain. Cities Soc.* **2021**, *66*, 102701. [CrossRef]
28. Rounsevell, M.D.A.; Reay, D.S. Land Use and Climate Change in the UK. *Land Use Policy* **2009**, *26*, S160–S169. [CrossRef]
29. Lai, L.; Huang, X.; Yang, H.; Chuai, X.; Zhang, M.; Zhong, T.; Chen, Z.; Chen, Y.; Wang, X.; Thompson, J.R. Carbon Emissions from Land-Use Change and Management in China between 1990 and 2010. *Sci. Adv.* **2016**, *2*, e1601063. [CrossRef] [PubMed]
30. Zhu, E.; Deng, J.; Zhou, M.; Gan, M.; Jiang, R.; Wang, K.; Shahtahmassebi, A. Carbon Emissions Induced by Land-Use and Land-Cover Change from 1970 to 2010 in Zhejiang, China. *Sci. Total Environ.* **2019**, *646*, 930–939. [CrossRef]
31. Jing, Q.; Bai, H.; Luo, W.; Cai, B.; Xu, H. A Top-Bottom Method for City-Scale Energy-Related CO2 Emissions Estimation: A Case Study of 41 Chinese Cities. *J. Clean. Prod.* **2018**, *202*, 444–455. [CrossRef]
32. Publications—IPCC-TFI. Available online: https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html (accessed on 9 November 2022).
33. Xiao, H.; Yuan, X.; Li, B.; Yan, W. Study on Carbon Emission Effect of Land Use Change: A Case Study of Chongqing. *J. Chongqing Norm. Univ.* **2012**, *29*, 38–42+115.

34. Liu, F.; Yang, R. Land use change and its impact on ecosystem service value in Wuhan. *Res. Water Soil Conserv.* **2021**, *28*, 177–183+193+2. [CrossRef]
35. Ma, X.; Pei, T. Exploratory Spatial Data Analysis of Regional Economic Disparities in Beijing During 2001–2007. *Adv. Spat. Data Handl. GIS* **2012**, 39–48. [CrossRef]
36. Anselin, L. Local Indicators of Spatial Association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
37. Liang, Q.; Li, Z. A New Algorithm of Bailey CA Ratio Based on SPSS Curve Estimation. *Shandong Transp. Technol.* **2017**, *04*, 98–101.
38. Kaya, Y. *Impact of Carbon Dioxide Emission Control on GNP Growth: Interpretation of Proposed Scenarios*; IPCC Energy and Industry Subgroup, Response Strategies Working Group: Paris, France, 1989.
39. Wang, L.; Li, Z. Analysis on the Characteristics and Driving Factors of Rural Homestead Scale Evolution – Based on Extended Kaya Identity and LMDI Method. *Agric. Outlook* **2021**, *17*, 10–16.
40. Ma, M. Study on the Influencing Factors and Peak Simulation of Carbon Emissions from Building Operation in China. Ph.D. Thesis, Chongqing University, Chongqing, China, 2020.
41. Li, J.; Cheng, J.; Guo, H.; Xu, P. Study on the influencing factors of heat transfer coefficient of supercritical fluid based on grey relational degree. *Hubei Electr. Power* **2022**, *46*, 58–64. [CrossRef]
42. Hou, M.; Pan, S.; Liu, H. World Energy Transformation and China's Oil and Gas Sustainable Development Strategy. *Nat. Gas Ind.* **2021**, *41*, 9–16.
43. Yang, X.; Xie, X. Kuznets Curve Analysis of the Effect of Wuhan Construction Land Expansion and Carbon Emission. *J. Huazhong Agric. Univ.* **2020**, *4*, 158–165+181–182. [CrossRef]
44. Li, Y.; Shen, Y.; Wang, S. Spatio-temporal characteristics and effects of land carbon emissions in anhui province based on land use change. *J. Soil Water Conserv.* **2022**, *36*, 182–188. [CrossRef]
45. Zhou, S.; Xi, F.; Yin, Y.; Bing, L.; Wang, J.; Ma, M.; Zhang, W. Carbon Emission Accounting and Driving Factors of Cultivated Land Use in Northeast China. *J. Appl. Ecol.* **2021**, *32*, 3865–3871. [CrossRef]
46. Wen, G.; Hu, R.; Tang, X.; Tang, Y.; Zheng, J.; Meng, J. Temporal and spatial characteristics of carbon emissions and ecological efficiency of cultivated land use in Dongting Lake region. *Ecol. Econ.* **2022**, *38*, 132–138.
47. Zhang, Y.; Huang, A.; Zu, J.; Liu, C.; Shi, Y.; Hao, J. Spatio-temporal evolution and driving mechanism of construction land use intensity in China. *J. Peking Univ.* **2020**, *56*, 893–906. [CrossRef]

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Evaluation of the Effectiveness of Rural Revitalization and an Improvement Path: A Typical Old Revolutionary Cultural Area as an Example

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Abstract: At present, the focus of global attention is on implementing rural revitalization strategies. However, constructing a set of scientifically based evaluation indexes for the evaluation of the effectiveness of rural revitalization implementation, exploring the implementation plan for rural revitalization, has become a common concern and a focus of discussion in political and academic circles. This study used a typical rural revitalization demonstration area in China as an example. We proposed a theoretical framework for rural revitalization research and constructed an index evaluation system for the evaluation of the effectiveness of rural revitalization implementation and influencing factors from two perspectives: material life and spiritual life. The results were as follows: Differences were found in the implementation effectiveness of rural revitalization strategies in the study area; especially, in areas with obvious rural cultural characteristics, their implementation level was relatively high. The implementation effectiveness of rural revitalization strategies was the result of multi-factor interactions. The village greening rate, innovation ability, and the age of village supporters were the main factors affecting rural revitalization, and the interaction effects of a village's innovation ability and other factors were significant. Therefore, we argue that in the process of promoting the sustainable development of villages, it is necessary to prominent the characteristics of village construction and improve the effectiveness of the implementation of village revitalization strategies at both the material and spiritual levels.

Keywords: rural revitalization; evaluation; rural revitalization demonstration area; TOPSIS model; geographic probe; impact mechanism

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1. Introduction

The village generally refers to where the agricultural population engaged in agrarian activities gathers, including farmhouses, livestock sheds, warehouses, yards, roads, canals, green spaces beside houses, and ancillary facilities required under specific environmental and professional production conditions. It is a regional complex with natural, social, and economic characteristics and also has multiple functions of production, life, ecology, culture, etc. Compared with cities, the development status of rural areas is often in a secondary position. Still, they promote and coexist with the urban regional system and together constitute the main space for human activities. At present, about 45% of the world's population lives in rural areas [1]. Its production and life conditions are also widely concerning, such as public infrastructure construction, the improvement of human settlements, the inclination of educational resources, the improvement of general security, etc. Research shows that maintaining the high-quality development of rural areas makes an essential contribution to regional economic growth, is the basis for maintaining the balance of the people–land system, and is also a prerequisite for the harmonious coexistence of man and nature [2]. However, in fact, the sustainable development of rural areas involves many aspects, including respect for nature, culture, and history, and the protection of the ecological environment. Therefore, improving the competitiveness of villages, building livable villages, and achieving sustainable and high-quality rural development have gradually become a focus for politicians and researchers in China and abroad [3,4]. While developed countries in the West started to pay attention to sustainable rural development relatively early and have more mature research frameworks and methods, research on sustainable rural development in developing countries needs to be strengthened [5–8].

Social problems in developed countries primarily exist in cities, while social problems in developing countries mainly exist in rural areas. This is an important difference between eastern and western cultures and is a concrete manifestation of the global development imbalance problem [6]. At present, rural development worldwide faces many challenges [2], including rural poverty and environmental degradation. In particular, solving the problem of rural poverty is also a primary goal in the United Nations' efforts to achieve sustainable development [9]. Thus, countries around the world have summarized many classical models using their own rural development characteristics to promote the prosperous re-creation of villages, thereby realizing sustainable rural development. For example, Japan's one village one product (OVOP) movement, which was proposed and implemented in the 1970s, intends to promote the development of villages by leveraging their endogenous power [10,11]. Furthermore, the one tambon (sub-district) one product (OTOP) movement in Thailand, which is being implemented with the help of the government, aims to improve the rural economy by subsidizing farmers and providing professional skill training to improve the international competitiveness of villages by strengthening their governance capacity and promoting domestic consumption [11]. To protect rural ecology, the rural landscape construction movement was launched in Germany [12]. In addition, the rural urbanization movement in the United States aims to alleviate the economic gap between rural and urban areas to maintain their economic balance by encouraging families and companies to leave urban centers and choose suburban settlements [13]. The new village movement (NVM) in Korea is dedicated to reducing the gap between urban and rural areas, improving rural competitiveness, and achieving a balance between urban and rural development by encouraging farmers to be self-reliant and build cooperative relationships among farmers [14]. It can be seen that, due to different national conditions, the strategies adopted for rural development are also different. Overall, the process of rural revitalization in these countries has gone through transformations in rural infrastructure, rural production mode, and rural development thought, resulting in different experiences that have shaped national rural development in recent decades.

As the world's largest developing country with a long history of agrarian culture, China has emerged as a modern economy. By the end of 2021, China's urbanization rate was 64.72% [15]. This was the result of one of the largest population migration movements in human history [16]; however, 510 million people still live in rural areas in China. The development of the rural population not only affects China's food security, rural industrial prosperity, traditional cultural landscape, and sustainable rural development but also affects the global socioeconomic balance and urban–rural integration [17–19]. With continuous economic and social progress, the unbalanced development of people's lives has become the main contradiction of Chinese society, and the incomplete development of rural areas has become the focus of social contradictions in China; furthermore, the demand for the spiritual needs of farmers (paying attention to the spiritual needs of farmers and bringing about a dynamic equilibrium between the supply of and demand for farmers' spiritual culture are essential tasks in the constructing of the new socialist countryside; improving the quality of the spiritual needs of farmers is not only the strong desire of a vast number of peasants but also an essential part of the construction of new rural areas; therefore, it is not only a critical means to promote the all-round development of farmers, but also an important measure to implement peasant-oriented revitalization, and it is not only a fundamental way to eliminate the gap between urban and rural areas but also an important measure to achieve urban–rural integration) is getting higher and higher. Especially given the rapid advancement of industrialization, informatization, and urbanization, rural problems such as the urban–rural development imbalance, rural population loss, and rural aging have gradually emerged [20–22], and phenomena such as leaving children behind [23], outdated farming systems [24], irregularity of land use [25,26], rural environmental defacement [27–29], weak legal awareness [30], and rural cultural depression [31] are common in rural China. According to researchers, in the coming decades, the population carrying capacity of rural China is forecasted to accommodate 400 million more people and to provide more diverse services to the world [4]. To this end, the Chinese government first proposed the strategy of "implementing rural revitalization" in a governmental work report in 2017 [32]. The main body of its revitalization is farmers. Revitalization includes the comprehensive revitalization of industry, talent, culture, ecology, and organization. The purpose is to solve the problems of agriculture, rustic areas, and farmers, further narrowing the gap between urban and rural areas to achieve sustainable rural development and ultimately achieve the general goal of industrial prosperity, ecological livability, rustic style civilization, effective governance, and affluent life [33]. In 2018, plans were formulated to specify and actualize industrial, talent, cultural, ecological, and organizational revitalization, in which they were emphasized and refined again [34]. In 2021 and 2022, important documents were released to clarify the work priorities for the implementation of rural revitalization, listing new requirements and indicating new directions for the realization of high-quality rural development [35,36].

After drawing on reports of successful cases of revitalizing the countryside in other countries around the world [37,38], Chinese researchers analyzed the characteristics and nature of the successful transformation of the Chinese countryside [18]. They started from the path of rural industrial development [39], the mechanisms and pathways of rural reconstruction [40], the new dynamics of urbanization and construction [41], the pathways and means of the transformation of farmers [42], the role of land improvement [43], and the new directions and systems for strengthening agricultural and rural science and technological innovations [44] to deeply analyze the essence of the countryside and to lay a strong foundation for exploring the implementation of rural revitalization in China. Specifically, the achievements related to the evaluation of the implementation effect of rural revitalization are mainly reflected in the following aspects: Researchers evaluated the implementation level of rural revitalization from different perspectives, including industrial development [45], ecological protection [46], grassroots governance [47], and information construction [48], based on the goals of rural revitalization in an attempt to identify the shortcomings of rural development. In particular, some researchers not only studied the problem of rural sustainability but also initiated discussions on rural development [10–14]. For example, Liu et al. [2] argued that villages not only contain local development history but are also microexpressions of global development. Qiao et al. [49] pointed out that the villages located in the plain–mountain interfaces, and its economic development is better. Village development also reflects the development history of a country, and even that of global civilization, at the micro-level through policy adjustment and village construction, as well as the life needs of the residents. In terms of research methodology, most cases or combinations of multiple cases were analyzed qualitatively [50], used in model exploration [51], or subjected to comparative analysis [52]. In terms of data collection, data were generally primarily obtained through in-depth interviews [53] or using a combination of statistical data review and small conference discussions [54]. In the word, the evaluation of the implementation effect of rural revitalization shows diversified characteristics. The village is the smallest organic unit of agricultural area development, and the evaluation system can better reflect the implementation effectiveness of rural revitalization by taking the village area or farm household as the evaluation unit, framing the evaluation system from the combined material and spiritual perspectives [55], and obtaining data through farm household participation [56]. However, studies exploring the implementation effectiveness of rural revitalization and its influencing factors and enhancement paths at this microscopic scale are lacking [57]. With the implementation of China's rural revitalization strategy, evaluating the effectiveness of its implementation is an important aspect of understanding rural development differences and summarizing the shortcomings of rural development. This not only provides guidance for rural revitalization implementers in terms of overcoming problems but also helps the government to formulate targeted development strategies [58]. However, rural development is a complex, long-term, gradual, multidisciplinary, intersectional, and multi-party participatory process; thus, constructing a set of scientifically based and universal evaluation indexes for the effectiveness of rural revitalization implementation has become a common concern and a focus of discussions in political and academic circles.

Therefore, in this study, a theoretical framework of rural revitalization was constructed by sorting out the current situation of rural development in China. This analysis enriches the theory of rural development and the existing research results for China and is of great significance for the national macroeconomic regulation of the rural development strategy. Finally, taking a Chinese rural revitalization demonstration area with typical revolutionary culture as a case study, we measured the implementation level of the rural revitalization at the village level and explored the main influencing factors. The results of this study provide a reference for local governments to formulate rural revitalization policies. These research results also provide a decision-making reference for local governments to differentiate their rural revitalization policies and provide useful case studies for reference in the implementation of sustainable rural development in other regions.

2. Theoretical Framework for Evaluation of Rural Revitalization Implementation Effectiveness

Sustainable development has been an enduring topic in the pursuit of a harmonious human–land relationship because it not only sustains the interests of the state, society, and enterprises but is also crucial to the realization of human civilization and individual welfare [59]. China's countryside is highly diverse and uneven due to its unique natural, social, and multi-ethnic characteristics [60,61]. Therefore, the countryside also faces a series of pressures in the process of development, such as life pressure, production pressure, and ecological pressure. For these characteristics, the Chinese government stresses that industry is the core of rural revitalization; talent is the driving force of rural development; culture is the soul of a region; ecology is the support point of rural revitalization; and organization is the link between economic management and administration in the implementation of rural revitalization [34].

On this basis, according to the concept of rural revitalization and current scholars' research on rural revitalization, this paper focuses on the potential and external environment of rural development and establishes a theoretical framework for evaluating the implementation effect of rural revitalization (Figure 1). Research shows that the village contains a kind of people–land–money wisdom, with strong local characteristics [62], while the village is faced with production, life, ecology, and other pressures in the process of development. Realizing rural revitalization is actually the result of implementing the recreation of rural values, as well as the result of the coupling and coordinated development of industry, talent, culture, ecology, organization, etc. It is also the specific manifestation of farmers' high-quality life. This not only requires the external stimulation of the countryside but also needs to strengthen the endogenous driving force of the countryside. Through the joint action of endogenous and exogenous driving factors, the countryside can enrich its material life, enhance its production strength, and enrich the spiritual life of farmers, so as to achieve the overall revitalization of the countryside. In addition, the level of implementation of rural revitalization cannot be judged solely based on material conditions, but rather it should also consider the spiritual needs of farmers, such as the desire for knowledge, the respect of others or social groups for themselves, and the enjoyment of democratic rights. Therefore, the evaluation of the implementation effect of rural revitalization can be carried out from both the material living standard and the spiritual affluence, which can better help researchers to understand the regional status of rural development.

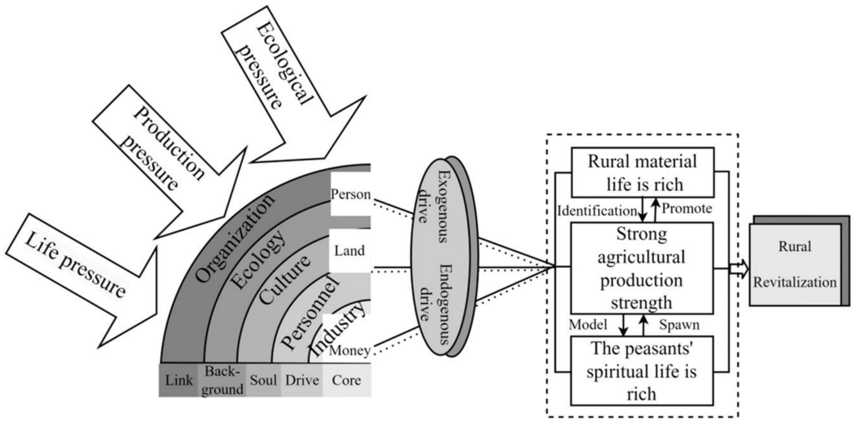

Figure 1. Framework for evaluating the effectiveness of the implementation of rural revitalization in China.

3. Research Methodology and Data Sources

3.1. Overview of the Study Area

Jinggangshan is located in the southwestern part of Jiangxi Province, in the middle of Luoxiao Mountains, at the junction of Jiangxi and Hubei provinces (Figure 2). The total area of the mountainous region accounts for 87% of the study area, with an average altitude of 381.5 m. By the end of 2021, the permanent population of Jinggangshan was 155,900, of which the urbanization rate was 63.18% and the total rural population was 140,200. The economic activities of the city are dominated by the tertiary industry, which accounts for 71.3% of the total. The agricultural activities are dominated by tea, garden fruit planting, and aquaculture. The per capita disposable income of urban residents in the city is RMB 42,495, and that of rural residents is RMB 14,551. In the late 1920s, the older generation of Chinese leaders carried out fierce revolutionary struggles in this area, creating a strong revolutionary culture in this region and leaving behind many valuable cultural resources. [63]. Revolutionary culture refers to the culture built up by the Chinese people during the great struggle led by the Communist Party of China. It is an advanced culture with distinctive Chinese characteristics, taking Marxism as the guidance, taking "revolution" as the spiritual core and value orientation, inheriting the excellent traditional culture of China, and drawing on the great achieved civilization. Breath is an essential place for learning revolutionary culture and a 5A tourist attraction (the quality of tourist attractions in China is divided into five levels: the higher the level is, the greater its tourism value is; tourist attractions are classified, therefore, from high to low, as AAAAA, AAAA, AAA, AA, and A) in China (Figure 3).

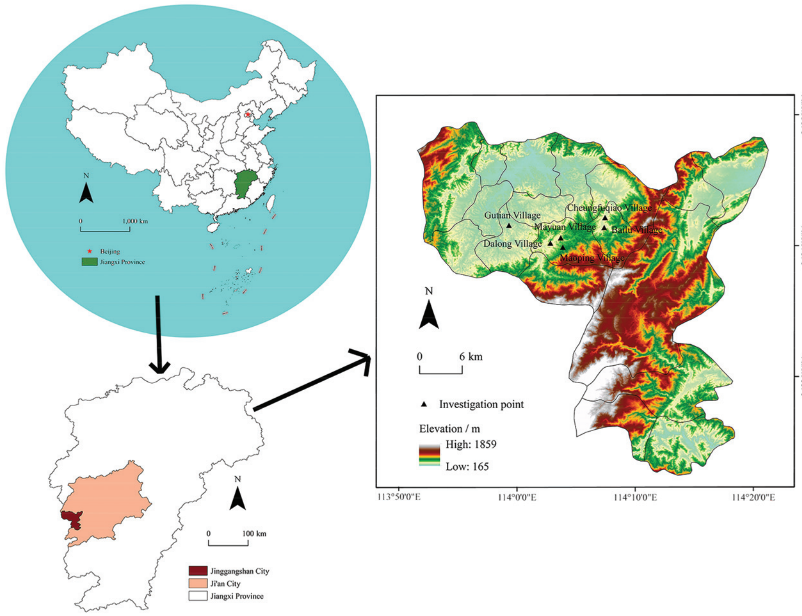

Figure 2. Map showing the location and elevation map of the study area.

(**A**) (**B**)

Figure 3. (**A**) Shrimp breeding base. (**B**) A tourist village with lots of tea.

According to the criteria for identifying key counties for poverty alleviation and development in rural China [64] and based on the education, health, culture, employment, economy, and social security conditions, a total of 4638 poor households containing 16,934 people were identified in Jinggangshan. These were among the first batch of key counties for poverty alleviation and development in China [65]. In 2017, Jinggangshan became one of the first counties in China to escape poverty, and its poverty incidence rate dropped from 6.06% to 1.60% [66], laying a solid foundation for further sustainable rural development. The study area was centered on Maoping Village (MP) in Jinggangshan, which is a nationally famous revolutionary cultural site and radiates surrounding villages with strong revolutionary culture, with a total area of 268.703 km^2 and a total population of 25,137. Dalong Village (DL) is where the town government of Maoping Town is located. Berlu Village (BL) is located in the middle of the revolutionary base area in Jinggangshan Mountains. Changfuqiao Village (CFQ) is a place where there are many talents. Gutian Village (GT), which is located at the Long-shi exit of Jingmu Expressway, has convenient transportation links to other villages. Mayuan Village (MY) is a model village with rich resources. The area retains old revolutionary sites where important meetings were conducted, including the residences of the old revolutionaries. This was one of the main birthplaces of the Jinggang

Mountain spirit and is an important demonstration area for the implementation of the rural revitalization strategy in China.

3.2. Rural Revitalization Evaluation System

According to the framework for evaluating the effectiveness of the implementation of rural revitalization strategies, the general requirements for the rural revitalization of the industry, culture, ecology, organization, and talent were taken as the purpose; a series of policy requirements, instructions, national standards, and action plans issued by the Chinese government were used as the basis [34,67,68], and the existing research results reported by Feng et al. [44], Chih-H et al. [69], Gao et al. [70], and Du et al. [71] on rural revitalization evaluation were referred to. Based on the principles of scientific objectivity, accuracy, representativeness, universality, and the accessibility of indicators, 20 elements were extracted from five dimensions, namely, industrial development, ecological construction, cultural development, rural governance, and farmers' lives, and 35 evaluation indicators that could provide feedback on the material level of rural areas and the living standards of rural residents were constructed to comprehensively evaluate the effectiveness of the implementation of rural revitalization strategies (Table 1). The indicators and the categories they fell under were as follows: Industry is the core of sustainable development in villages. Indicators such as the new characteristic planting and breeding industries in villages, the new agricultural production and development talents, the total output value of the industrial development, and the total amount of village credit loans were selected to characterize the vitality and potential of village industrial development and the ability to expand the development of regional characteristics [23,72]. Ecological construction is the foundation of sustainable development in villages. Seven indicators for this were selected, including the greening coverage of villages, centralized water supply covering farm households, new domestic waste treatment facilities, and the comprehensive utilization of livestock and poultry manure generated by farming to provide feedback on the status of ecological protection and restoration in villages, as well as the status of comprehensive waste treatment in villages [28,29]. Culture is the soul of sustainable rural development. The main focus was on the richness of the cultural and sports activities of village residents, the inheritance of revolutionary culture, and the promotion of changes in customs. Indicators such as the number of cultural and sports activities organized for villagers, the number of cultural activities held in the village by units at all levels, the average number of participants per cultural activity held in the village, the number of revolutionary culture education activities carried out in the village, and the number of activities carried out in the village to change customs and traditions were selected to provide feedback on the construction of village culture [2,31]. Organizational construction includes three aspects, i.e., organizational leadership construction, the villagers' autonomy, and the rule of law, covering nine indicators such as the number of newly developed party members, the number of villagers' congresses conducted, law promotion and publicity, the number of criminal cases, and the number of public security investigations and punishments, which reflect the modernized governance system of rural social synergy, public participation, and the protection of the rule of law [23,25]. The living conditions of rural residents are the most direct feedback of sustainable rural development. Eight indicators, including the number of households using public toilets with water flushing, the number of new cultural squares, the number of farm households with internet broadband access in the village, the village's collective economic income, and the per capita disposable income of rural residents, were selected to provide feedback on the rural residents' sense of access, happiness, and security given the rural living environment, economic status, village affluence, and informatization level [2,73].

Table 1. Index system for evaluating the effectiveness of rural revitalization.

Dimensional Layer	Element Layer	Indicator Layer	Attribute	AVG	MAX	MIN	SD
Industrial development	Cultivating or improving rural specialty industries	The village's new special planting area (m^2)	+	50	200	0	71.6473
		New special breeding scale (one)	+	1725	2100	1000	376.1095
	Improving agricultural production and management, and scientific and technological personnel	The village's new agricultural production and management, and the development of talent (people)	+	8.3333	13	4	3.2998
	Total income growth of agricultural and rural specialty industries	Total industrial development output value (million CNY)	+	160.8333	520	0	188.3352
		Specialty industry output value (million CNY)	+	80	220	0	100
	Total rural credit	Total amount of credit in the village (million CNY)	+	240.8833	463	30.1	161.5218
Ecological construction	Greening of the countryside	Village greening coverage (%)	+	71.1567	75.65	66.71	3.5697
	Rural roads and production (tourism) road construction and management	New traffic roads (km)	+	0.8167	1.1	0.5	0.2115
		New production roads (km)	+	0.975	1.2	0.8	0.1216
	Drinking water safety	Farmers covered by centralized water supply (households)	+	272.6667	385	155	81.9932
	Amount of harmless rural waste treatment	New domestic sewage treatment facilities in the village (per year)	+	0.5	1	0	0.5
		New domestic waste treatment equipment (per year)	+	0.6667	3	0	1.1055
	Comprehensive utilization of livestock and poultry manure	Comprehensive utilization rate of livestock manure generated from farming (%)	+	90.6667	98	80	6.4205
Cultural development	Enriching the cultural and sports lives of farmers	Organizing villagers to participate in cultural and sports activities (events)	+	1.8333	3	1	0.8975
		Units at various levels that come to the village to hold cultural activities (events)	+	1.8333	3	1	0.8975
		Units at all levels that come to the village to hold cultural activities on average per event (people)	+	101.3333	270	30	84.7480
	Focusing on revolutionary culture heritage	Revolutionary culture education in the village (times)	+	2.6667	5	1	1.2472
	Promoting the changes in customs and traditions	The number of activities to change customs and traditions in the village (times)	+	2	3	1	0.5774
Organization Building	Strengthening grassroot party organizations	Number of newly developed party members (people)	+	1.1667	2	0	0.6872
		Number of times per quarter in which the village party assembles and the branch are held (1.0 times, 2.1-2 times, 3.3 times, 4.4 times, and above)	+	2.5	4	2	0.7638
	Energizing villagers' self-governance	Number of times the village held a village assembly (times)	+	2.3333	5	1	1.2472
		Number of village representatives in the village (number)	+	23.3333	36	13	8.8255
		Number of meetings of village representatives (times)	+	4.5	6	3	1.1180
		Number of consultation activities organized in the village (times)	+	6	10	2	3.1091
	Promoting the rule of law in villages	Number of legal literacy campaigns conducted in the village (times)	+	4.3333	6	3	1.2472
		Criminal cases tried (times)	+	0	0	0	0
		Village security investigation (people)	+	0	0	0	0

Table 1. *Cont.*

Dimensional Layer	Element Layer	Indicator Layer	Attribute	AVG	MAX	MIN	SD
Farmers' lives	Promoting the improvement of rural toilet facilities	Number of public toilets that flush	+	2.1667	3	1	0.6872
		Number of public toilets available in the village	+	2.1667	3	1	0.6872
		Farmer households using flush toilets	+	297.8333	402	150	88.0841
	Promoting the construction of village-level public service infrastructure	Number of new sports and fitness places in the village	+	0.5	2	0	0.7638
		Number of new cultural squares	+	0.8333	1	0	0.3727
	Coverage of broadband internet	Farmer households with internet access in the village	+	218	307	125	63.4928
	Development of village's collective economy	The village's collective economic income (CNY)	–	388,450	507,000	314,400	58,983.0979
	Increase in income level of residents	Per capita disposable income of farmers in the village in 2021 (CNY)	–	15,169	16,400	14,600	589.2410

Note: "+" it means that a larger indicator value was more favorable. "–" it means that a larger indicator value was more unfavorable.

3.3. Factors Influencing the Effectiveness of the Implementation of Rural Revitalization Strategies

To further confirm the factors affecting the implementation level of rural revitalization, we constructed 12 indicators from three dimensions, i.e., rural development, rural construction, and rural governance (Figure 4), and quantitatively analyzed the decisive influence factors of six model villages in the demonstration area in Jinggangshan using a geographic detector model. The size of the q-value of the influencing factor reflected the explanatory power of the effect of the changes in the factor on the level of rural revitalization. Based on the results of previous studies [4] and considering the scientific, systematic, and representative nature of constructing indicators, the accessibility of data, and the feedback about the problem, natural capital (X1), village innovation capacity (X2), production potential (X3), collective economic status of the village (X4), greening rate in the village (X5), public facilities (X6), transportation status (X7), informatization rate (X8), age optimization of village supporters (X9), village rule-of-law situation (X10), villagers' autonomy status (X11), and revolutionary culture inheritance (X12) were selected as the specific factors for exploring the level of implementation of the rural revitalization strategies. The q-values of each indicator in the geodetector were summed, and the average value was taken as the comprehensive q-value of each dimension.

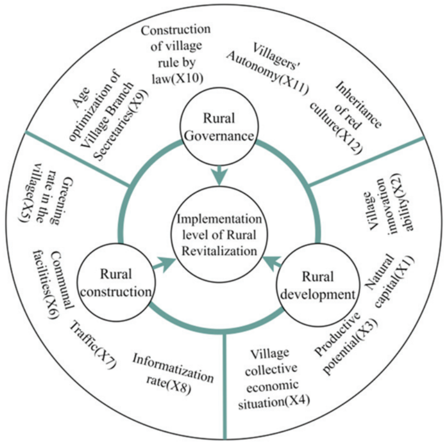

Figure 4. Factors influencing the rural revitalization level in the Jinggangshan rural revitalization demonstration area.

3.4. Research Methods

3.4.1. Entropy Weighting Method

The entropy value of an indicator reflects the amount of information it provides to decision makers, and it can objectively reflect the importance of the indicator. Therefore, the entropy value method is widely used to determine the weights of evaluation indicators [74]. The specific calculation process is shown below.

(1) Standardization: The standardization of the raw data of the indexes was performed using the polar difference method [74]. The calculation was performed as shown below. Positive indicators:

$$y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \tag{1}$$

Inverse indicators:

$$y_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{2}$$

In Equations (1) and (2), y_{ij} is the standardized value; x_{ij} is the original value of the indicator; and max(x_{ij}) and min(x_{ij}) are the maximum and minimum values of the jth indicator for the ith village. When a larger indicator value was more favorable to the development level of rural revitalization, the positive indicator was standardized using Equation (1); conversely, when a larger indicator value was more unfavorable to the development level of rural revitalization, Equation (2) was used.

(2) Calculation of weights:

$$Wij = \frac{1 + k\sum\limits_{i=1}^{m}[\ln(pij)Xij/\sum\limits_{i=1}^{m}Xij]}{\sum\limits_{i=1}^{n}\left\{1 + k\sum\limits_{i=1}^{m}[\ln(pij)Xij/\sum\limits_{i=1}^{m}Xij]\right\}} \tag{3}$$

where W_{ij} denotes the weight of each indicator; p_{ij} denotes the proportion of the jth indicator of the ith village to the sum of the jth indicator; and e_{ij} represents the entropy value of each indicator in the interval [0,1]. k = 1/ln(hm), where m is the number of evaluation indicators, n is the year, and h is the number of villages.

3.4.2. TOPSIS Model

The technique for order preference by similarity to ideal solution (TOPSIS) method was first proposed in 1981, and it is also known as the superior–inferior solution distance method. The TOPSIS model is used to evaluate the relative superiority and inferiority of an objective. If the evaluation object is the closest to the optimal solution and the farthest from the worst solution, it is considered to be the best solution. Otherwise, it is non-optimal [75]. The specific calculation process is as shown below.

(1) Establish the weight specification matrix, O_{ij}:

$$O_{ij} = W_{ij} \times y_{ij}(i = 1, 2, 3, \cdots, n; j = 1, 2, 3, \cdots, m) \tag{4}$$

(2) Determine the positive and negative ideal solutions:

$$S_j^+ = \max(O_{1j}, O_{2j}, \cdots, O_{nj}); S_j^- = \min(O_{1j}, O_{2j}, \cdots, O_{nj}) \tag{5}$$

(3) Determine the sum of the Euclidean distance of each evaluation unit from the optimal and inferior solutions:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(S_i^+ - O_{ij})^2} \tag{6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (S_i^- - O_{ij})^2} \quad (7)$$

(4) Calculate the closeness between the index value and the ideal value for each evaluation area:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (8)$$

where C_i is [0~1]. The closer the value of C_i to 1 is, the closer the solution is to the ideal solution, and the closer the value is to the ideal value for the evaluation area; that is, the higher the level of the rural revitalization of the ith village was, and the lower the level of rural revitalization was [75].

3.4.3. Geodetector

A geodetector is a statistical method for detecting spatial dissimilarity by analyzing the spatial similarity between independent and dependent variables to reveal the driving forces [76]. Current geodetector methods include factor detection, risk detection, interaction detection, and ecological detection. These have mostly been used in research fields such as natural and social sciences [76]. In this study, we relied on factor detection and interaction detection in the geodetector method to explore and identify the differences in the degrees of influence of the factors on the development level of rural revitalization. The specific model is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \quad (9)$$

$$SSW = \sum_{h=1}^{L} N_h \sigma^2, SST = N\sigma^2 \quad (10)$$

where q is the degree of explanation of the influencing factors on the heterogeneity of the rural revitalization development level in the rural revitalization demonstration area in Jinggangshan, and the range of values is between 0 and 1. The larger the q-value was, the greater the differentiation of the rural revitalization development level was. If the stratification was generated by an influencing factor, then the closer the q-value was to 1, the stronger the explanatory power of this factor was for the differentiation of the rural revitalization and development level. When q = 0, the factor had no impact on the rural revitalization and development level. L is the level of rural revitalization and development or the stratification of the various influencing factors, i.e., the stratification of the independent variables or dependent variables. NH and N are the numbers of units in layer h and the entire region, respectively. Parameters σ_h^2 and σ^2 are the variances of the Y values in stratum h and the entire district, respectively. SSW is the sum of the variances within the strata, and SST is the total variance of the district [76].

Interaction detectors are usually used to identify the characteristics of interactions between different influencing factors, i.e., to determine whether the effects of a two-factor interaction on dependent variable Y are mutually independent by comparing the q-value of a single factor with that of a two-factor interaction. The detection value of q $(X_i \cap X_j)$ is judged to identify whether the driving factor of the interaction enhances or weakens the explanatory power of the analyzed variables. The details of the judgment process were described by Wang et al. [76].

3.5. Data Sources

In 2021, the Chinese government selected a total of 40 demonstration areas for rural revitalization in less developed, old revolutionary regions based on whether the villages had a strong revolutionary cultural foundation, beautiful rural nature and idyllic scenery, sound infrastructure, a certain rural industrial base, and rural residents living and working in peace and harmony. Based on the characteristics of rural development, the selected villages in these areas are representative in terms of production and life and could fully reflect characteristics such as local cultural vitality and the rural industrial development potential. The rural revitalization demonstration zone in Jinggangshan, Jiangxi Province, includes six villages in three townships. We conducted field research in 2022 on six villages in three townships (Figure 5). Through interviews with industry departments, townships, villages, and farmers within these counties, we collected detailed information about these villages, including the basic situation of the county, industrial development status, construction of the demonstration zone, the development of special breeding industries, rural economic development status, rural ecological environment, villagers' living standard, rural governance status, farmers' spiritual lives, and other data and textual information that could reflect the material implementation level of rural revitalization and the farmers' spiritual life status. These data were used to form an important village database.

Figure 5. Photo of farmer interview.

4. Results and Analysis

4.1. Measurement of the Development Level

4.1.1. Overall Measurement

The overall rural revitalization implementation level was clearly differentiated in the six villages. Based on the evaluation index of the rural revitalization implementation level and the resource characteristics of the rural revitalization demonstration villages in Jinggangshan, we calculated the closeness (C) value of each village using the TOPSIS model (Figure 6). The top-ranked village was MP, with a closeness (C) value of 0.474, followed by DL (C value of 0.470); GT (C value of 0.454); BL, which is located in the middle of the Jinggangshan revolutionary base area (C value of 0.414); MY (C value of 0.340); and finally CFQ (C value of 0.237). By analyzing the closeness ranking of each demonstration village, we concluded that there were differences in the level of rural revitalization among the six model villages, and the differences were relatively clear, with the maximum closeness value being twice as high as the minimum closeness value. The implementation level of rural revitalization in areas with strong revolutionary culture was significantly higher than that in other areas. Taking MP as an example, we dug deeper into the potential connotations of revolutionary culture; enriching revolutionary culture elements; adherence to the concept of revolutionary culture leading and green development; the creation of a comprehensive scenic spots integrating food, accommodations, transportation, entertainment, tourism, and shopping; development from a single industry to full industry structure; and revitalizing culture to feed the revitalization of industry. It was found that the implementation of these measures had achieved considerable results.

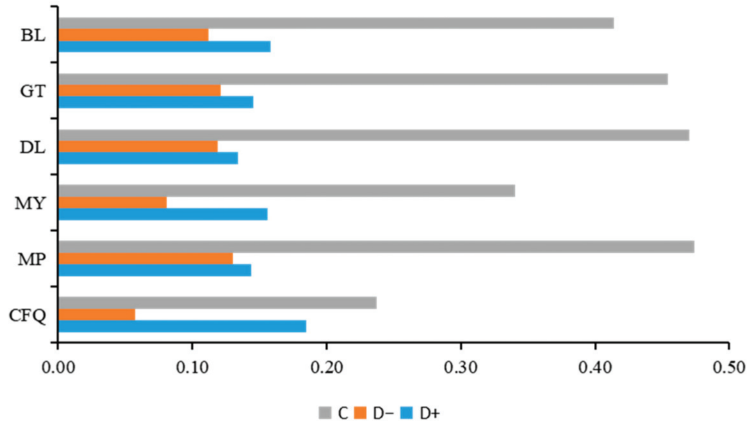

Figure 6. Evaluation of the closeness of rural revitalization in Jinggangshan.

4.1.2. Analysis of the Dimensions of Implementation Effectiveness

Based on the results of the development level of rural revitalization, the top two closeness values of the five dimensions (i.e., industrial development, ecological construction, cultural development, organizational construction, and farmers' lives) were defined as the main effects and side effects.

The main side effects of the five dimensions were significantly differentiated.

Based on a horizontal comparison (Figure 7), the main role of the rural revitalization implementation level in CFQ's was the dimension of farmers' lives, with a closeness value of 0.295, while ecological construction and cultural development together constituted the side effects of the village, with closeness values of 0.271 and 0.294, respectively. The main role in MP was organizational construction, with a closeness value of 0.613; and there were two side effects, namely, industrial and cultural development, with closeness values of 0.549 and 0.512, respectively. The main role in MY was organizational construction and ecological construction, with closeness values of 0.553 and 0.469, respectively. The main role in DL was ecological construction, with a closeness value of 0.770, and the side effect was the farmers' lives, with a closeness value of 0.486. The main role in GT was the industrial development and cultural development dimension, with closeness values of 0.609 and 0.545, respectively, and the side effects were ecological construction and farmers' lives, with closeness values of 0.386 and 0.368, respectively. The main role in BL was farmers' lives, with a closeness value of 0.637; and the side effects were industrial development and cultural development, with closeness values of 0.455 and 0.452, respectively. Thus, it can be seen that in the implementation of rural revitalization in the demonstration area in Jinggangshan, the roles of each dimension were significantly differentiated and exhibited a gradient and hierarchical distribution. The village with the largest gradient span was DL, ranking first in the closeness of farmers' lives but sixth in the closeness of ecological construction. CFQ had a gentler gradient ranking between 4 and 6 in the closeness of each dimension with a strong dependence among the dimensions.

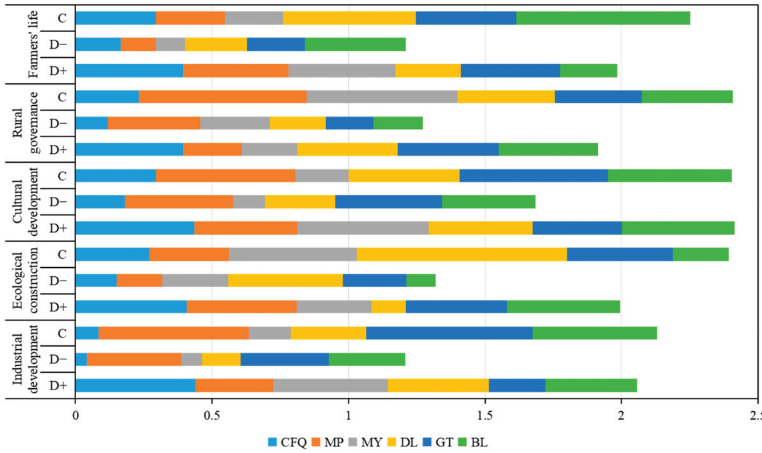

Figure 7. Evaluation of the closeness of each dimension of the rural revitalization level in the demonstration area in Jinggangshan.

The differentiation of the effects of the five dimensions on the model villages was significant.

The longitudinal analysis (Figure 6) revealed that there was a balance in the mean levels of the effects of the five dimensions on the overall effects in the six model villages, with the maximum mean difference being 0.047. The mean value of the effect of the organizational construction dimension on the level of rural revitalization in the six model villages was the largest (0.4015), and the mean value of industrial development was the smallest (0.3548). By contrast, the difference in the effect of ecological construction on the level of rural revitalization in the six model villages was the greatest, with a difference of 0.564, and the closeness value of DL was 0.770, while the closeness value of BL was 0.206. In descending order, the values were as follows: cultural development (0.350) > organizational construction (0.380) > farmers' lives (0.424) > industrial development (0.524) > ecological construction (0.564). Based on the analysis of the overall effect level of each dimension, although there was a balance in the average level of the effect of each dimension in the six model villages overall, the variability in the effect force of cultural development in the six model villages was smaller than that of ecological construction, indicating that rural cultural development had a strong driving effect on improving the overall development level of the villages.

4.2. Analysis of Factors Influencing the Level

4.2.1. Main Controlling Factors

Overall, the influencing factors with the greatest explanatory power on the implementation level of rural revitalization in the demonstration area in Jinggangshan were ranked as shown in Figure 8. In descending order, they were X5 (0.8465) > X2 (0.8379) > X9 (0.7220), X4 (0.7220) > X8 (0.3886) > X11 (0.3746) > X1 (0.3352) > X3 (0.3025) > X7 (0.2831) > X10 (0.2256) > X12 (0.1552) > X6 (0.1321). By analyzing the q-value magnitude of the effect of each dimensional influencing factor, we found that rural development had the highest intensity effect on the level of implementation of rural revitalization development (0.5494), followed by rural construction (0.4126), and rural governance (0.3694) had the lowest intensity effect on the implementation level of rural revitalization development.

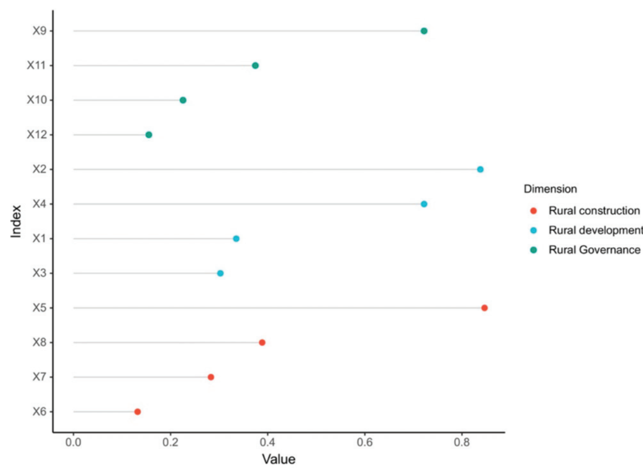

Figure 8. Results of impact factor detection of rural revitalization level in the Jinggangshan rural revitalization demonstration area.

The single-factor detection analysis revealed that there were significant differences in the explanatory powers of the different influence factors on the implementation level of rural revitalization, and the interactions between the influencing factor exhibited non-linear enhancement or two-factor enhancement effects, indicating that the result of the interaction between any two of the 12 influencing factors was greater than the sum of the individual effects of the two selected factors or was greater than the maximum value (Table 2). Based on the analysis of the two-factor interaction detection results, we concluded that the two-factor enhancement effect was significant for the interactions of each dominant factor, meaning that the *q*-values of the interactions of most of the dominant factors were greater than the *q*-values of the interaction of each single factor. Furthermore, the complementary enhancement effect, 1 + 1 > 2, i.e., the non-linear enhancement effect, occurred for the interaction of some of the dominant factors. In particular, the factors that interacted with X6, X10, and X11 exhibited a non-linear enhancement effect, and the driving effect was more apparent. In addition, regarding the intensity of the interaction detection of each dominant factor, the village innovation capacity (X2) interacted with 72.73% of the other dominant factors. The interaction *q*-value of the village innovation capacity (X2) was greater than 0.996, indicating that the combination of the village innovation capacity (X2) and the other factors was more helpful in improving the implementation level of rural revitalization. For the best interaction factors, the interaction between village development and the village governance factors was the most significant, but the degrees of influence of the specific factors varied, and the interaction results were differentially distributed, generally exhibiting a two-factor enhancement effect.

4.2.2. Influence Mechanism

Based on the results of previous studies [39,62] and the results presented in Section 4.2.1, the influence mechanism of the implementation effect of rural revitalization was further analyzed (Figure 9) to provide a reference for realizing localized and need-based solutions to rural problems, enhancing rural competitiveness, improving rural development, and realizing comprehensive rural revitalization.

Table 2. Results of factor interaction analysis.

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
X1	0.3352											
X2	0.9962	0.8379										
X3	0.4816	0.8688	0.3025									
X4	0.9962	0.9962	0.8386	0.7220								
X5	0.9847	1	0.9477	0.8758	0.8465							
X6	0.9962	0.8649	0.8688	0.8004	0.8759	0.1321						
X7	0.9656	0.8987	0.6982	0.8285	0.9477	0.4606	0.2831					
X8	0.9847	1	0.7009	0.9998	0.9846	0.5504	0.7009	0.3886				
X9	0.9962	0.9962	0.8386	0.7683	0.8758	0.8004	0.8285	0.9998	0.7220			
X10	0.9656	1	0.8386	0.8386	1.0000	0.5504	0.9656	0.5504	0.8386	0.2256		
X11	1.0000	1	0.5395	0.7780	0.9998	0.8285	0.5294	0.7007	0.7780	0.8386	0.3746	
X12	0.9656	1	0.7009	0.8759	0.8759	0.3396	0.4201	0.7009	0.8759	0.9656	0.7009	0.1552

Note: If the interaction detection result is C(A + B) > A + B, this is defined as two-factor enhancement. If the interaction detection result is C(A + B) > max(A,B), this is defined as non-linear enhancement. The red font indicates a two-factor enhancement effect, while the black font indicates a non-linear enhancement effect.

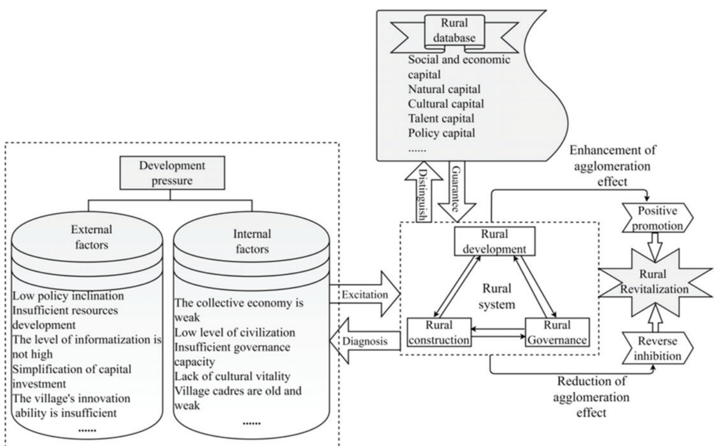

Figure 9. Influence mechanism of the level of rural revitalization in the Jinggang Mountain rural revitalization demonstration area, Jiangxi Province.

China's rural development is challenged by many external factors, including poor policy inclination towards rural areas and insufficient resource development. It is also constrained by internal factors such as old and weak village cadres, poor industrial development status, weak rural governance capacity, and insufficient cultural vitality. As an important part of the development principles of the five-year plan for implementing the rural revitalization strategy (2016–2020), rural green development focuses on reducing environmental risks, protecting rural landscapes, and creating an economically efficient, socially harmonious, and ecologically friendly path to sustainable rural development for the benefit of human well-being [28]. The green development of the countryside is a key factor in the improvement of the level of rural revitalization. The long-term greening level of Chinese villages is not high; the level of environmental damage is serious; the village organization is disorganized; the dependence on policy tilt in carrying out rural revitalization is too high; the level of social capital integration is low; and the attraction of talent and industrial development used to promote the vitality of rural development is low, resulting in villages having a low capacity to actively develop by improving their own abilities. The direct result of this phenomenon is that the endogenous power for village development is insufficient, and the impact on the implementation level of village revitalization is significant. As the main birthplace of the Chinese revolution, the city of

Jinggangshan in Jiangxi Province is rich in culture, and the revolutionary spirit of their ancestors has had a strong influence on the area. The villagers generally have a higher concept of the rule of law, and cultural heritage and development have less influence on the implementation level of rural revitalization. Therefore, the low level of village greening and the lack of attractiveness of the villages in turn lead to the low ability of villages to attract talent, the high pressure of industrial development, and the low level and single source of the village's collective economic income being the most important factors that affect the implementation of rural revitalization.

Rural development is the key to the implementation of rural revitalization, and it is a dynamic process that is constantly optimized through self-organization and structure. Rural development is the result of endogenous drivers, exogenous drivers, physical spaces, humanistic spaces, and the joint action of these factors in the different stages of development; and the interaction among factors can be considered to be part of a dissipative structure and nonlinear open system that is far from equilibrium [77,78]. Rural construction is an important task in the implementation of the rural revitalization strategy, and the basis of all of this is rural governance.

First, overall, rural development plays the greatest role in influencing the implementation level of rural revitalization, while rural governance plays a smaller role. This indicates that with the development of urbanization and informatization, the overall quality of farm households has been significantly improved; the situation of rural rule-of-law construction has been significantly improved; and there is already a solid foundation for China's countryside to enter the next stage of upgrading and transformation [79].

Second, specifically, the concept of green development is still a key element in the process of rural revitalization [29]. The Chinese government pays increasing attention to the concept of green development [80,81]. At present, green development has created significant wealth for the development of China's countryside, and the increase in the value of resources has made a great contribution to the ecological protection and sustainable development of China's countryside. The progress of implementing the concept of rural green development (which aims to alleviate the contradiction in the process of economic development by reducing resource consumption and strengthening environmental and ecological governance, which essentially reflects the concept of sustainable development) directly affects the potential for sustainable rural development [23], and this in turn restricts the introduction of rural talents and social capital investment, while stimulating the vitality of rural development requires not only government intervention but also the inflow of talents and social participation. For example, 87% of the Jinggangshan rural revitalization demonstration zone is mountainous. According to data from Forest Resource Management in Jinggangshan in 2020, the greening rate (greening rate = [(area of tree forest + area of bamboo forest + area of shrub forest + area of four-sided tree cover)/total land area] × 100%) of the demonstration zone was 70.79% in 2020. In 2021, the greening rate was 75% (data provided by Jinggangshan Forestry Bureau), and the greening rate of the countryside is increasing. This can provide an ecological environmental basis for the revitalization of the countryside in the demonstration area. However, the greening rate is still lower than the overall rate in Jinggangshan (>86% in 2021) [82], and the greening level of the demonstration area plays an important role in the implementation of rural revitalization.

Third, regarding the countryside itself, the area is rich in natural and cultural capital. However, the development of such a large village database requires the participation of all sectors. To a certain extent, the age composition of the village leaders reflects that the ability of the village in accepting new technologies, information, and to introduce network development, while a higher collective economic village income reflects a better economic base, higher tolerance rate, and greater attractiveness to social capital [71].

Fourth, regarding the endogenous power of villages, the implementation of rural revitalization should not adopt a one-size-fits-all approach but rather should be promoted based on the local rural characteristics. Culture is the soul of a country, and cultural self-confidence is the strength that a country and a nation present to the world [31]. At present, most of the countryside in China retains a primitive state of culture, and rural revitalization is the most powerful way to build villages with distinctive characteristics and advantages, to develop cultural and sports industries with rural characteristics, to promote the revitalization of traditional crafts in rural areas, to activate and make prosperous the rural cultural market, and to drive villagers to develop independently [83]. The center of the demonstration area is Maoping Village, which has a strong revolutionary culture, and its influence radiates to the surrounding area, developing the countryside with its revolutionary sites and culture, leveraging social capital investment through the central lottery 50 million public welfare fund and policy financial funds, providing a strong financial guarantee for the rural construction of the demonstration area, relying on revolutionary culture, and building an industry-academia-research framework through market-oriented operation. Based on the revolutionary culture, the education base is built through market-oriented operations. The integration of agriculture and tourism has developed into a specialized residential industry; special cultural industry parks have been created, and the implementation of rural revitalization has been promoted.

Fifth, the construction of public facilities also had a certain influence on the construction of rural revitalization in the demonstration area, but its influence degree was lower than those of the remaining 11 factors.

5. Discussion

5.1. Development and Enhancement Path of Rural Revitalization

In recent years, the issue of rural development has been the focus of researchers worldwide. The study of the sustainable development of rural areas and the development of rural culture is quite popular in social science research both in China and abroad [2,21,23]. Based on the example of the rural revitalization demonstration area in Jinggangshan, Jiangxi Province, a region that has a typical revolutionary culture, in this study, the implementation level of rural revitalization and its influencing factors were explored from a microscopic perspective, and these issues were evaluated in the context of the current level of development, thereby enriching the previous research results [71,74,84]. The analysis results also provide a reference for policymakers in decision making regarding rural revitalization and provide a case study for the implementation of rural revitalization in China. However, this study differs from previous studies in terms of the selection of the study area and the construction of the evaluation indicators [71,85]. For example, regarding the design of the rural revitalization evaluation indexes, the data used in this study were obtained through four-level semi-structured interviews at the county, township, village, and farmer levels. In addition, the research unit was more microscopic and closer to the actual cases, so it had stronger explanatory power for rural areas [9,85]. The evaluation system was constructed from the two perspectives of rural material living conditions and spiritual life, and we investigated farmers' perceptions of rural areas and their lives. In addition, the evaluation system investigated the awareness of rural households and their personal feelings about rural development to determine the needs of the first beneficiaries of rural development, making the evaluation of the effectiveness of rural revitalization more reasonable.

Based on the results of the effectiveness of the implementation of rural revitalization, the overall differentiation was clearly significant, and there was an equalization of the average levels of the different evaluation dimensions on the implementation effectiveness of rural revitalization. The smallest variability in the mean value of the effect of industrial development on the effectiveness of the implementation of rural revitalization indicated that the countryside paid more attention to the industry in the development process. This finding was consistent with the studies by Du et al. [71] and Robert et al. [86]. Moreover, rural cultural development had a relatively strong driving effect on enhancing rural competitiveness, and this research result was mainly due to rural culture and the development of cultural continuity in the rural planning process [49,69,87].

From the analysis of the factors influencing rural revitalization, the greening rate of the countryside, the innovation ability of the countryside, and the age optimization of the village cadres had significant impacts on the implementation level of rural revitalization and were very important elements in the process of rural development. This indicates that in the process of rural revitalization, the vitalization development of villages is the basis for all rural development and construction, and it is also an important supporting element for the regional development of a village [23,88]. In addition, the green development of villages is a prerequisite and necessary condition for maintaining sustainable development [28]. This is also consistent with the results obtained by Wang et al., who proposed that improving the environment of the habitat area has a positive effect on enhancing the development of agricultural agglomeration and promoting the sustainable development of rural areas [89]. The rejuvenation of village leaders is an important guarantee of the sustainable development of village businesses as well as a booster of the sustainable development of villages. This result effectively complemented current research on village development [23,28].

5.2. Revelation of Rural Revitalization

Taking the old revolutionary cultural area in Jinggangshan, Jiangxi Province, China, as an example, in this study, we revealed the effectiveness, influencing factors, and mechanisms of rural revitalization implementation, and we further summarized the universal experience of implementing a rural revitalization strategy. These analysis results improve our understanding of the rural territorial system itself and the comprehensive development of the countryside and its complex relationships. The results of this study provide a basis for rural revitalization and sustainable rural development. However, rural revitalization still faces many problems and challenges [23], and the multiple values of rural cultural resources such as history, economy, and ecology need to be further explored [90].

Culture is the soul of the countryside and forms a foundation for the extension of rural society. The Chinese government encourages to lead and drive rural revitalization from the perspective of cultural industry, calls for multi-participation with farmers as the main body, government-led market operation and scientific planning, and coordinates five aspects of industry, talent, organization, culture and ecology to realize and promote the implementation of cultural empowerment of rural revitalization. Studies showed that the decline of traditional Chinese villages is generally manifested in two ways: the disappearance of traditional natural villages and the decline in culture. The causes of rural decline can be divided into two types: the impact of modern industrialization and urbanization development, and the decline in rural elite culture [23,24,91]. Based on this, we constructed a theoretical framework (Figure 10) in terms of two guiding ideas and evolutionary paths of cultural revitalization to provide feedback concerning the role of rural cultural development in the implementation of a rural revitalization strategy and to provide a new implementation perspective for sustainable rural development. Accordingly, the cultural industry is divided into two parts: natural resources and human resources. The cultural industry empowers rural humanities and natural resources to produce feedback for multiple values of rural culture, such as history, economy, ecology, and remediation. It also combines the synergy of government guidance, market operation, social regulation, talent return, village collective implementation, and farmer participation to stimulate rural cultural vitality; inherit farming civilization (which refers to a cultural collection of national system, etiquette and custom system, culture, and education established by people in long-term agricultural production to meet the needs of agricultural production and life); promote industry and sales; coordinate the integration of agriculture, culture, and tourism; and promote the integrated development of agriculture, industry, and service industries. Thus, the new pattern of "strong agriculture, rich farmers and beautiful countryside" can be realized by developing cultural industries. These factors aid in the implementation of the five types of revitalization and promote the overall revitalization of the countryside.

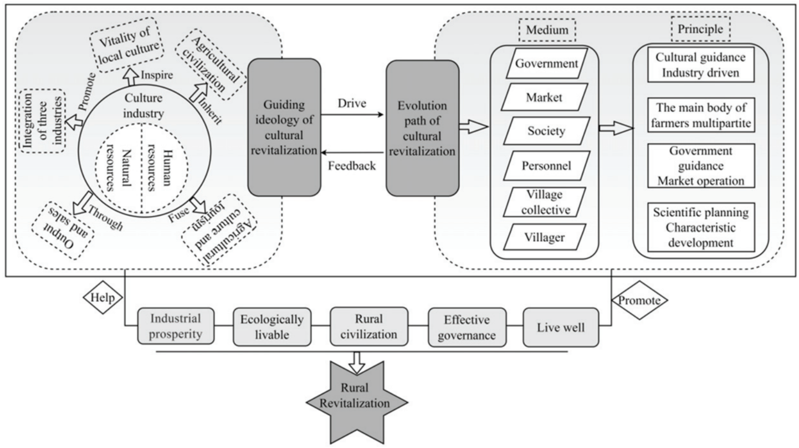

Figure 10. Schematic diagram showing the framework of rural revitalization from the perspective of cultural revitalization.

5.3. Recommendations to Promote Rural Revitalization

The implementation of rural revitalization requires the joint efforts of many parties, and this paper attempts to put forward development suggestions in the below aspects.

For policymakers, it is important to comprehensively grasp factors such as material, spiritual, and social relationship forms to deeply analyze the development history of rural civilization, to form a basic picture of development, to understand the inner mechanisms and the evolutionary path of civilization in each region, to strengthen integrated planning and scientific layouts, and to increase the implementation of policies related to the composition of cultural zones to connect the dots into lines and the lines into surfaces to constitute cultural zones and improve the creativity and comprehensive strength of rural culture.

Regarding the specific responsible parties, when considering the needs of urban and rural populations in all aspects, they should pay more attention to the expectations of rural residents for rural development and construct implementation plans in a targeted manner by identifying and coordinating the opinions of different groups, such as the elderly, middle-aged, youth, adolescents, children, and immigrants to create an ecologically livable countryside from a spiritual perspective while satisfying the residential and living environment of farm households to achieve common prosperity in the countryside.

For social scientists engaged in rural revitalization research, there is still a lack of systematic, detailed, and in-depth analyses of the theoretical aspects of the level of rural revitalization from the perspective of rural cultural development, as well as the construction of indicators for the evaluation of the effectiveness of the implementation of rural revitalization strategies and the pathways and methods of improvement. Intangible culture is transformed into tangible services, and the value of the services is evaluated as a way to encourage working decision makers to sustainably stimulate rural development; to explore the ecological and economic values of rural culture; to seek a model of coupled development of rural culture and industry emphasizing coordinated social, cultural, and economic properties at the urban–rural interface; and to provide development that can sustainably maintain the level of social expectations [49,78,85].

6. Conclusions

Based on the background of the macro-policy regulation of rural revitalization, in this study, we constructed an index system for evaluating the effectiveness of the implementation of rural revitalization that considers rural residents' material needs and their spiritual lives. Made more accurate by further analyzing the factors with the analysis results and data affecting the implementation of rural revitalization in the case study areas, this study enriched existing research results with several interesting findings; for instance, we found that the implementation of rural revitalization requires not only a focus on the development of industries but also an increase in the development and utilization of the inner resources of the rural areas, such as the rural unique cultural resources. Based on the analysis of the influencing factors, the implementation of rural revitalization was a result of the joint effect of multiple factors. In general, village development had a stronger influence on the implementation level of rural revitalization than village construction and village governance. Based on the analysis of each influencing factor, the harmonious development of human and nature was found to be still the primary task of rural revitalization, which was also consistent with the SDGs. At the same time, the important task of rural industrial development and the foundation of rural revitalization were both rural innovation capabilities. In the foreseeable future, it is expected that the results of this study and the proposed policy recommendations are expected to provide theoretical references for sustainable rural development and high-quality rural development in different countries and regions, as well as provide microscopic indicators for the evaluation of the effectiveness of rural revitalization. In addition, the evaluation of the rural culture can utilize feedback regarding the status of rural industrial development (the status of the economic enhancement of cultural tourism integration and the status of the industry–academia–research scheme), which can better reflect the relationship between cultural revitalization and rural revitalization implementation. This has significance and value for the cultural development of other areas. For the design of rural revitalization evaluation indexes, the index system of rural culture and education can be enriched by constructing indicators such as the number of rural elementary schools, the number of rural teachers, the age of rural teachers, and the number of rural libraries [92], which makes the setting of the rural revitalization evaluation index system more perfect.

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References

1. The Food and Agriculture Organization of the United Nations (FAO). Food and Agriculture Data. 2018. Available online: http://www.fao.org/faostat/en/#home (accessed on 10 June 2022).
2. Liu, Y.; Li, Y. Revitalize the world's countryside. *Nature* **2017**, *548*, 275–277. [CrossRef] [PubMed]
3. Morris, B. The components of the Wired Spanning Forest are recurrent. *Probab. Theory Relat. Fields* **2003**, *125*, 259–265. [CrossRef]
4. Yurui, L.; Luyin, Q.; Qianyi, W.; Karácsonyi, D. Towards the evaluation of rural livability in China theoretical framework and empirical case study. *Habitat Int.* **2020**, *105*, 102241. [CrossRef]
5. Terry, M. Beyond agriculture? Regulating the new rural spaces. *J. Rural. Stud.* **1995**, *11*, 285–296. [CrossRef]
6. Bijker, R.A.; Haartsen, T. More than counter-urbanisation: Migration to popular and less-popular rural areas in the netherlands. *Popul. Space Place* **2012**, *52*, 643–657. [CrossRef]
7. Terry, M. New rural territories regulating the differentiated rural spaces. *J. Rural Stud.* **1998**, *14*, 107–117. [CrossRef]

8. Terry, M.; Roberta, S. Rural development and the regional state: Denying multifunctional agriculture in the UK. *J. Rural. Stud.* **2008**, *24*, 422–431. [CrossRef]
9. Xie, Z.; Zhang, F.; Lun, F.; Gao, Y.; Ao, J.; Zhou, J. Research on a diagnostic system of rural vitalization based on development elements in China. *Land Use Policy* **2020**, *92*, 104421. [CrossRef]
10. Thanh, L.H.; Nhat, L.T.; Dang, H.N.; Ho, T.M.H.; Lebailly, P. One Village One Product (OVOP): A rural development strategy and the early adaption in Vietnam, the case of Quang Ninh province. *Sustainability* **2018**, *10*, 4485. [CrossRef]
11. Anh, N.T. One Village One Product (OVOP) in Japan to One Tambon One Product (OTOP) in Thailand: Lessons for grass root development in developing countries. *J. Soc. Dev. Sci.* **2013**, *4*, 529–537. [CrossRef]
12. Kirschke, D.; Hger, A.; Schmid, J.C. New trends and drivers for agricultural land use in Germany. *Sustain. Land Manag. A Eur. Context.* **2021**, *8*, 39–61. [CrossRef]
13. Boustan, L.P.; Bunten, D.M.; Hearey, O. *Urbanization in the United States, 1800–2000*; National Bureau Of Economic Research: Cambridge, MA, USA, 2013. [CrossRef]
14. Jemal, A.; Fikadu, M.; Kyung, R.K. Korea's saemaul undong (New Village Movement): A Model for rural development in Ethiopia. *J. Korean Soc. Int. Agric.* **2013**, *25*, 217–230. [CrossRef]
15. National Bureau of Statistics. Statistical Bulletin of the People's Republic of China on National Economic and Social Development in 2021. 2022. Available online: http://www.stats.gov.cn/tjsj/zxfb/202202/t20220227_1827960.html (accessed on 15 June 2022).
16. Bai, X.; Shi, P.; Liu, Y. Realizing China's urban dream. *Nature* **2014**, *509*, 158–160. [CrossRef]
17. Long, H.; Liu, Y.; Li, X.; Chen, Y. Building new countryside in China a geographical perspective. *Land Use Policy* **2010**, *27*, 457–470. [CrossRef]
18. Yurui, L.; Yi, L.; Pengcan, F.; Hualou, L. Impacts of land consolidation on rural human: Environment system in typical watershed of the Loess Plateau and implications for rural development policy. *Land Use Policy* **2019**, *86*, 339–350. [CrossRef]
19. Liu, Y.; Long, H.; Chen, Y.; Wang, J.; Li, Y.; Li, Y.; Yang, Y.; Zhou, Y. Progress of research on urban-rural transformation and rural development in China in the past decade and future prospects. *J. Geogr. Sci.* **2016**, *26*, 1117–1132. [CrossRef]
20. Agation, R.; Shahed, K. Johor Bahru's response to transnational and national influences in the emerging Straits Mega-city region. *Habitat Int.* **2013**, *40*, 154–162. [CrossRef]
21. Munya, A.; Hussain, N.H.M.; Njuguna, M.B. Can devolution and rural capacity trigger de-urbanization? Case studies in Kenya and Malaysia respectively. *GeoJournal* **2015**, *80*, 427–443. [CrossRef]
22. Liu, Z.; Liu, S.; Jin, H.; Qi, W. Rural population change in China: Spatial differences, driving forces and policy implications. *J. Rural. Stud.* **2017**, *51*, 189–197. [CrossRef]
23. Yin, X.; Chen, J.; Li, J. Rural innovation system: Revitalize the countryside for a sustainable development. *J. Rural. Stud.* **2022**, *93*, 471–478. [CrossRef]
24. Yuan, P.; Zhao, X.-R.; Zeng, S. Extenics based innovation of new professional farmer cultivation under the strategy of Rural Vitalization. *Procedia Comput. Sci.* **2019**, *162*, 131–138. [CrossRef]
25. Zhang, Y.; Wang, W.; Feng, Y. Impact of different models of rural land consolidation on rural household poverty vulnerability. *Land Use Policy* **2022**, *114*, 105963. [CrossRef]
26. Jiang, Y.; Long, H.; Tang, Y.-T.; Deng, W.; Chen, K.; Zheng, Y. The impact of land consolidation on rural vitalization at village level: A case study of a Chinese village. *J. Rural. Stud.* **2021**, *86*, 485–496. [CrossRef]
27. Li, S.; Hui, B.; Jin, C.; Liu, X.; Xu, F.; Su, C.; Li, T. Considering farmers' heterogeneity to payment ecosystem services participation: A choice experiment and agent-based model analysis in Xin'an river basin, China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 7190. [CrossRef] [PubMed]
28. Yan, J.; Zhang, D.; Xia, F. Evaluation of village land use planning risks in green concepts: The case of Qiwangfen village in Beijing. *Land Use Policy* **2021**, *104*, 105386. [CrossRef]
29. Li, L.; Zeng, Y.; He, Y.; Qin, Q.; Wang, J.; Fu, C. Developing village-based green economy in an endogenous way: A case study from China. *Public Health* **2022**, *19*, 7580. [CrossRef] [PubMed]
30. Song, Y.; Zhan, Y.; Qi, Y.; Xu, D.; Deng, X. Does political participation influence the waste classification behavior of rural residents? Empirical evidence from rural China. *Agriculture* **2022**, *12*, 625. [CrossRef]
31. Yang, C.-H.; Sun, Y.; Lin, P.-H.; Lin, R. Sustainable development in local culture industries: A case study of Taiwan aboriginal communities. *Sustainability* **2022**, *14*, 3404. [CrossRef]
32. Make a Decisive Decision to Build a Moderately Prosperous Society in All Respects and Win the Great Victory of Socialism with Chinese Characteristics in the New Era. 2017. Available online: http://www.gov.cn/zhuanti/2017-10/27/content_5234876.htm (accessed on 20 June 2022).
33. Jokinen, A. Free-time habitation and layers of ecological history at a southern Finnish lake. *Landsc. Urban Planning* **2002**, *61*, 99–112. [CrossRef]
34. Strategic Planning for Rural Revitalization (2018–2022 Year). 2018. Available online: http://www.gov.cn/zhengce/2018-09/26/content_5325534.htm (accessed on 20 June 2022).
35. Opinions on Comprehensively Promoting Rural Revitalization and Accelerating Agricultural and Rural Modernization. 2021. Available online: http://www.gov.cn/zhengce/2021-02/21/content_5588098.htm (accessed on 25 June 2022).
36. Opinions on the Key Work of Comprehensively Promoting Rural Revitalization in 2022. 2022. Available online: http://www.gov.cn/zhengce/2022-02/22/content_5675035.htm (accessed on 25 June 2022).

37. Sunding, D.; Zilberman, D. The agricultural innovation process: Research and technology adoption in a changing agricultural sector. *Agric. Prod.* **2001**, *1*, 207–261. [CrossRef]
38. Alon, T. To make a desert bloom the israeli agricultural adventure and the quest for sustainability. *Agric. History* **2007**, *81*, 228–257. [CrossRef]
39. Wen, L.; Liu, Z.; Gao, Z. Evolutionary path and mechanism of village revitalization: A case study of Yuejin village, Jiangsu, China. *Sustainability* **2022**, *14*, 8162. [CrossRef]
40. Hussain, S.; Maqbool, R.; Hussain, A.; Ashfaq, S. Assessing the socio-economic impacts of rural infrastructure projects on community development. *Buildings* **2022**, *12*, 947. [CrossRef]
41. Xu, Z.; Si, W.; Song, H.; Yao, L.; Xiang, K.; Cheng, Z. Empirical analysis of population urbanization and residents' life satisfaction-based on 2017 CGSS. *Sustainability* **2022**, *14*, 7580. [CrossRef]
42. Huang, Q.; Zheng, X.; Wang, R. The impact of the accessibility of transportation infrastructure on the Non-Farm employment choices of rural laborers: Empirical analysis based on China's micro data. *Land* **2022**, *11*, 896. [CrossRef]
43. Liao, L.; Long, H.; Gao, X.; Ma, E. Effects of land use transitions and rural aging on agricultural production in China's farming area: A perspective from changing labor employing quantity in the planting industry. *Land Use Policy* **2019**, *88*, 104152. [CrossRef]
44. Feng, G.; Zhang, M. The coupling coordination development of rural e-commerce and rural revitalization: A case study of 10 rural revitalization demonstration counties in Guizhou. *Procedia Comput. Sci.* **2022**, *199*, 407–414. [CrossRef]
45. Sa, H. Do ambiguous property rights matter? Collective value logic in Lin Village. *Land Use Policy* **2020**, *99*, 105066. [CrossRef]
46. Shen, J.; Chou, R.-J. Rural revitalization of Xiamei: The development experiences of integrating tea tourism with ancient village preservation. *J. Rural. Stud.* **2022**, *90*, 42–52. [CrossRef]
47. Liu, W.; Zhou, W.; Lu, L. An innovative digitization evaluation scheme for Spatio-temporal coordination relationship between multiple knowledge driven rural economic development and agricultural ecological environment: Coupling coordination model analysis based on Guangxi. *J. Innov. Knowledge* **2022**, *7*, 100208. [CrossRef]
48. Yiwen, Z.; Kant, S.; Liu, J. Principal-agent relationships in rural governance and benefit sharing in community forestry: Evidence from a community forest enterprise in China. *For. Policy Econ.* **2019**, *107*, 101924. [CrossRef]
49. Qiao, J.; Lee, J.; Ye, X. Spatiotemporal evolution of specialized villages and rural development: A case study of Henan Province, China. *Ann. Am. Assoc. Geogr.* **2016**, *106*, 57–75. [CrossRef]
50. Ma, L.; Dou, H.; Wu, S.; Shi, Z.; Li, Z. Rural development pressure and "three-stay" response: A case of Jinchang City in the Hexi Corridor, China. *J. Rural. Stud.* **2011**, *91*, 34–36. [CrossRef]
51. Zhou, Y.; Li, X.; Liu, Y. Rural land system reforms in China: History, issues, measures and prospects. *Land Use Policy* **2019**, *91*, 104330. [CrossRef]
52. Terluin, I.J.; Post, J.H. Differences in economic development in rural regions of advanced countries: An overview and critical analysis of theories. *J. Rural. Stud.* **2003**, *19*, 327–344. [CrossRef]
53. Li, B.; Zhuo, N.; Ji, C.; Zhu, Q. Influence of smartphone based digital extension service on farmers' sustainable agricultural technology adoption in China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9639. [CrossRef]
54. Tri, S.N.; Suharni, R.; Indriyati, S. Potential of social capital and community participation in village development. *J. Econ. Policy* **2019**, *12*, 68–85. [CrossRef]
55. Tang, W.; Zhu, J. Informality and rural industry rethinking the impacts of E-Commerce on rural development in China. *J. Rural. Stud.* **2020**, *75*, 20–29. [CrossRef]
56. Tang, S.; Lee, H.F.; Huang, X.; Zhou, J. Poverty Stories of rural households in China: The case of North Jiangsu. *J. Rural. Stud.* **2022**, *91*, 1–9. [CrossRef]
57. Guo, Y.; Liu, Y. Poverty alleviation through land assetization and its implications for rural revitalization in China. *Land Use Policy* **2021**, *105*, 105418. [CrossRef]
58. Yin, Q.; Sui, X.; Ye, B.; Zhou, Y.; Li, C.; Zou, M.; Zhou, S. What role does land consolidation play in the multi-dimensional rural revitalization in China? A research synthesis. *Land Use Policy* **2022**, *120*, 106261. [CrossRef]
59. Kaal, H.G.J. A conceptual history of livability. Dutch scientists, politicians, policy makers and citizens and the quest for a livable city. *City* **2011**, *15*, 532–547. [CrossRef]
60. Long, H.; Zou, J.; Liu, Y. Differentiation of rural development driven by industrialization and urbanization in eastern coastal China. *Habitat Int.* **2009**, *33*, 454–462. [CrossRef]
61. Long, H.; Liu, Y.; Wu, X.; Dong, G. Spatio-temporal dynamic patterns of farmland and rural settlements in Su-Xi-Chang region: Implications for building a new countryside in coastal China. *Land Use Policy* **2009**, *26*, 322–333. [CrossRef]
62. Li, Y.; Fan, P.; Liu, Y. What makes better village development in traditional agricultural areas of China? Evidence from long-term observation of typical villages. *Habitat Int.* **2019**, *83*, 111–124. [CrossRef]
63. Revolutionary Culture Is an Important Source of Cultural Self-Confidence. 2019. Available online: http://theory.people.com.cn/n1/2019/0109/c40531-30511387.html (accessed on 28 June 2022).
64. Outline of China's Rural Poverty Alleviation and Development. 2011. Available online: http://www.gov.cn/gongbao/content/2011/content_2020905.htm (accessed on 28 June 2022).
65. The National Rural Revitalization Administration. List of Key Counties for National Poverty Alleviation and Development. 2012. Available online: http://nrra.gov.cn/art/2012/3/19/art_343_42.html (accessed on 1 July 2022).

66. The National Rural Revitalization Administration. A Survey Report on Poverty Alleviation in Jinggangshan City and Ji'an County, Jiangxi Province. 2017. Available online: http://nrra.gov.cn/art/2017/7/12/art_5_65730.html (accessed on 1 July 2022).
67. National Public Service Platform for Standards Information. Guidelines for the Construction of Beautiful Village. 2015. Available online: https://openstd.samr.gov.cn/bzgk/gb/newGbInfo?hcno=C9EB368DECB1E90242DDB7A431F6FFA6 (accessed on 2 July 2022).
68. Implementation Plan of Rural Construction Action. 2022. Available online: http://www.gov.cn/gongbao/content/2022/content_5695035.htm (accessed on 2 July 2022).
69. Yang, C.-H.; Lin, H.-L.; Han, C.-C. Analysis of international tourist arrivals in China: The role of world heritage sites. *Tour. Manag.* **2010**, *31*, 827–837. [CrossRef]
70. Gao, H.; Wang, S. The intellectual structure of research on rural to urban migrants: A bibliometric analysis. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9729. [CrossRef]
71. Du, G.M.; Xue, R.H.; Wang, J.Y. Evaluation and promotion path of rural revitalization at the village scale: Taking Baiquan County, Heilongjiang Province as an example. *Econ. Geogr.* **2021**, *41*, 19–27. [CrossRef]
72. Bi, Q.; Chen, W.; Li, L.; Wang, X.; Cai, E. Agricultural population supported in rural areas under traditional planting mode based on opportunity cost analysis. *Land* **2022**, *11*, 1340. [CrossRef]
73. Zang, Y.; Liu, Y.; Yang, Y.; Woods, M.; Fois, F. Rural decline or restructuring? Implications for sustainability transitions in rural China. *Land Use Policy* **2020**, *94*, 104531. [CrossRef]
74. Yu, W.; Zhang, P. Research on the temporal and spatial differentiation characteristics and influencing factors of China's agricultural development resilience. *Geogr. Geogr. Inf. Sci.* **2019**, *35*, 102–108. [CrossRef]
75. Hwang, C.; Paidy, S.; Yoon, K.; Masud, A. Mathematical programming with multiple objectives: A tutorial. *Comput. Oper. Res.* **1980**, *7*, 5–31. [CrossRef]
76. Wang, J.; Xu, C. Geographical detectors: Principles and prospects. *Acta Geogr. Sin.* **2017**, *72*, 116–134. [CrossRef]
77. Wu, B.; Liu, L.; Carter, C.J. Bridging social capital as a resource for rural revitalisation in China? A survey of community connection of university students with home villages. *J. Rural. Stud.* **2022**, *93*, 254–262. [CrossRef]
78. Ma, Y.; Qiao, J.; Han, D. Interpreting the humanistic space of urban-rural interface using. *J. Rural. Stud.* **2022**, *93*, 513–521. [CrossRef]
79. Li, Y.-R.; Cao, L.-Z.; Wang, P.-Y.; Chang, G.-J. On rural habitat improvement and rural revitalization. *J. Nat. Res.* **2022**, *37*, 96–109. [CrossRef]
80. The Fourteenth Five Year Plan for China's National Economic and Social Development and the Outline of the Vision Goals for 2035. 2021. Available online: http://www.gov.cn/xinwen/2021-03/13/content_5592681.htm (accessed on 4 July 2022).
81. China's Opinions on Accelerating the Construction of Ecological Civilization. 2015. Available online: http://www.gov.cn/xinwen/2015-05/05/content_2857363.htm (accessed on 4 July 2022).
82. Basic Information of Jinggangshan. 2021. Available online: http://www.jgs.gov.cn/news-show-420.html (accessed on 4 July 2022).
83. Opinions on Promoting the Revitalization of the Cultural Industry Empowered Countryside. 2022. Available online: http://www.gov.cn/zhengce/2022-04/08/content_5684002.htm (accessed on 4 July 2022).
84. Jing, W.; Zhang, W.; Luo, P.; Wu, L.; Wang, L.; Yu, K. Assessment of Synergistic Development Potential between T ourism and Rural Restructuring Using a Coupling Analysis: A Case Study of Southern Shaanxi, China. *Land* **2022**, *11*, 1352. [CrossRef]
85. Zhan, Z.; Cenci, J.; Zhang, J. Frontier of rural revitalization in China: A spatial analysis of national rural tourist towns. *Land* **2022**, *11*, 812. [CrossRef]
86. Robert, F.C.; Frey, L.; Sisodia, G.S. Village development framework through self help group entrepreneurship, microcredit, and anchor customers in solar microgrids for cooperative sustainable rural societies. *J. Rural. Stud.* **2021**, *88*, 432–440. [CrossRef]
87. Zhou, Z.; Zheng, X. A cultural route perspective on rural revitalization of traditional villages: A case study from Chishui, China. *Sustainability* **2022**, *14*, 2468. [CrossRef]
88. Wang, W.; Gong, J.; Wang, Y.; Shen, Y. Exploring the effects of rural site conditions and household livelihood capitals on agricultural land transfers in China. *Land Use Policy* **2021**, *108*, 105523. [CrossRef]
89. Wang, W.; Gong, J.; Wang, Y.; Shen, Y. The Causal Pathway of Rural Human Settlement, Livelihood Capital, and Agricultural Land Transfer Decision-Making: Is It Regional Consistency? *Land* **2022**, *11*, 1077. [CrossRef]
90. Portillo, J.E.; Wagner, G.A. Do cultural districts spur urban revitalization: Evidence from Louisiana. *J. Econ. Behav. Organ.* **2021**, *188*, 651–673. [CrossRef]
91. Wong, S.W.; Dai, Y.; Tang, B.-S.; Liu, J. A new model of village urbanization? Coordinative governance of state-village relations in Guangzhou city, China. *Land Use Policy* **2021**, *109*, 105500. [CrossRef]
92. Santamaría, C.N.; Sampedro, G.R. The rural school: A review of the scientific literature. *Rev. Estud. Sobre Despoblación Desarro. Rural. Núm.* **2020**, *30*, 147–152. [CrossRef]

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Dynamic Changes and Regional Differences of Net Carbon Sequestration of Food Crops in the Yangtze River Economic Belt of China

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Abstract: The carbon sequestration of food crops is of great significance to slow down agricultural greenhouse gas emissions in agricultural production and management. This paper analyzes the dynamic change and regional differences of net carbon sequestration of food crops from temporal and spatial perspectives for the case study area of the Yangtze River economic belt (YREB) in China. We use the calculation formula of carbon sequestration and carbon emission to calculate the net carbon sequestration in the Yangtze River economic belt. On this basis, we analyze the dynamic trend and regional differences of net carbon sequestration in the Yangtze River economic belt. Furthermore, we use the Gini coefficient to measure the quantitative gap of net carbon sequestration of grain crops in different regions of the Yangtze River economic belt. The results show that: (1) from 2000–2018, the net carbon sequestration of food crops keeps rising within the studied area, while the carbon emission shows a fluctuating downward trend; (2) remarkable regional differences in the net carbon sequestration of food crops have occurred, and most provinces (cities) show an upward trend for the studied area; (3) the unequitable distribution of net carbon sequestration of food crops is clearly displayed in the upper, middle, and lower reaches of the studied area. Moreover, the most uneven place is located on the lower reaches, and the least uneven place is in the upper reaches. These findings are important points of reference for reducing the carbon emissions of the agricultural industry in the Yangtze River economic belt of China and in China more generally.

Keywords: Yangtze River economic belt (YREB); grain-planting industry; net carbon sequestration; carbon emission; Gini coefficient

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1. Introduction

Nowadays, food security and greenhouse gas emissions are two important issues in agricultural production all over the world [1–3]. It is well known that there are two ways to reduce greenhouse gas emissions, i.e., reducing the absolute amount of carbon emissions from the source and increasing carbon sequestration. With regard to food security, scholars pay more attention to the economic value of food crops [4,5] but often ignore the ecological value of food crops [6–8]. Food crops can absorb carbon dioxide, regulate the climate, and return farmland soil and straw to the field, which can also fix carbon. Therefore, food crops have an important carbon sequestration function. The carbon sequestration in grain production mainly refers to the carbon absorption in the process of grain growth, which is caused by photosynthesis, while the carbon emission in grain production mainly refers to the emission of greenhouse gases such as CO_2, CH_4, and N_2O on farmlands, which is caused by the input of agricultural materials and the growth of grain crops. The net carbon sequestration in food crops refers to the difference between carbon sequestration and carbon emission. According to relevant scholars [9,10], there are a lot of carbon sequestrations in crop biomass, which can not only increase the organic carbon content of agricultural soil, improve the soil fertility, and increase the grain yield, but they also can reduce the agricultural greenhouse gas emissions and gradually form a valuable ecosystem.

Compared with other sectors, the food production sector is a special sector with dual attributes of carbon source and carbon sequestration. On the one hand, a large number of greenhouse gases are produced in the process of food production, related to the application of petrochemical production such as pesticides and fertilizers. At present, among the carbon dioxide emissions from global human activities, the total carbon dioxide emissions from agricultural production and land-use change account for 24% [11]. In 2017, China accounted for about 29.01% of the total agricultural carbon emissions in Asia and about 12.54% of the total agricultural carbon emissions in the world [12]. On the other hand, the process of crop production can also produce carbon sequestration, offsetting part of the carbon emissions produced from food production itself. That is to say, crops can absorb a large amount of carbon dioxide through photosynthesis during the growth process, which plays a role in purifying the air to a certain extent. As an important agricultural base, China has important contribution to carbon sequestration for food crops [13,14]. Especially, at the general debate of the 75th UN General Assembly, China announced that it would strive to reach the peak of carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060 [15]. Therefore, the study on China's grain net carbon sequestration is of great significance for achieving the carbon peak and carbon neutrality commitment of the Paris Agreement [16].

Food crops' carbon sequestration is an important part of agricultural carbon sequestration, and it is very meaningful to study it. At present, the research on food crops' carbon sequestration is relatively few, and it is mainly focusing on agricultural production. Agricultural carbon sequestration mainly focuses on the following four aspects. Firstly, many scholars have launched the quantitative measurement of agricultural carbon sequestrations. Vleeshouwers et al. [17] constructed a model including climate, agricultural soil, and crops to measure carbon sequestrations in European agricultural soils and found that due to the interaction between crops, soil, and climate, there are great regional differences in the effectiveness of agricultural emission reduction measures and substantial differences in the spatial pattern between carbon sequestrations caused by different measures. Alamdarlo [18] estimated carbon sequestrations in the agricultural sector in the Iranian provinces based on Kuznets and space econometric theory. Dhananjay et al. [19] predicted agricultural carbon emissions in Saskatchewan, Canada, by improving the process-based denitrification decomposition (DNDC) models and concluded that prudent management of agricultural irrigation and fertilizers has a significant impact on enhancing the provincial agricultural carbon sequestration potential. Secondly, the influencing factors of agricultural carbon sequestrations receive much attention, which includes the differences in agricultural systems [20], organic fertilizer inputs and conservation farming [21], land-use change [22], and consumption of agricultural material energy such as straw combustion, feces management, etc. [23,24]. Thirdly, there is research on the agricultural carbon sequestration trading and compensation mechanism. Existing scholars mainly pay attention to ecological compensation issues, compensation principles, compensation methods and standards for agricultural carbon sequestration [25], monitoring, report, and verification (MRV) systems of forest carbon sequestration trading and related systems and policies [26], comparison of similarities and differences in carbon trading across countries [27,28], and so on. Fourthly, it is about the development prospects of agricultural carbon sequestrations. Hoffert et al. [29] consider that changing traditional farming patterns can contribute to reducing agricultural emissions and increasing remittances, especially by implementing conservation farming methods. Ugur et al. [30] used the Granger causal test to explore the relationships between economic growth, agricultural carbon emissions, and energy consumption in Turkey and found that Turkey can promote steady economic growth by effectively reducing agricultural carbon emissions.

A few scholars have studied food crops' carbon sequestration. She et al. [31] evaluated the carbon inputs and outputs of crop production systems in six typical agricultural regions in China. The results showed that the carbon sequestration of the same crop in different regions was significantly different, as well as different crops in the same region. Among the three major crops in China, the total annual net carbon sink of rice was the highest. Kang et al. [32] analyzed the impact of grain production on ecological carbon sink in China. Research shows that grain production helps to increase ecological carbon sink. Compared with northeast and western regions, the carbon sink effect of grain production in eastern and central regions is greater.

In summary, scholars have carried out a lot of research on measuring agricultural carbon sequestration, influencing factors of carbon sequestration, the carbon sequestration trading and compensation mechanism, carbon sequestration development prospects, etc.

However, from the perspective of research object, the existing research mainly takes forest carbon sequestration as the research object, and there is less research taking food crops as the research object; from the perspective of research content, the research about carbon sequestration rarely considers the impact of carbon emission. Therefore, based on the calculation of the carbon sequestration and carbon emission of grain crops, taking grain crops as the research object, the net carbon sink as the research content, and the Yangtze River economic belt (YREB) as a case study area, this paper analyzes the dynamic changes and regional differences of net carbon sequestration of grain crops in different regions of China's Yangtze River economic belt.

This paper has three specific objectives to obtain: (1) to estimate the net carbon sequestration of grain crops from two aspects, i.e., carbon sources and carbon sequestrations; (2) to analyze the dynamic trend and regional differences of net carbon sequestration; (3) to measure the quantitative gap of net carbon sequestration of grain crops in different regions by using the Gini coefficient.

2. Materials and Methods

2.1. Site Description

The Yangtze River economic belt (YREB) lies between 20°–35° N and 90°–122° E, covering the three major regions of east, middle, and west in China, which consist of eleven provinces (cities), including Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Yunnan, Guizhou, etc. (Figure 1). Its area is about 2,052,300 km^2, accounting for 21.4% of total area of China. Moreover, its population and gross production value all surpass 40% of that of China. The YREB can be divided into upper reaches, middle reaches, and lower reaches. The upper reaches include Chongqing, Sichuan, Guizhou, and Yunnan, the middle reaches include Jiangxi, Hubei, and Hunan, and the lower reaches include Shanghai, Jiangsu, Zhejiang, and Anhui. In November 2018, Chinese government fully exerted the location advantage of the YREB, guided by ecological priority and green development, to promote the coordinated development of the upper, middle, and lower reaches of the Yangtze River and the high-quality development of the regions along the Yangtze River.

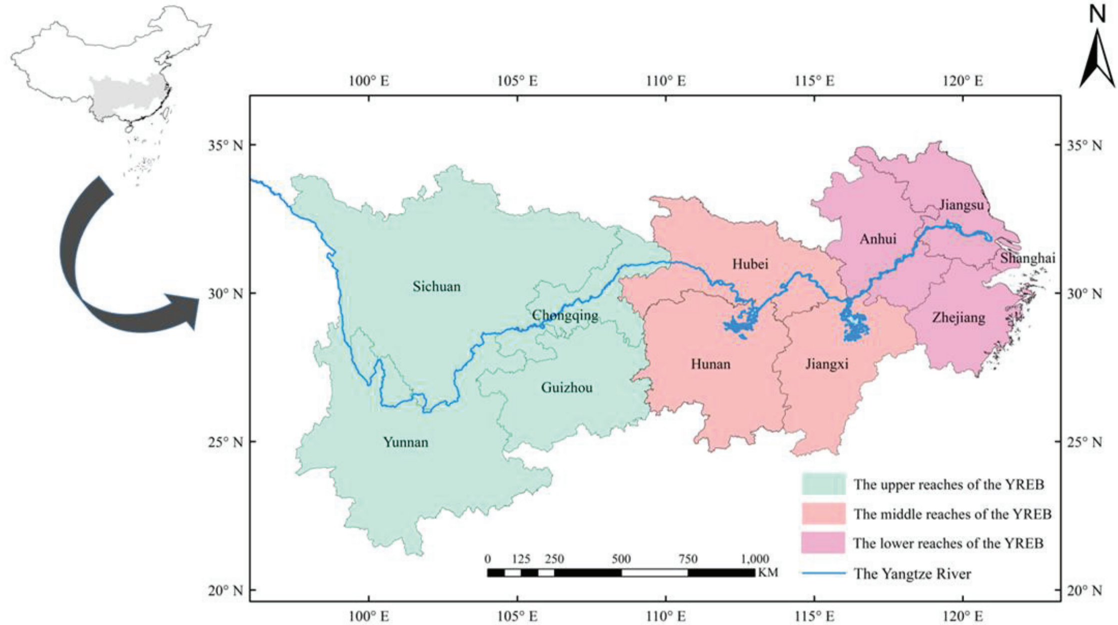

Figure 1. Location map of Yangtze River economic belt.

The YREB is an important food production base in China. It is abundant in natural resources, especially arable land, which together cover one third of the total area of China. In addition, the output value of agriculture, forestry, animal husbandry, and fishery accounts for about 40% of that of China. The YREB consists of several plains, such as Jianghan Plain in Hubei province, Dongting Lake Plain in Hunan province, Chengdu Plain in Sichuan province, Poyang Lake Plain in Jiangxi province, and Taihu Plain in Jiangsu and Zhejiang province and other country-level commodity grain bases. Its grain production accounts for about 40% of the country.

Based on the differences in conditions of geography, soil, climate, technology, etc., as well as the total amount of food production and consumption in different regions of the studied area, China is divided into three regions, i.e., the main grain-producing area, the main grain marketing area, and the grain balance area. Main grain-producing area refers to key grain production areas that have suitable natural resource conditions for cultivating food crops and have certain technical advantages and economic effects. The main grain marketing area refers to the grain consumption area with more people and less land, low food self-sufficiency with rate of grain, and large gap in grain production and demand, which is mainly distributed in economically developed areas, such as the southeast coast of China and large cities. The grain balance area refers to the western region of China which is mainly located in remote areas with relatively backward economy, self-sufficiency in food production, and basic balance between production and demand in food.

The YREB has six main grain-producing areas, two main grain marketing areas, and three grain balance areas. The six main grain-producing areas are distributed in Sichuan, Hubei, Hunan, Jiangsu, Jiangxi, and Anhui provinces. The two main grain marketing areas are located on Zhejiang province and Shanghai city. The three grain balance areas are situated in Yunnan, Guizhou provinces, and Chongqing city. The Chinese government has committed to building the YREB as a good ecological environment and high-quality development economic belt.

As the planting industry is the main agricultural area type in the studied area, exploring the net carbon sequestration of grain-planting industry is of great significance to promote the green transformation of grain production and protect the agricultural ecological environment in the studied area.

2.2. Research Methods

2.2.1. Research Framework

In this paper, the net carbon sequestration of food crops is estimated in the following steps (as shown in Figure 2). First, it is clarified that the net carbon sequestration is influenced by both carbon sequestration and carbon emission (consisting of three components: agricultural materials, rice growth, and grain growing fields), and on this basis, a regional difference evaluation model is constructed using the Gini coefficient. Then, this paper analyzes the dynamic change and regional differences of net carbon sequestration of food crops for the case study area of the YREB in China. In terms of time, this paper separately analyzes the dynamic change trend of net carbon sequestration in the whole study area, and based on this, the net carbon sequestration and the level of carbon sequestration of food crops in 11 provinces (cities) were analyzed dynamically. In terms of space, through the Gini coefficient, this paper analyzes provincial differences of the net carbon sequestration level in the whole study area and the regional differences of the net carbon sequestration level in in the upper, middle, and lower reaches of the YREB. Finally, the results of this paper are discussed, and feasible suggestions and future research directions are given.

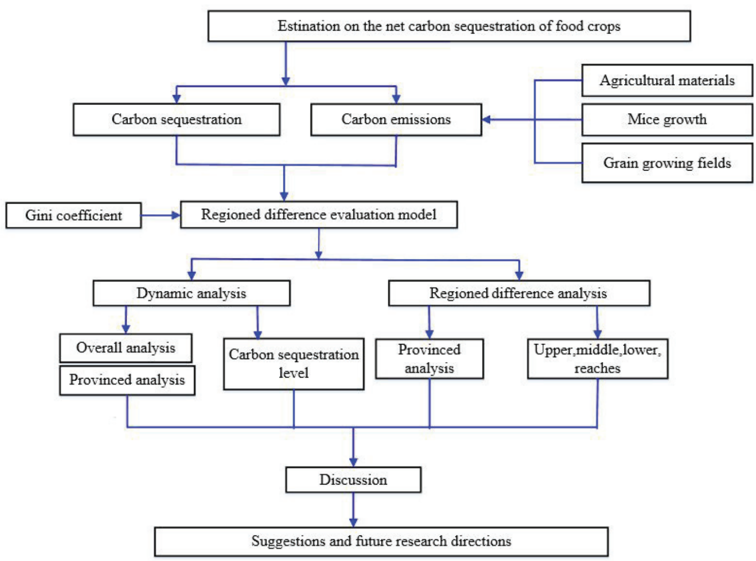

Figure 2. Research framework.

2.2.2. Estimation on the Carbon Sequestration of Food Crops

The net carbon sequestration of food crops is the difference between carbon sequestration and carbon emission, and the carbon sequestration level of food crops is the ratio of carbon sequestration to carbon emission. If the value is greater, the capacity of the net carbon sequestration is stronger, which can better reflect the effect of the net carbon sequestration in a region. The carbon sequestration of food crops was calculated as follows:

$$C_t = \sum_{i=1}^{k} C_i = \sum_{i=1}^{k} r_i \cdot y_i \cdot (1 - w_i) / EC_i \tag{1}$$

where C_t represents the total carbon absorption of food crops; i is the type of food crops; C_i, r_i, y_i , w_i, and EC_i are the carbon absorption, the carbon absorption rate, the economic yield, water content, and economic coefficient of certain food crops, respectively. The carbon absorption rate, water content, and economic coefficient of various food crops are from the Intergovernmental Panel on Climate Change (IPCC) report [33] (Table 1).

Table 1. Economic coefficients, water content, and carbon absorption rates of major food crops in China.

Category	Economic Coefficient	Water Content/%	Carbon Absorption Rate
Rice	0.45	12	0.414
Wheat	0.40	12	0.485
Corn	0.40	13	0.471
Beans	0.34	13	0.450
Tubers	0.70	70	0.423

2.2.3. Estimation on the Carbon Emission of Food Crops

The carbon emission of food crops consists of three parts. The first part comes from the input of agricultural materials, which mainly include chemical fertilizer, pesticide, agricultural film, plastic film, agricultural diesel, and agricultural land irrigation, etc. Here, we apply the weight coefficient A to separate the input of the food production from the generalized input of agricultural production. Especially, the weight coefficient A = the area of food crops sowing/the area of crops sowing. The second part originates from CH_4 emissions caused by the rice growth. The emission factor is taken as a comprehensive emission factor that takes into account regional differences, climate change, etc., which is more convincing and more realistic than a single emission coefficient, as shown in Table 2. The relevant coefficients are recommended by the report of IPCC [33]. The third part comes from N_2O emissions caused by grain growing fields [33]. As such, the carbon emission of food crops can be calculated with following equation:

$$E_t = \sum_{i=1}^{k} E_i = \sum_{i=1}^{k} T_i \cdot \delta_i \tag{2}$$

where i is the type of carbon sources; k is the number of carbon sources; E_t is the total carbon emission from the food crops; E_i is the amount of carbon emission from each carbon source; T_i is the amount of each carbon source; δ_i is the carbon emission coefficient of each carbon source.

Table 2. The CH_4 emission coefficient of rice during its growth cycle in different regions of Yangtze River economic belt (g/m^2).

Region	Early Rice	Late Rice	Mid-Season Rice	Region	Early Rice	Late Rice	Mid-Season Rice
Shanghai	12.41	27.5	53.87	Hunan	14.71	34.1	56.28
Jiangsu	16.07	27.6	53.55	Chongqing	6.55	18.5	25.75
Zhejiang	14.37	34.3	57.96	Sichuan	6.55	18.15	25.73
Anhui	16.75	27.6	51.24	Guizhou	5.1	21	22.05
Jiangxi	15.47	45.8	65.42	Yunnan	2.38	7.6	7.25
Hubei	17.51	39	58.17				

2.2.4. Construction of Regional Difference Evaluation Model of Net Carbon Sequestration

Gini coefficient is an important index that can measure the inequality of income and wealth distribution, which can comprehensively investigate the difference of income distribution among residents. As such, this paper uses Gini coefficient to measure the regional distribution fairness of carbon sequestration from food crops in the YREB and further to investigate the regional differences of net carbon sequestration of food production. Here, we propose a hypothesis: if the proportion of carbon sequestration from food crops of each province (city) in the overall region is completely consistent with the proportion of carbon emission from food crops of one, there is absolute fairness among the regional distributions of net carbon sequestration in the YREB.

Otherwise, we consider there are regional differences. From Figure 3, A represents the area between the absolute average distribution curve of carbon sequestration and the actual distribution curve of carbon sequestration. B is the area between the actual distribution curve of carbon sequestration and horizontal axis. The Gini coefficient of net carbon sequestration from food crops is A/(A + B).

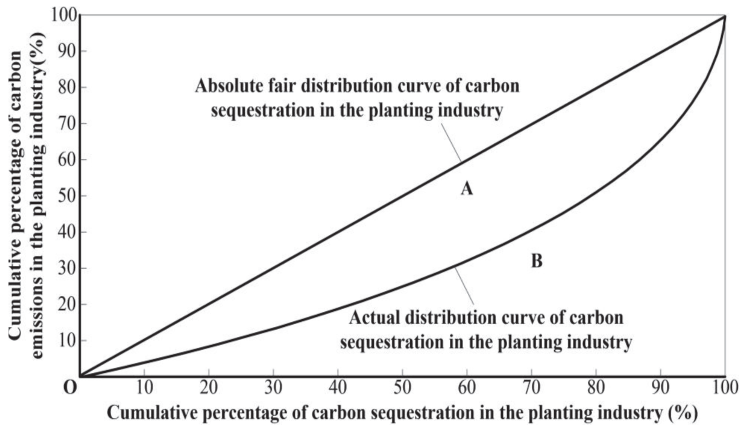

Figure 3. Lorentz curve diagram of net carbon sequestration.

Generally, the Gini coefficient is between 0 and 1. The smaller the Gini coefficient is, the more even the distribution is. On the contrary, the larger the Gini coefficient is, the more uneven the distribution is. Based on the value of Gini coefficient, we can obtain five types, i.e., absolute average, relatively average, relatively reasonable, large gap, and wide gap, which are represented by below 0.2, between 0.2 and 0.3, between 0.3 and 0.4, between 0.4 and 0.5, and more than 0.5, respectively [34]. Moreover, 0.4 is usually regarded as the "warning line" of income gap. According to this international standard, the distribution equity of net carbon sequestration from food crops is calculated with following equation:

$$Ginicoefficient = 1 - \sum_{j=1}^{n} \left(X_j - X_{j-1}\right)\left(Y_j + Y_{j-1}\right) \tag{3}$$

where j is the province; X_j is the cumulative percentage of carbon sequestration from food crops; Y_j is the cumulative percentage of carbon emissions from food crops. When j = 1, X_{j-1}, and Y_{j-1} are regarded as 0, the horizontal axis represents the cumulative percentage of carbon sequestration from food crops of each province (city) in the overall region. When the proportion of carbon sequestration from food crops in certain province (city) is greater than that of carbon emission, it means that the ecological environment of this province (city) is good for food production. Meanwhile, this indicates the region has higher ecological capacity and can share part of the carbon emission from food crops for other provinces (cities).

2.3. Data Sources

This paper takes the five kinds of main food crops as the research objects, i.e., rice, wheat, corn, beans, and tubers, and the time range is 2000–2018.

For the indicator of the carbon sequestration of food crops, the data on the carbon absorption, the carbon absorption rate, the economic yield, water content, and economic coefficient of certain food crop are from the IPCC report, and the data on the economic yield are from the *China Rural Statistical Yearbook*; for the indicator of the carbon emission of food crops, the data on the output of various food crops, the sowing area of the rice, the amount of chemical fertilizer, pesticide, agricultural film, plastic film, agricultural diesel, and the agricultural land irrigation invested in the food production are from the *China Rural Statistical Yearbook*, and the data on the CH_4 emissions caused by the rice growth and the N_2O emissions caused by grain growing fields are from the IPCC report.

3. Results and Analysis

3.1. Dynamic Analysis on the Net Carbon Sequestration of Food Crops

3.1.1. Overall Dynamic Analysis on the Net Carbon Sequestration of Food Crops

The total amount of the carbon sequestration, carbon emission, and net carbon sequestration from food crops in the YREB from 2000–2018 is shown in Figure 4. The net carbon sequestration of food crops maintains an upward trend, while the carbon emission shows a fluctuating downward trend. From 2000–2018, the net carbon sequestration of the region increases from 7.70669×10^7 t to 1.306066×10^8 t, which increases by 69.47%. The carbon emission decreases from 9.02022×10^7 t to 7.78215×10^7 t, which decreases by 15.09%. The total carbon sequestration increases from 1.672690×10^8 t to 2.024332×10^8 t, which increases by 21.02%. On the whole, the carbon sequestration from food crops in the YREB is gradually increasing. The carbon emission shows a "decline-rise-decline" trend, which indicates that the ecological environment of the food production in the YREB is gradually improving.

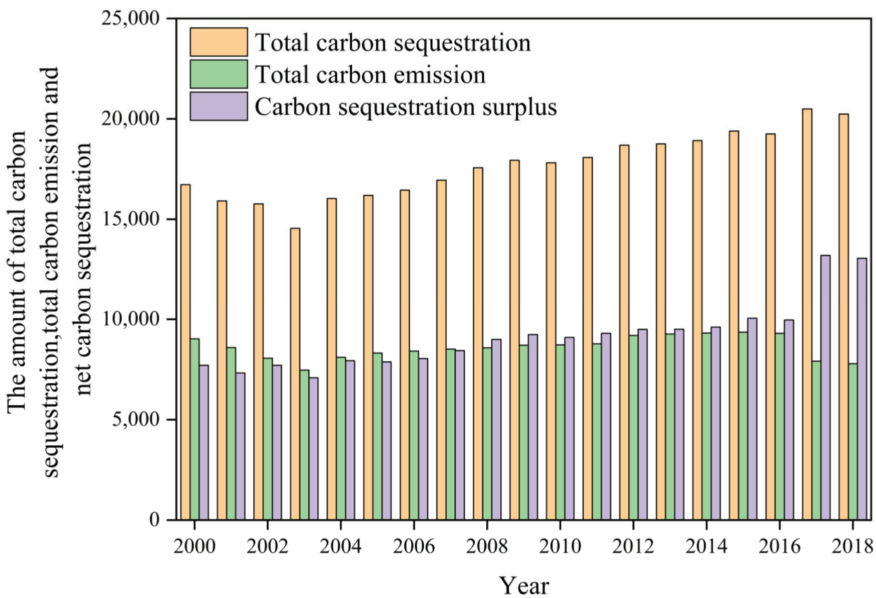

Figure 4. The total carbon sequestration, total carbon emission, and net carbon sequestration from food crops in the YREB (10^4 t C).

3.1.2. Dynamic Analysis on the Net Carbon Sequestration of Food Crops in Various Provinces (Cities)

The levels of net carbon sequestration of food crops in various provinces (cities) in the YREB are shown in Figure 5. Here, we only show the results of 2000, 2006, 2012, and 2018 in Figure 5. The detailed results are presented in the Supplementary File (Table S1). Compared with 2000, the net carbon sequestration of food crops in various provinces (cities) in 2018 shows obvious regional differences. Except for Shanghai and Guizhou, the other nine provinces (cities) show an upward trend. Especially, Guizhou as a grain balance area shows the largest decline rate of 18.88%. In addition, Shanghai as a main grain sales area has a decline rate of 12.19%. The possible reason is that the grain sown area has been greatly reduced with the transformation of industrial structure in Guizhou and Shanghai, which leads to a decrease of carbon sequestration accordingly. According to the *China Statistical Yearbook*, the grain-sowing area of Guizhou falls from 3153.3 thousand hm^2 to 2740.2 thousand hm^2 from 2000 to 2018, and the grain-sowing area of Shanghai falls from 258.8 thousand hm^2 to 133.1 thousand hm^2. In addition, the rising range of the net carbon sequestration in Anhui is the largest, which increases by 183.59%, which is followed by Hunan and Jiangxi, i.e., 171.67% and 137.87%, respectively. Although the ranking of net carbon sequestration in Hubei and Jiangsu province in 2018 is not at the top, with the gradual increase of grain-sowing area, the net carbon sequestration is also increasing gradually.

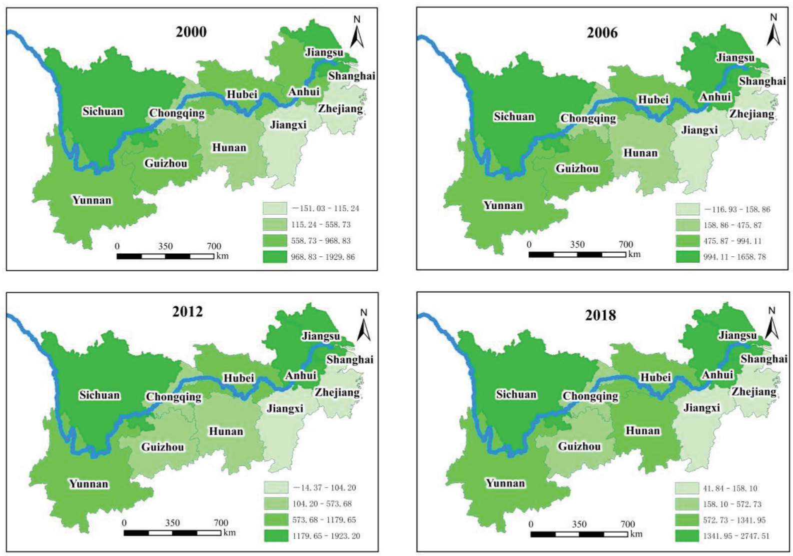

Figure 5. Changes of total net carbon sequestration of food crops in 11 provinces (cities) of YREB.

Taking 2018 as a horizontal comparison year, the net carbon sequestration of food crops in 11 provinces (cities) of the YREB is ranked as follows: Anhui > Jiangsu > Sichuan > Yunnan > Hubei > Hunan > Guizhou > Chongqing > Zhejiang > Jiangxi > Shanghai. Five provinces in the major grain-producing area are at the top of the ranking, i.e., Anhui, Jiangsu, Sichuan, Hubei, and Hunan. Two provinces in the main grain sales area list in the lower ranking, i.e., Shanghai and Zhejiang, and two provinces in the grain balance area are in the middle of the ranking, i.e., Yunnan and Guizhou. We demonstrate that the main grain-producing area receives more attention to the protection of grain ecological environment, compared with the main grain sales area and the grain balance area. The gap of net carbon sequestration of food crops is very large in the major grain-producing area, i.e., 2.74751 $\times$ 10^7 t for Anhui, 2.24578 $\times$ 10^7 t for Jiangsu, only 1.33197 $\times$ 10^7 t for Hubei, and 1.15972 $\times$ 10^7 t for Hunan, respectively. The possible reason is that Anhui and Jiangsu have relatively advanced agricultural production technology and production concept, which results in a relatively good agricultural ecological environment.

3.2. Dynamic Analysis on the Carbon Sequestration Level of Food Crops in Various Provinces (Cities)

The carbon sequestration levels of food crops in various provinces (cities) are shown in Figure 6. The carbon sequestration level of food crops in 2018 is ranked as follows: Yunnan > Sichuan > Guizhou > Chongqing > Anhui > Jiangsu > Hubei > Shanghai > Hunan >

Zhejiang > Jiangxi. Compared with the ranking of net carbon sequestration, the ranking of Yunnan, Sichuan, and Guizhou is relatively at the top, while that of Jiangsu, Hubei, and Hunan lags behind. In addition, the rising range of Anhui is the largest, attaining 90.59%. Correspondingly, the rising range of Guizhou is the smallest, attaining only 90.59%.

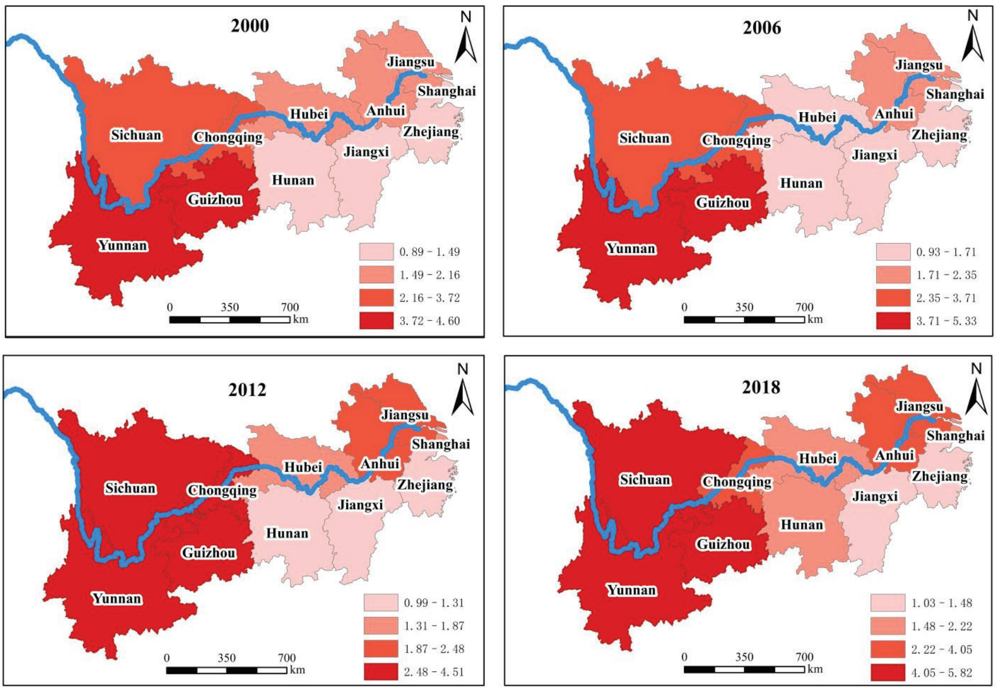

Figure 6. Changes of carbon sequestration level of food crops in 11 provinces (cities) of YREB. (Note: The level of carbon sequestrations is the ratio between carbon sequestrations and carbon emissions).

According to the time series changing characteristics of carbon sequestration level in each province (city), we can divide 11 provinces (cities) into three types of areas, i.e., the continuous growth area, the fluctuating growth area, and the fluctuating descent area. For the continuous growth area, the level of carbon sequestration shows an increasing trend at each time point compared with the previous time point. As such, six provinces (cities) such as Anhui, Jiangsu, Chongqing, Jiangxi, Hubei, and Hunan meet this characteristic. For the fluctuating growth area, the level of carbon sequestration shows an upward trend on the whole and a downward trend at some time points. As such, three provinces such as Zhejiang, Sichuan, and Yunnan meet this characteristic. For the fluctuating descent area, the level of carbon sequestration shows a downward trend on the whole and an upward trend at some time points. As such, two provinces (cities) such as Shanghai and Guizhou meet this characteristic.

3.3. Regional Difference Analysis on the Net Carbon Sequestration of Food Crops

In this paper, the regional differences of the net carbon sequestration level of food crops are analyzed in the upper, middle, and lower reaches of the YREB.

3.3.1. Regional Differences of Net Carbon Sequestration Level of Food Crops in 11 Provinces (Cities) of the YREB

From Figure 7, the Gini coefficient of the net carbon sequestration level of food crops in 11 provinces (cities) shows an upward trend overall from 0.234 in 2000 to 0.287 in 2018, which increases by 22.65% during the studied period. It shows that the regional difference of the net carbon sequestration level of food crops in various provinces (cities) is gradually expanding. The Gini coefficient value indicates that the distribution characteristics of the net carbon sequestration level in various provinces (cities) are in the state of "relatively average" from 2000–2018. Especially, the regional difference of net carbon sequestration level in various provinces (cities) became smaller from 2006–2016, while becoming wider after 2016.

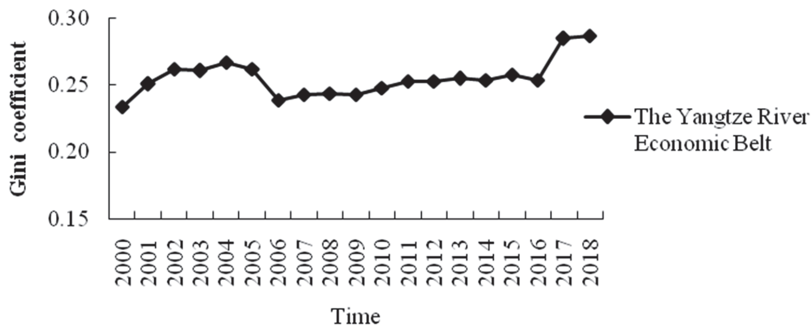

Figure 7. The Gini coefficient of the net carbon sequestration level of food crops in the 11 provinces (cities) of the YREB.

3.3.2. Regional Differences of Net Carbon Sequestration Level of Food Crops in the Upper, Middle, and Lower Reaches of Yangtze River Economic Belt

As is shown in Figure 8, the values of the Gini coefficient in the upper, middle, and lower reaches of the YREB are ranked as follows: lower reaches > middle reaches > upper reaches. This indicates that the regional difference in the lower reaches is the largest, followed by the middle reaches and the upper reaches, which may be caused by the differences of food production in various provinces (cities). Taking the lower-reaches region as an example, the food-sowing area in Zhejiang and Shanghai is relatively small and declining year by year. The food-sowing area in Jiangsu and Anhui is gradually increasing, from 5304.3 thousand hm^2 to 5475.9 thousand hm^2 in Jiangsu and from 6183.8 thousand hm^2 to 7316.3 thousand hm^2 in Anhui during the studied period. The regional difference of the net carbon sequestration level in the middle reaches is relatively small, which is attributed to the small difference of the food-sowing area.

From Figure 8, the Gini coefficient value in the upper-reaches region is between 0.171 and 0.218, which indicates the distribution characteristic of the net carbon sequestration level changes from the "absolute average" state to the "comparative average" state, showing a fluctuating upward trend. Moreover, the value of the Gini coefficient in 2007 is the smallest, which indicates that the regional difference of the distribution of net carbon sequestration was the smallest. In 2013, the value of Gini coefficient reached the maximum value, which signifies that the regional difference of the distribution of net carbon sequestration was the largest.

The values of the Gini coefficient for food crops in the lower reaches are between 0.252 and 0.293, which indicates the distribution characteristics are in a "comparative average" state. The change trend is similar with that in the middle reaches. However, the regional difference of the net carbon sequestration is larger than that in the middle-reaches region, which generally presents a "decline-rise-decline-rise" state. In 2006, the Gini coefficient reached the minimum value, which indicates that the regional difference of net carbon sequestration in 2006 was the smallest. In 2000, the Gini coefficient reached the maximum value, so the regional difference of the distribution of net carbon sequestration in 2000 was the largest.

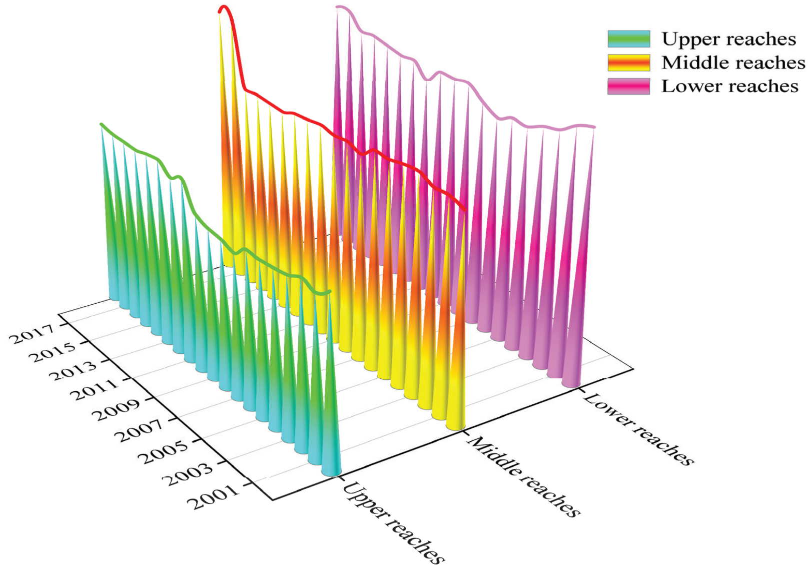

Figure 8. Evolution of intra-regional gap of net carbon sequestration of grain food crops in the YREB.

The values of Gini coefficient in the middle reaches are between 0.235 and 0.309, which indicates the distribution of net carbon sequestration changed from the "comparative average" state to the "relatively reasonable" state. The regional distribution difference of the middle reaches is between the upper reaches and lower reaches, and the change trend shows a "decline-up" state. In 2005, the Gini coefficient reached the minimum, so the regional difference of the distribution of net carbon sequestration in 2005 was the smallest. In addition, the Gini coefficient reached the maximum value in 2017, which indicates the regional difference of the distribution of net carbon sequestration in 2017 was the largest.

4. Discussion

4.1. The Spatio-Temporal Patterns of Net Carbon Sequestration of Food Crops in the YREB

The net carbon sequestration of food crops in the YREB experiences two different stages from declining to increasing over the study period. In the first stage (2000–2003), the net carbon sequestration continued to decline; this is probably because farmers' enthusiasm for planting the food crops is reduced by the heavy tax burden, which directly affected the production of rice, wheat, and maize, resulting in a decline in the net carbon sequestration of food crops during this period. In the second stage (2004–2018), the net carbon sequestration was on a rising trend. Since 2004, the agricultural tax has been abolished in China, which promoted the increase of grain-sowing areas, and the total output of grain in the Yangtze River economic belt continued to grow, resulting in the continuous increase of net carbon sequestration of food crops.

Understanding and analyzing the heterogeneous heterogeneity characteristics of the net carbon sequestration level in different areas' provinces and cities contributes to establishing the corresponding emission reduction concept. The net carbon sequestration of food crops in various provinces (cities) shows obvious regional difference from 2000 to 2018; except for Shanghai and Guizhou, the other nine provinces (cities) show an upward trend. The carbon sequestration of food crops in the main grain-producing areas is higher than that in other areas, from which can be inferred that the provinces in the main grain-producing areas pay more attention to the protection of environment.

The petrochemical agriculture that relies on the input of chemical fertilizers and pesticides contributes to the increase of grain production in a certain period time, but it also brings great damage to the environment such as water resources, arable land, and the atmosphere, as well as food quality. As such, the green transformation needs to be implemented to increase the organic matter content of soil, improve the quality of water resources and air, and finally ensure food safety. At the same time, technicians should perform demonstrations and training of green conservation farming technology, such as straw returning, green control of diseases and insect pests, soil testing formulas, scientific fertilization, and medicine, so as to reduce carbon emissions from food production at the source.

4.2. The Regional Differences of Net Carbon Sequestration of Food Crops in the YREB

The values of the Gini coefficient indicate that the regional difference in the lower reaches is the largest, followed by the middle reaches and the upper reaches. The main reason for the above differences may lie in the differences of grain-sowing areas in the upper, middle, and lower reaches of the Yangtze River economic belt. Among all regions, the level of economic development in the lower reaches is the highest, and with the increase of the urbanization rate, a large amount of agricultural land has been occupied by industrial land; thus, the area of cultivated land has gradually shrunk in some provinces, such as in Zhejiang and Shanghai. As a result, the difference of grain-sown areas in this region is growing. However, there are many mountains in the downstream area; thus, there is less arable land in some provinces, such as Yunnan and Guizhou, so there is also a certain difference in this region. The provinces in the middle reaches are mainly the main grain-producing provinces, so the difference of grain-sown areas in this region is relatively small.

To avoid the above problems, the government should carry out the following tactics, including the expansion of the sown area, curbing the non-agricultural conversion of arable land, improving the multiple cropping index of the arable land, increasing the investment in grain breeding technology, speeding up the modernization of the entire grain industry chain, etc., so as to expand the sown area of food, increase the carbon sequestration of food crops, and finally reduce the regional differences of net carbon sequestration of food crops in the YREB. In addition, downstream provinces should also give some ecological compensation to midstream provinces to reward their contributions to food carbon sequestration.

4.3. Advantages and Limitations of This Study and Future Research Directions

Compared with previous studies, the research vision of this study is further expanded. This study develops an objective framework for evaluating the environmental benefits of grain planting from the perspective of net carbon sequestration and analyzes the spatial and temporal characteristics of the net carbon sequestration in different areas. It is no longer limited to the single-perspective research of agricultural carbon emission, and it conducts research from the two perspectives of agricultural carbon emission and agricultural carbon sequestration, which can better analyze the environmental problems of agricultural production. In this study, the concept of net carbon sequestration is used to analyze carbon sequestration and carbon emission in the same framework.

However, there are also some limitations in this study. Firstly, there are some limitations in the definition and calculation system of carbon emission, carbon sequestration, and net carbon sequestration, which need to be further refined and improved. Secondly, due to the limitations of the existing data, we apply the same indicators in different areas of the YREB, where they may have different features such as economic coefficient, water content, and carbon absorption in the upper, middle, and lower reaches. Thirdly, factors such as population growth, the industrialization rate, and other influencing factors also have an impact on the carbon sequestration of food production. However, the existing methods for measuring carbon emissions and carbon sequestration of food crops mainly consider the internal factors related to the growth of food crops and do not consider the external factors such as population and industrialization rate. In future research, we will use econometric research methods to analyze the impact of population, industrialization rate, and other influencing factors on carbon emissions and carbon sequestration of food crops. In addition, this study does not analyze the economic benefits of net carbon sequestration of food crops, which will be taken into consideration in future studies.

5. Conclusions

This study analyzes the dynamic change and regional differences of net carbon sequestration of food crops from temporal and spatial perspectives for the case study area of 11 provinces (cities) of the YREB from 2000–2018 in China. The net carbon sequestration of food crops keeps continuously increasing, while carbon emissions show a fluctuating downward trend over the study period. Remarkable regional differences in the net carbon sequestration of food crops exist, and most provinces (cities) show an upward trend for the studied area. Except for Shanghai and Guizhou, the remaining nine provinces (cities) show an upward trend, and the decline range of Guizhou is the largest. The spatial distributions of the net carbon sequestration of food crop show obvious heterogeneity in the upper, middle, and lower reaches of studied area. Specifically, the Gini coefficient value in the YREB is ranked as: lower reaches > middle reaches > upper reaches. That is to say that the most uneven place is located on the lower reaches, followed by the middle reaches, and the least uneven place is in the upper reaches. To further facilitate the activity related to reducing the carbon emissions of the agricultural production sector, we will explore the economic benefits and the influencing factors of net carbon sequestration from food production in the future.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/ijerph192013229/s1, Table S1: Changes of total net carbon sequestration and carbon sequestration level of food crops in 11 provinces (cities) of Yangtze River economic belt (2000–2018).

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References

1. Godfray, H.; Garnett, T. Food security and sustainable intensification. *Philos. Trans. R. Soc. B Biol. Sci.* **2014**, *369*, 20120273. [CrossRef]
2. Conijn, J.G.; Bindraban, P.S.; Schrder, J.J.; Jongschaap, R. Can our global food system meet food demand within planetary boundaries? *Agric. Ecosyst. Environ.* **2018**, *251*, 244–256. [CrossRef]
3. Spang Edward, S.; Achmon, Y.; Donis-Gonzalez, I.; Gosliner, W.A.; Jablonski-Sheffield, M.P.; Momin, A.; Quested, T.E.; Winans, K.S.; Tomich, T.P. Food Loss and Waste: Measurement, Drivers, and Solutions. *Annu. Rev. Environ. Resour.* **2019**, *44*, 117–156. [CrossRef]
4. Nijbroek, R.P.; Andelman, S.J. Regional suitability for agricultural intensification: A spatial analysis of the Southern Agricultural Growth Corridor of Tanzania. *Int. J. Agric. Sustain.* **2016**, *14*, 231–247. [CrossRef]
5. Mungai, L.M.; Messina, J.P.; Snapp, S. Spatial Pattern of Agricultural Productivity Trends in Malawi. *Sustainability* **2020**, *12*, 1313. [CrossRef]

6. Aguirre-Liguori, J.A.; Santiago, R.B.; Peter, T.; Eguiarte, L.E. Climate change is predicted to disrupt patterns of local adaptation in wild and cultivated maize. *Proc. Biol. Sci.* **2020**, *286*, 486. [CrossRef]
7. Smith, P.; Calvin, K.; Nkem, J.; Campbell, D.; Cherubini, F.; Grassi, G.; Korotkov, V.; le Hoang, A.; Lwasa, S.; McElwee, P.; et al. Which practices co-deliver food security, climate change mitigation and adaptation, and combat land degradation and desertification? *Glob. Chang. Biol.* **2020**, *26*, 1532–1575. [CrossRef]
8. Savary, S.; Willocquet, L. Modeling the impact of crop diseases on global food security. *Annu. Rev. Phytopathol.* **2020**, *58*, 313–341. [CrossRef] [PubMed]
9. Toro, A.; Harsányi, E. What is the Connection between Soil Carbon Dioxide Emission, Global Warming and Food Security? *Eur. J. Sustain. Dev.* **2019**, *8*, 21. [CrossRef]
10. Smith, P. Carbon sequestration in croplands: The potential in Europe and the global context. *Eur. J. Agron.* **2004**, *20*, 229–236. [CrossRef]
11. EPA. Global Greenhouse Gas Emissions Data. Available online: https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data (accessed on 20 May 2020).
12. Fang, J.; Yu, G.; Liu, L.; Hu, S.; Chapin, F.S. Climate change, human impacts, and carbon sequestration in China. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 4015–4020. [CrossRef] [PubMed]
13. Tang, H.; Liu, Y.; Li, X.; Muhammad, A.; Huang, G. Carbon sequestration of cropland and paddy soils in China: Potential, driving factors, and mechanisms. *Greenh. Gases Sci. Technol.* **2019**, *9*, 872–885. [CrossRef]
14. Chen, X.; Ma, C.; Zhou, H.; Liu, Y.; Huang, X.; Wang, M.; Cai, Y.; Su, D.; Atif Muneer, M.; Guo, M.; et al. Identifying the main crops and key factors determining the carbon footprint of crop production in China, 2001–2018. *Resour. Conserv. Recycl.* **2021**, *172*, 105661. [CrossRef]
15. Luo, Y. "Facing the virus" anaphora in political speech: A faircloughian analysis of president Xi Jinping's address to United Nations general assembly. *Linguist. Cult. Rev.* **2021**, *5*, 1039–1053. [CrossRef]
16. Höhne, N.; Gidden, M.J.; den Elzen, M.; Hans, F.; Fyson, C.; Geiges, A.; Rogelj, J. Wave of net zero emission targets opens window to meeting the Paris Agreement. *Nat. Clim. Chang.* **2021**, *11*, 820–822. [CrossRef]
17. Vleeshouwers, L.M.; Verhagen, A. Carbon emission and sequestration by agricultural land use: A model study for europe. *Glob. Chang. Biol.* **2010**, *8*, 519–530. [CrossRef]
18. Alamdarlo, N.H. Water consumption, agriculture value added and carbon dioxide emission in iran, environmental kuznets curve hypothesis. *Int. J. Environ. Sci. Technol.* **2016**, *13*, 2079–2090. [CrossRef]
19. Yadav, D.; Wang, J. Modelling carbon dioxide emissions from agricultural soils in Canada. *Environ. Pollut.* **2017**, *230*, 1040–1049. [CrossRef]
20. Huang, J.Y.; Chen, Y.; Pan, J.; Liu, W.; Yang, G.; Xiao, X.; Zheng, H.; Tang, W.; Tang, H.; Zhou, L.J. Carbon footprint of different agricultural systems in china estimated by different evaluation metrics. *J. Clean. Prod.* **2019**, *225*, 939–948. [CrossRef]
21. Tao, F.; Palosuo, T.; Valkama, E.; Mäkipää, R. Cropland soils in china have a large potential for carbon sequestration based on literature survey. *Soil Tillage Res.* **2019**, *186*, 70–78. [CrossRef]
22. Yao, Z.; Zheng, X.; Liu, C.; Wang, R.; Xie, B.; Butterbach-Bahl, K. Stand age amplifies greenhouse gas and no releases following conversion of rice paddy to tea plantations in subtropical china. *Agric. For. Meteorol.* **2018**, *248*, 386–396. [CrossRef]
23. Johnson, M.F.; Franzluebbers, A.J.; Weyers, S.L.; Reicosky, D.C. Agricultural opportunities to mitigate greenhouse gas emissions. *Environ. Pollut.* **2007**, *150*, 107–124. [CrossRef]
24. Zou, X.X.; Li, Y.E.; Li, K.; Cremades, R.; Qin, X.B. Greenhouse gas emissions from agricultural irrigation in China. *Mitig. Adapt. Strateg. Glob. Chang.* **2015**, *20*, 295–315. [CrossRef]
25. Xiong, C.; Yang, D.; Huo, J.; Wang, G. Agricultural net carbon effect and agricultural carbon sink compensation mechanism in hotan prefecture, china. *Pol. J. Environ. Stud.* **2017**, *26*, 365–373. [CrossRef]
26. Ochieng, R.M.; Visseren-Hamakers, I.J.; Brockhaus, M.; Kowler, L.F.; Herold, M.; Arts, B. Historical development of institutional arrangements for forest monitoring and redd+ mrv in peru: Discursive-institutionalist perspectives. *For. Policy Econ.* **2016**, *71*, 52–59. [CrossRef]
27. Goodale, C.L.; Apps, M.J.; Birdsey, R.A.; Field, C.B.; Heath, L.S.; Houghton, R.A.; Jenkins, J.C.; Kohlmaier, G.H.; Kurz, W.; Liu, S.; et al. Forest carbon sinks in the northern hemisphere. *Ecol. Appl.* **2002**, *12*, 891–899. [CrossRef]
28. Hultman, N.E.; Pulver, S.; Pacca, S.; Saran, S.; Powell, L.; Romeiro, V.; Benney, T. Carbon markets and low-carbon investment in emerging economies: A synthesis of parallel workshops in Brazil and India. *Energy Policy* **2011**, *39*, 6698–6700. [CrossRef]
29. Lashof, D.A.; Ahuja, D.R. Relative contributions of greenhouse gas emissions to global warming. *Nature* **1990**, *344*, 529–531. [CrossRef]
30. Soytas, U.; Sari, R. Energy consumption, economic growth, and carbon emissions: Challenges faced by an EU candidate member. *Ecol. Econ.* **2009**, *68*, 1667–1675. [CrossRef]
31. She, W.; Wu, Y.; Huang, H.; Chen, Z.; Cui, G.; Zheng, H.; Guan, C.; Chen, F. Integrative analysis of carbon structure and carbon sink function for major crop production in China's typical agriculture regions. *J. Clean. Prod.* **2017**, *162*, 702–708. [CrossRef]
32. Kang, K.; Chen, Y.; Guo, P.; Chen, J. Study on the Impact of Grain Production on Ecological Carbon Sequestration. *Chin. J. Agric. Resour. Reg. Plan.* **2022**, 1–11. Available online: https://kns.cnki.net/kcms/detail/11.3513.S.20220720.1912.012.html (accessed on 25 July 2022). (In Chinese)

33. IPCC. *IPCC Guidelines for National Greenhouse Gas Inventories*; IPCC: Geneva, Switzerland, 2006.
34. Padilla, E.; Serrano, A. Inequality in CO_2 Emissions across Countries and Its Relationship with Income Inequality: A Distributive Approach. *Energy Policy* **2006**, *34*, 1762–1772. [CrossRef]

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Correlation between Spatio-Temporal Evolution of Habitat Quality and Human Activity Intensity in Typical Mountain Cities: A Case Study of Guiyang City, China

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Abstract: The acceleration of the urbanization process brings about the expansion of urban land use, while changes in land-use transformation affect the urban habitat quality, and land-use change brings a threat to regional sustainable development. Against such a backdrop, the assessment of land use on the habitat quality and the relationship between the intensity of human activities is becoming a hot spot in terms of the current land use coordinated with habitat quality. Based on the land-use data of Guiyang in 2000, 2005, 2010, 2015 and 2020, the spatial–temporal evolution characteristics of habitat quality in the study area, combined with the spatial correlation between human activity intensity and habitat quality, were hereby analyzed using the InVEST model. The impact of human activity intensity on habitat quality was correspondingly analyzed. The results show that: (1) From 2000 to 2020, the habitat quality level in Guiyang remained stable without drastic changes, but the changes showed hierarchical distribution and were scattered, mainly reflected in the urban expansion areas of the urban–rural fringe and the key areas of industrial development, and the ecological environment quality fluctuated in a small range. (2) From 2000 to 2020, the intensity of human activities in Guiyang was mainly affected by the relatively concentrated distribution, featuring obvious and significant changes. From 2010 to 2015, the high-impact area surrounded the Guanshan Lake New Area, and the regional habitat quality presented a downward trend. In 2020, the high-impact area of the main urban area and the key industrial development zone was expected to be formed, while the low-impact area was still distributed in forest areas with complex natural conditions. (3) From 2000 to 2020, there was a significant positive correlation between human activity intensity and habitat quality in Guiyang, and such a spatial correlation was weak from 2000 to 2005. The period from 2015 to 2020 witnessed the rapid development of urban construction in Guiyang, human construction activities continue to affect the urban habitat quality. The results show that the intensity of human activities on the promoting function of land use, and the dependencies between them should be considered at the same time, and that explorations on the influence of human activities on land-use intensity and habitat quality of space link are crucial to improving the efficiency of urban land use and ecological environment protection, as well as the coordination between land use and the sustainability of urban development.

Keywords: land-use change; habitat quality; mountainous cities; human activity intensity; Guiyang City

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1. Introduction

With the acceleration of the urban industrialization and urbanization process, as well as the constant enhancement of the scale and intensity of human transformation of natural resources, human economic activities have been continuously exerting a certain impact on the function, structure and space of the regional ecological environment. At the same time, due to the unique natural attributes and complexity of the mountain structure, the blindness of urban development and construction has led to the deterioration of the ecological environment and the frequent occurrence of secondary disasters, such as geological disasters in mountain cities, which seriously restricts the healthy development of cities and the quality of habitats [1,2]. Based on such a background, assessment of the correlation between the intensity of human activities and the spatial–temporal changes in habitat quality has become a hot issue in the research field in the case of evaluating the health and habitat quality level in mountain cities [3,4].

The types of geological structure in mountainous cities affect the layout of urban construction, while urban expansion and change affect the change of the types of regional land resource structure, thereby leading to the transformation of urban cultivated land, grassland, woodland and construction land, and bringing a certain degree of negative impact on the fragmentation and sustainability of the ecological landscape pattern [5]. Urban expansion and change increase the demand for land resources. Land is the basis of urban development, and affects the change of urban ecological environment and land-use map spots, which also results in the change of the land-use spatial pattern. In this case, analyzing the impact of spatio-temporal changes in land use on habitat quality and exploring the correlation characteristics between changes in human activity intensity and habitat quality are endowed with an important reference value for the ecological protection in urban areas and the healthy development in mountainous cities [6]. Based on the previous study of the impact of land use change on habitat quality, scholars have carried out several assessment studies from different perspectives, scales, and regions combined with diversified methods. In the early studies, habitat quality changes of wildlife habitats were evaluated mainly through biodiversity and habitat changes [7]. This method is time-consuming and laborious, affected by the carrying capacity of the natural environment, and subject to a strong subjectivity and limited regional conditions, making it difficult to carry out investigations on different scales. Then, the InVEST model was generated to better simulate the changes in land ecological service quality under different land cover backgrounds. The qualitative and quantitative methods were used to evaluate the changes in habitat quality, thereby realizing the spatial and visual expression of habitat quality function assessment, and vividly describing the spatial–temporal variation characteristics of habitat quality. It provides a reference basis for decision makers to evaluate the benefit and impact of human activity intensity. The advantages of fewer data requirements and high simulation accuracy of the InVEST model have made it widely used in the field of habitat quality assessment [8]. At present, both domestic and foreign scholars have used the assessment model for the ecological service value, NPP and NDVI habitat index evaluation, geographic detector, human activity intensity and geographic regression model to quantitatively evaluate the spatial change and impact of habitat quality [9–12]. However, there are relatively few studies on assessing habitat quality changes in mountainous cities using the InVEST model, and few studies are conducted on the correlation with human activity intensity. To this end, evaluating the impact of land use on habitat quality using quantitative methods has become one of the hot issues in the qualitative assessment of habitat quality change [13], and the application of land-use change data to the analysis on regional habitat quality changes is of great practical significance for the qualitative assessment of urban habitat quality and sustainability.

Guiyang is an innovative city in southwest China, also a typical karst landform region city, and most of the cities are mountainous landforms. In this case, the influencing factors of human activity intensity on habitat quality were hereby discussed, and the correlation between them was analyzed by taking Guiyang city as an example. The results possess certain representativeness and typicality for the development and health quality assessment of mountain cities in southwest China. Based on the land-use change data of 2000, 2005, 2010, 2015 and 2020, the interaction between habitat quality evolution and regional human activity intensity in Guiyang was hereby explored, which is endowed with important research significance for the development of ecological environment quality in regional mountain cities. Research on the land-use change of time and space on the effect of land environment quality was conducted, and the results show a correlation between the two assumptions. Quantitative evaluation of the habitat quality change of Guiyang City from 2000 to 2020 was conducted by virtue of the InVEST model and through many index map overlay analysis human activity intensity index (HAI). Finally, the bivariate spatial autocorrelation and geographically weighted regression model methods were used to explore the impact of human activity intensity on habitat quality and its correlation, so as to provide a reference for the study of urban construction and ecological environment quality in Guiyang, as well as the ecological environment and sustainability of mountainous cities in southwest China.

2. Data Material Sources and Research Methods

2.1. Overview of the Study Area

Guiyang City is located in the middle part of the original hills of the central Guizhou Mountains, which belongs to the watershed zone of the Yangtze River and the Pearl River. The terrain is high in the southwest and low in the northeast. The highest elevation of the province is 2885 m and the lowest is 152 m. The geomorphology here mainly consists of mountainous and hilly areas (Figure 1), among which, the mountain area covers about 4217 km^2, accounting for 52.43%, while the hill area is about 2840 km^2, taking up 35.31%, and other types of land account for about 12.26%. By the end of 2020, the total population was 5.9898 million, the primary industry value was USD 0.0025 billion, that of the secondary industry was USD 0.0214 billion, that of the tertiary industry was USD 0.0355 billion, the per capita GDP was USD 9940.76, and the total financial revenue was USD 12,136.9624 billion. The total land area of the city is 8043 km^2 in the year 2022, and the land type area is taken as an example. Among them, the cultivated land area covers an area of 2112.49 km^2, accounting for 26.26%; the forestland area is 3906.57 km^2, accounting for 48.57%; the grassland area is 1342.58 km^2, accounting for 16.69%; the water body area is 135.19 km^2, taking up 1.68%; the construction land area covers 542.36 km^2, accounting for 6.74%; and the unutilized land is 3.84 km^2, accounting for 0.047%.

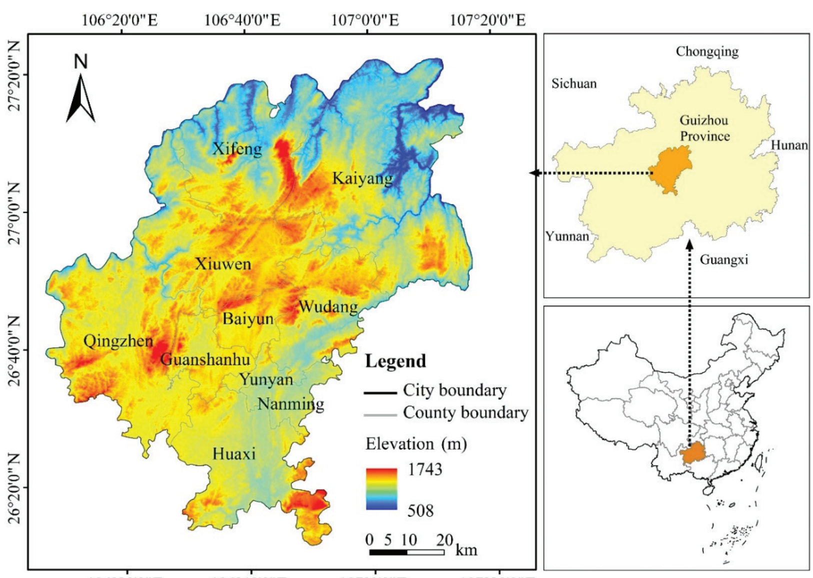

Figure 1. Geographic location and elevation of Guiyang City.

2.2. Data Sources

In this paper, the land-use change data were downloaded from the Resources and Environment Data Sharing Center of Chinese Academy of Sciences (http://www.resdc.cn), (accessed on 1 January 2020). After cutting and splicing, the land-use data of Guiyang City were intercepted. The spatial resolution of the data is the 30 m × 30 m data type, and the data accuracy can reach more than 90% after testing. The data included the economic development data from the statistical yearbook published by the People's Government of Guiyang (http://www.guiyang.gov.cn), (accessed on 1 January 2020), the data in 2020 economic development in 2021 Guiyang City from statistical yearbook data, and DEM elevation data of the spatial resolution of 30 m. The base map derived from the geographic information public service platform (https://guizhou.tianditu.gov.cn), (accessed on 1 January 2020) in the administrative division scope of data in Guizhou, Guiyang City on the basis of Guiyang City in 2021 (not including Guian new district).

2.3. Research Framework

The research is based on the land use change data for 2000, 2005, 2010, 2015 and 2020. Firstly, the research data and DEM data were collected for preprocessing. After vectorization, accuracy testing and verification procedures were carried out. Secondly, for land data and statistical yearbook data, the characteristics of land spatial change were described using the transfer matrix, atlas analysis, InVEST model and other methods. Thirdly, the human activity intensity index and bivariate spatial autocorrelation were adopted to analyze the closeness and influence of their spatial connection. Finally, the spatial characteristics based on the characteristics of land-use change and habitat quality change in these five periods were summarized, and the response trend of habitat quality change was analyzed. The research framework was shown in Figure 2.

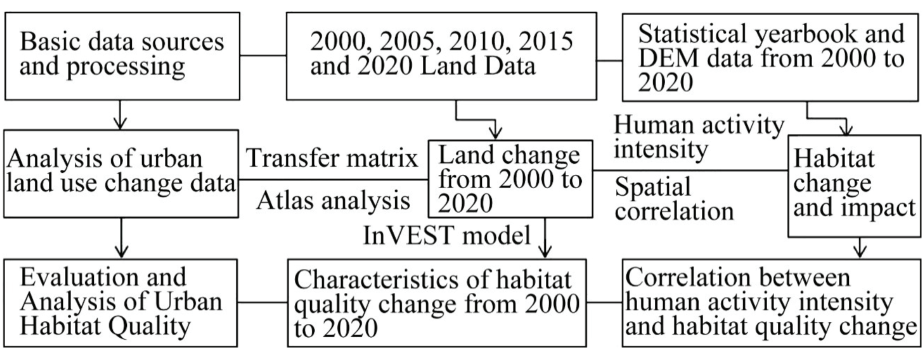

Figure 2. Research framework.

3. Research Methods

3.1. Habitat Quality

Land change is the most direct factor affecting habitat quality. Through the habitat quality module in the InVEST model, it evaluates the habitat quality of the region. This module combines the regional landscape type information, and evaluates the sensitive sources of threat factors using threat factors and land-use types on the basis of land-use change data, and is generally used to represent the characteristics of regional habitat quality change [14]. The calculation formula is as follows:

$$Q_{xj=H_j}\left(1-\frac{D_{xj}^{z}}{D_{xj}^{z}+K^{Z}}\right) \quad (1)$$

where Q_{xj} represents the habitat quality index of raster x in land type j; H_j, the habitat suitability of type j land types; D_{xj}, the threat degree of raster x in the land type j; K is half satiety constant; and z is constant 2.5. The formula of the threat degree is:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} \left(\frac{w_r}{\sum_{r=1}^{R} w_r} \right) r_y i_{rxy} \beta_x S_{jr} \tag{2}$$

where R denotes the threat factor; y is the total number of r threat grids; Y_r is the number of a set of threat grids in r threat factors; W_r is the weight of threat factor; r_y is the threat factor value of grid y; i_{rxy} is the threat level of grid x of threat factor r_y of threat grid y; β_x is the legal protection level of grid cell x; S_{jr}, the sensitivity degree of land type j to threat factor r; D_{xy} is the straight-line distance between grid x and y; and $Drmax$ is the maximum distance of threat factor r. The linear formula of i_{rxy} can be expressed as:

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{rmax}} \right) (\text{ Linear distance decay function}) \tag{3}$$

$$i_{rxy} = exp\left(-\left(\frac{2.99}{d_{\ rmax}} \right) d_{xy} \right) (\text{ Exponential distance decay function}) \tag{4}$$

According to the existing results of urban habitat quality research and the actual situation of Guiyang, the reference value range given by the model was determined. Zhou T, He J and Liu J [15–17] selected the cultivated land, the construction land and the unutilized land as threat factors in relevant studies, and consulted experts in related fields. The sources and weights of habitat quality threats (Table 1) and the relative sensitivity of habitat suitability and threat sources (Table 2) in Guiyang were thus formulated.

Table 1. Maximum influenced distance and weight of threat factors.

Threat Factor	Maximum Distance (km)	Weight	Decay Type
Cultivated land	4	0.6	Linear
Construction land	8	0.4	Exponential
Unutilized land	6	0.5	Linear

Table 2. Habitat suitability of land-use types and relative sensitivity to various threat factors.

Land-Use Type	Habitat Suitability	Threat Factor		
		Cultivated Land	Construction Land	Unutilized Land
Cultivated land	0.3	0	0.5	0.3
Forestland	1.0	0.8	1	0.4
Grassland	0.9	0.8	0.6	0.3
Water body	0.7	0.6	0.7	0.3
Construction land	0.0	0.6	0.9	0.3
Unutilized land	0.5	0	0	0

3.2. Human Activity Intensity

Human activity intensity is an important driving factor affecting regional habitat quality change. Quantitative assessment of human activity intensity is the basis for analyzing ecosystem stability. The index model for human activity intensity was hereby used to quantitatively describe the impact of regional ecosystem change, and then to evaluate the relationship between human activities and land-use change. The index model for human activity intensity, which can describe the impact of human activity intensity on the ecosystem, was selected for evaluation [18], and its calculation formula is as follows:

$$\mathrm{HAI} = \sum_{i=1}^{n} \frac{A_i P_i}{TA} \tag{5}$$

where HAI stands for human activity intensity index; n is the number of land types; A_i is the area of Class i land type; P_i is the intensity coefficient of human activities of type i ecological value; and TA is the total area.

According to the existing research results [19], the coefficient table for human activity intensity (Table 3) of different land types was determined for calculation, and the value of the human activity intensity index in the unutilized land was taken as the reference [20]. According to the calculation results, the impact types were divided into five grades, i.e., low HAI $\leq$ 0.2, low 0.2 < HAI $\leq$ 0.4, medium 0.4 < HAI $\leq$ 0.6, high 0.6 < HAI $\leq$ 0.8 and high 0.8 < HAI [20].

Table 3. Human activity intensity coefficient of different land-use types.

Parameter	Grassland	Forestland	Cultivated Land	Unutilized Land	Reservoir and Pond	Construction Land
Lohani	0.09	0.12	0.61	0.05	0.33	0.96
Leopold	0.08	0.14	0.59	0.07	0.29	0.94
Delphi	0.09	0.13	0.64	0.08	0.35	0.96
Average value	0.09	0.14	0.61	0.07	0.32	0.95

3.3. Bivariate Autocorrelation Analysis

The spatial distribution characteristics and aggregation degree of factor attributes were explored, and spatial correlation and tests were conducted through global and local spatial autocorrelation. The global Moran's I index verifies the spatial agglomeration trend of relevant attributes in the region [21], and the calculation formula is as follows:

$$I = n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right) / \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2 \tag{6}$$

where X_i and X_j are the observed values of the elements in the *i* and *j* regions; and W_{ij}, the weight matrix of the *i* and *j* spatial positions. When *i* and *j* are adjacent, W_{ij} = 1; otherwise, W_{ij} = 0. The global Moran's index *I* is between (−1, 1), and Moran's index value is positive, suggesting that the spatial autocorrelation is spatially clustered; otherwise, the spatial distribution tends to be scattered when the elements are significantly different; and the random distributions are irrelevant when Moran's index is 0.

The bivariate spatial autocorrelation method was used by Anselin et al., to analyze the spatial relationship between human activities and habitat quality [22]. The formula of Moran's I index can be expressed as:

$$I_{kl}^{i} = z_k^i \sum_{j=1}^{n} w_{ij}\, z_l^j \tag{7}$$

where W_{ij} stands for *i* and *j* space position weight matrix, respectively; $Z_k^i = \frac{x_k^i - \overline{x}_k}{k}$ $Z_l^i = \frac{X_l^i - \overline{x}_l}{l}$, $\overline{x}_k$, $\overline{x}_l$, is the average of the properties of *K* and *L*; and x_k^i, X_l^i are the values of *i* attribute *k* and *L*, respectively;

According to the calculation of Local Moran's I index, the regions of the birth environment quality and the human activity type were divided into four types of human activity and habitat quality types: high high, low high, low low and high low.

3.4. Analysis of Geographically Weighted Regression Model

The geographically weighted regression model is a spatial analysis technique for parameter estimation, which is based on the establishment of a traditional regression model (OLS), and can simulate the spatial non-stationarity of different geographic spaces and verify the influence of different geospatial variables on regions [23]. The calculation formula can be expressed as:

$$y_i = \beta_0(u_i + v_i) + \sum_k \beta_K(u_i + v_i)\ x_{\ ik} + \varepsilon_i \tag{8}$$

where y_i is the influence value of variable regression; (u_i, v_i) is the geographic coordinates of i samples; x_{ik} is the value of the k independent variable in the i sample unit; k is the number of independent variables; i is the number of sample units; ε_i is a random interference term; and $\beta_k(u_i, v_i)$, the unit value of continuous function $\beta_k(u, v)$ in sample i.

4. Results and Analysis

4.1. Spatial Evolution Characteristics of Habitat Quality

Through the habitat quality module of the InVEST model, the habitat quality level area and change ratio table of Guiyang (Table 4) and the habitat quality spatial change distribution map of Guiyang from 2000 to 2020 (Figure 3) were obtained. Referring to previous research results [16], the results of habitat quality assessment in Guiyang were divided into five categories, i.e., low (0–0.2), relatively low (0.2–0.4), moderate (0.4–0.6), relatively high (0.6–0.8) and high (0.8–1), according to the Equal Interval method in ArcMap using ArcGIS10.3 software.

Table 4. Area and change proportion of habitat quality grade in Guiyang from 2000 to 2020.

Habitat Quality Grade	2000 Year		2005 Year		2010 Year		2015 Year		2020 Year	
	Area/km^2	Proportion%	Area/km^2	Proportion%	Area/km^2	Proportion%	Area/km^2	Proportion%	Area/km^2	Proportion%
Low	190.90	2.37	225.86	2.81	251.68	3.13	290.95	3.66	559.26	6.95
Relatively low	2565.49	31.90	2739.62	34.06	2578.42	32.06	2529.74	31.81	2487.48	30.93
Moderate	831.04	10.33	929.39	11.56	813.57	10.12	816.74	10.27	831.13	10.33
Relatively high	1406.02	17.48	1396.46	17.36	1368.57	17.02	1371.45	17.25	1456.94	18.11
High	3049.34	37.91	2751.47	34.21	3030.56	37.68	2943.22	37.01	2707.99	33.67

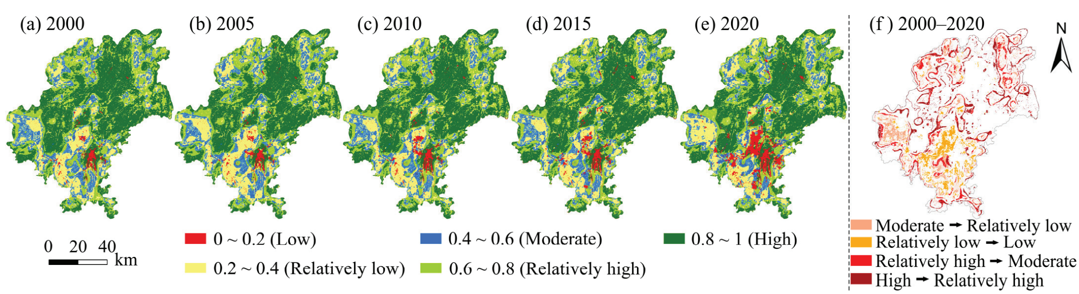

Figure 3. Spatial variation of habitat quality in Guiyang from 2000 to 2020.

From the time scale perspective, due to the acceleration of urbanization construction, habitat quality changed around the urban core area, and small range fluctuation was observed from 2000 to 2010. From 2010 to 2020, the demand for the land to be used for industrialization and urban construction in Guiyang increased continuously, resulting in a small range of fluctuations in the land map spots in non-central urban areas. Areas with more obvious changes included Guanshanhu District, Baiyun District, Huaxi District, Zazuo Town, Zhandjie Town and other areas with significantly reduced habitat quality.

From the spatial scale perspective, the habitat quality grade in Guiyang mainly belonged to the low and high categories, which was relatively concentrated on the whole.

The variation characteristics of the habitat quality area from 2000 to 2020 were 2565.49 km^2 in 2000, accounting for 31.90%, and 2487.48 km^2 in 2020, taking up 30.93%. The area with low habitat quality was 0.97% in space, and the decline rate was rather limited. In 2000, the area with high habitat quality in Guiyang was 3049.34 km^2, 37.91%, which was changed to 2707.99 km^2 in 2020, accounting for 33.67%. The area with high habitat quality decreased to 341.35 km^2, accounting for 4.24%. Mainly affected by urbanization and industrialization, some forest resources and ecological land were destroyed, thereby resulting in a gradual decline in habitat quality.

In general, the habitat quality in Guiyang was good and relatively stable from 2000 to 2020, and there were few areas with large fluctuations. However, small area fluctuations were found in the core areas of economic development and urban expansion areas such as Yanshanhong Town, Zazuo Town and Zhanjie Town in the suburban area of the study area.

4.2. Spatio-Temporal Characteristics of Human Activity Intensity

ArcGIS10.3 software was used to evaluate the driving factors of the impact of regional habitat quality, and analyze the ecosystem stability by the change of human activity intensity, and the human activity intensity index was calculated by the 1 km × 1 km unit. The human activity intensity index of Guiyang in the five periods of 2000, 2005, 2010, 2015 and 2020 was obtained (Figure 4). The intensity of human activities in Guiyang from 2000 to 2020 in the study area was dominated by a relatively concentrated distribution of impacts, with obvious changes and significant differences found in the spatial impacts. HAI 2000 high concentration distribution in Yunyan District and the main Nanming portions characterized and Baiyun District, the main reason is that the main population centralization degree is higher, and is related to the height of the middle part of the industrial concentration. Low activity areas are mainly concentrated in Kaiyang, the map of Xifeng County, a remote area of the region, and the forest coverage rate is higher. In 2005, the influence area of HAI increased significantly, and the high activity influence mainly extended outward around the central city, forming the structure layout of an echelon encircle with the high influence part. From 2010 to 2015, the high-impact human activity space moved to Guanshan Lake District, and some exurb counties such as Chengguan Town in Kaiyang County were also subject to a certain impact. In 2020, the human activity intensity space in Guiyang formed a high-impact area represented by Yunyan District, Nanming District and Huaxi District. The human activity intensity in this area had a great impact on regional habitat quality, showing a positive correlation between human activity intensity and habitat quality. At the same time, the counties in Kaiyang, Xiuwen and Xifeng counties and the towns with better economic development showed a high spatial pattern influenced by the intensity of human activities. In addition, the areas with low impact of human activities in 2020 were distributed in areas with high forest coverage and complex topography, which had less impact of human activities and relatively high habitat quality.

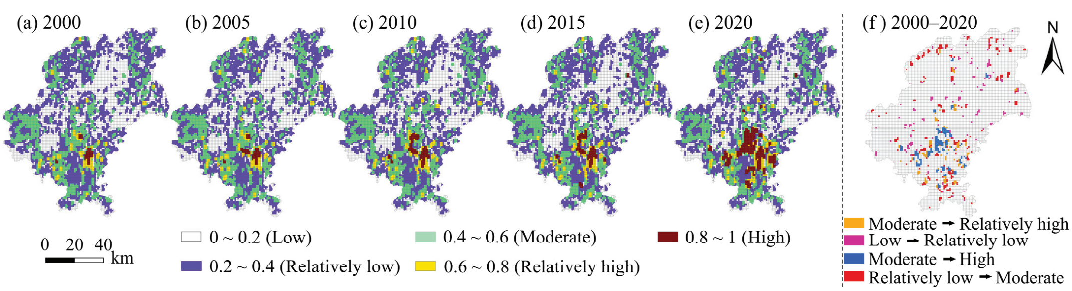

Figure 4. Spatial distribution of human activity intensity in Guiyang from 2000 to 2020.

4.3. Bivariate Spatial Correlation of Human Activity Intensity

The spatial autocorrelation index between human activity intensity and habitat quality in Guiyang from 2000 to 2020 was analyzed using Geoda 095i software, and the scatter plot of Moran's I from 2000 to 2020 was obtained (Figure 5). As shown in the figure, the distribution of Moran's I is relatively uniform in all quadrants, with more distributed in the first quadrant, indicating the obvious spatial correlation characteristics of the intensity of human activities and habitat quality space. The scatter analysis of Moran's I trend shows that the intensity of human activities and habitat quality space in the study area are correlated, and that the correlation is relatively significant. The correlation between the two periods from 2000 to 2005 was weak, presenting a gradually weakening trend. The first quadrant of 2010 showed a relatively obvious positive correlation, and the change from 2015 to 2020 was relatively significant, indicating a negative correlation. The spatial correlation between the intensity of human activities and habitat quality was weak from 2000 to 2005. Considering the constraints of economic development and the topographic conditions, less amount of land was used for ecological land transfer and construction in Guiyang during this period, and the impact of human economic activities on urban habitat quality was weak as well. In 2010, due to the implementation of the policy of returning farmland to forest or grassland, the regional habitat quality was improved to a certain extent. However, the habitat quality in Guiyang decreased significantly from 2015 to 2020, which was attributed to the upsurge of urban construction in Guiyang, and the intensity of human activities affected the regional habitat quality level. The transformation of a large number of ecological land and water body areas into construction land gave rise to the relatively obvious and frequent spatial land-use map changes. The spatial differentiation of the regions with correlation in Moran's scatter plot was analyzed using the LISA cluster analyzing method, and the LISA cluster map was drawn by the Z test ($P = 0.05$) (Figure 6). The relationship between human activity intensity and habitat quality was significant, but the high-high and the low-low types showed a clustering trend. From 2000 to 2020, the proportion of high-high agglomeration distribution areas presented a trend of gradual decrease, and the decrease was not obvious. The significance level of LISA cluster analysis shows that most areas of Guiyang are not significant, while the high-high type showed a high significance level that was staggered in the 0.01 and the 0.05 region. From 2000 to 2020, the distribution with a significance level of 0.01 showed a dynamic change. In 2010, the area of 0.01 distribution decreased, representing an increase in the spatial difference, while the area of 0.05 distribution increased, indicating that the spatial difference was being gradually narrowed.

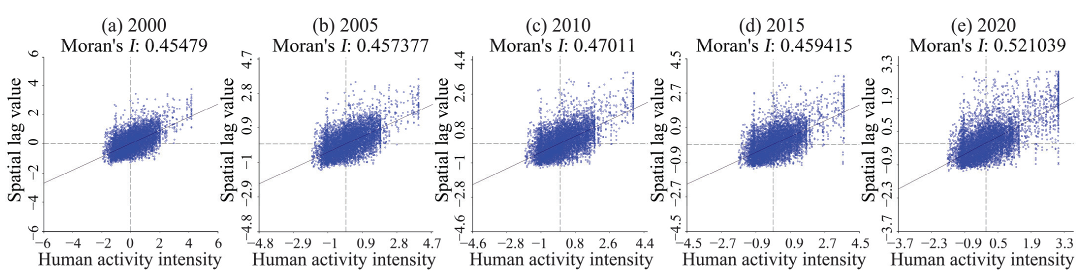

Figure 5. Moran's scatter plot of changes in human activity intensity and habitat quality in Guiyang from 2000 to 2020.

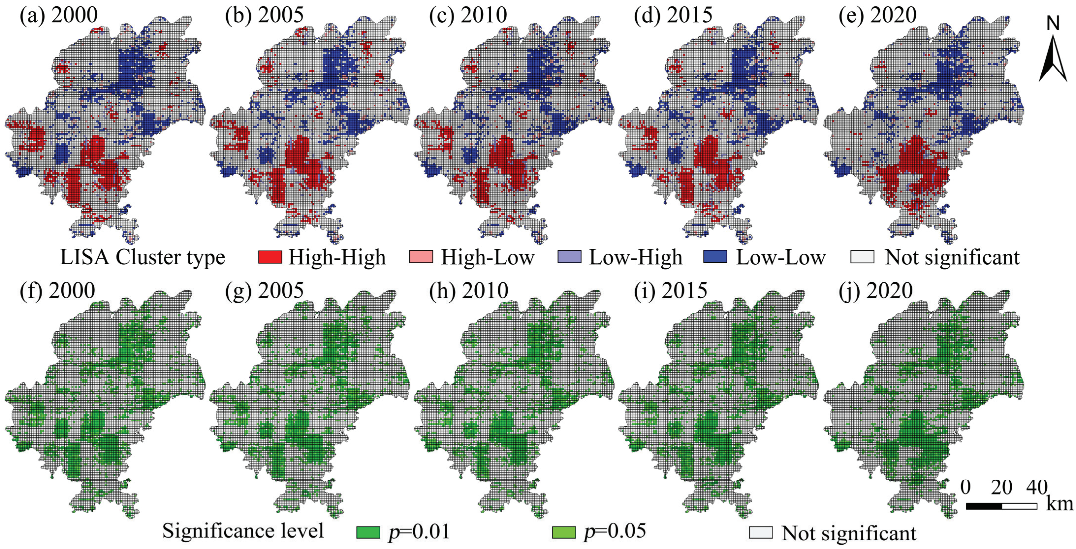

Figure 6. LISA clustering analysis and significance level of human activity intensity and habitat quality changes in Guiyang from 2000 to 2020.

4.4. Spatial Variation of the Impact of Human Activity Intensity on Habitat Quality

The least square model and geographically weighted regression model were analyzed using ArcGis10.3 software, and the AICc values were −5063.480 and −8781.726, respectively. When the AICc value of the least square method and the geographically weighted regression model is greater than 3, the results of the geographically weighted regression simulation are more reasonable [23]. In this study, the difference between the two is 3718.246, indicating a better result of geographically weighted regression than that of the least square model. The R2 of the geographically weighted regression model increased to 0.410, further indicating the favorability and suitability of the simulation results of the geographically weighted regression for this study (Figure 7).

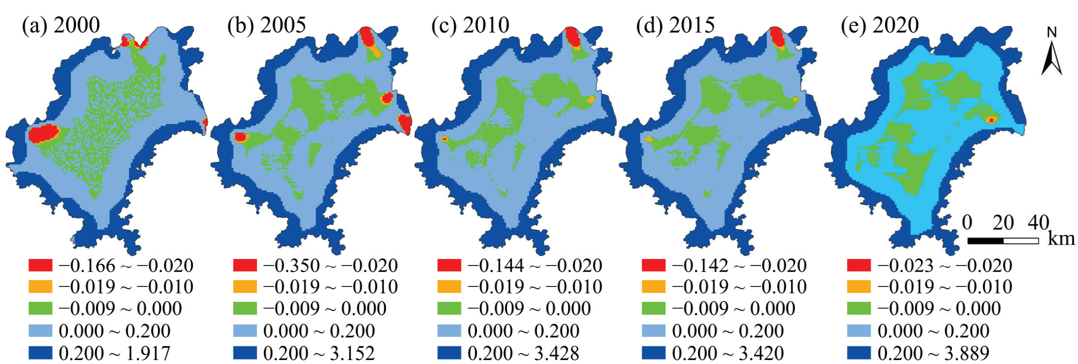

Figure 7. Spatial distribution map of regression coefficients of human footprint index in Guiyang from 2000 to 2020.

From the time scale perspective, the human activity intensity index exercised a significant impact on habitat quality in Guiyang from 2000 to 2020, with the negatively affected area covering an area of 21.52% in 2000, 16.95% in 2015 and 18.32% in 2020, presenting dynamic change characteristics and an unstable trend. From 2000 to 2020, there was a positive correlation between the surrounding area of Guiyang and the area with a high forest coverage rate. The habitat quality in this area, such as Huaxi District and Xiuwen County, maintained a favorable trend due to the regional land nature. The areas with the negative impact of human activity intensity and habitat quality were mainly distributed in the main urban areas and key areas of economic development, where the regional habitat quality was declining due to urban construction and other reasons.

From the spatial scale perspective, the intensity of human activities on the spatial difference of habitat had a significant difference in the quality and performance as the impact significant of the Guiyang City core area, while the impact of the city's surrounding areas is weak. Most of the core areas of the main city are negative value areas, while the marginal areas and forest areas are positive value areas. Based on this phenomenon, shows that the impact of human activity intensity on habitat quality mainly was negative. It is mainly caused by the restriction of territorial space planning and the influence of regional natural conditions. Especially in recent years, the development and construction of the new city in Guanshanhu District have been greatly accelerated, resulting in the intensification of human activities, which exerts a significant impact on the local regional habitat quality. In this case, attention should be paid to the harmonious relationship between habitat quality for the local land use and development, and the promotion of the sustainability of regional habitat quality development.

5. Discussion

Previous studies on the quality of human settlements in Guiyang are mainly based on the evaluation of a single habitat quality unit in the city, and the lack of comprehensive consideration of the spatio-temporal coupling relationship between habitat quality changes and human activity intensity. Based on the land-use change data of Guiyang from 2000 to 2020, the spatial and temporal characteristics of habitat quality changes in Guiyang were hereby analyzed using the habitat quality module of InVEST model. At the same time, the human activity intensity index, bivariate autocorrelation method and geographically weighted regression model were used to analyze the impact and spatial correlation characteristics of habitat quality, and to evaluate the spatial and temporal changes of habitat quality evolution. The results are endowed with a reference value and practical significance for the analysis of factors affecting the development, construction and habitat quality change of similar cities in the study area.

Habitat quality is an index reflecting regional ecological environment change, while land use change is an important factor affecting habitat quality change. Urban land use and development lead to the continuous expansion of the scale and scope of land use, but also have a certain impact on the quality of the ecological environment. Land-use transfer and change, with cultivated land, grassland and forestland converted into construction land as the main type, jointly form the habitat quality change pattern of "urban and rural areas and key industrial development areas", which also confirms that urban development and industrial construction affect habitat quality change [14,24–26].

The impact of human activities intensity on habitat quality presents a spatial correlation, indicating that the intensity of human activities in the study area affects the habitat quality change, and the impact of population aggregation, economic development and policies make the changes mainly concentrated on the central urban area and the densely populated areas. From 2015 to 2020, the quality of urban habitat in Guiyang showed a continuously declining trend, which is consistent with the rapid urban development period of Guiyang [27].

Guiyang City is a typical karst mountain city in southwestern China, and is provided with unique ecological resource advantages in the process of urban construction and development, but is also exposed to the problem of inefficient land utilization, affected by the natural factors in the process of relatively concentrated land use, and driven by the economic driver and inappropriate land development that present the declining trend in urban habitat quality, which also brings certain pressure to the urban planning and management, and future land use should take into consideration the market economy and administrative intervention. The development models of ecological quality are favorable, regulating the functions of urban land examination and approval, the intensive economical utilization of land, as well as the city and the habitat quality of balanced and sustainable economic development.

However, limited by the sources and methods of data, the study is still subject to problems concerning the selection of variables, the accuracy of land-use data, and the selection of sensitive sources, threat factors and weights of the InVEST model. Although it refers to the existing literature, the selection of data is still subjective to some extent. In future research, more qualitative and quantitative evaluation methods should be integrated into the research for higher-level data accuracy, for the better selection of index factors, and also for the improvement of the research methods, so as to provide more data and method support for the research. It is expected that the research results can be of practical significance and guidance for the coordination of urban economic development and ecological environment.

6. Conclusions

Land change is the most direct factor affecting habitat quality. This paper innovatively proposes a comprehensive regional factor index for evaluating urban habitat quality assessment and land use. This index comprehensively considers the correlation between habitat quality change and human activity intensity, and reveals the spatio-temporal characteristics of land use, human activity intensity and urban spatial pattern evolution. We evaluated the impact of land use change on habitat quality and the coordination between them. Based on the data on land use change in 2000, 2010 and 2020, the spatial and temporal characteristics of urban development and the interaction between land use were analyzed, and urban development was identified as a better level for the promotion of habitat quality, thereby providing references and suggestions for the improvement of relevant problems. Based on the above ideas and methods, the conclusions can be drawn as follows:

(1) From 2000 to 2020, the habitat quality level in Guiyang remained stable without drastic changes, but the changes showed a hierarchical and scattered distribution, mainly reflected in the urban expansion areas of the urban–rural fringe and the key areas of industrial development, and the ecological environment quality fluctuated in a small range.

(2) From 2000 to 2020, the intensity of human activities in Guiyang was mainly affected by the relatively concentrated distribution, presenting obvious and significant changes. From 2010 to 2015, the high-impact area surrounded the Guanshan Lake New Area, and the regional habitat quality showed a downward trend. In 2020, the high-impact area of the main urban area and key industrial development zone was formed, while the low-impact area was still distributed in forest areas with complex natural conditions, which was less affected by the intensity of human activities.

(3) From 2000 to 2020, there was a significantly negative correlation between human activity intensity and habitat quality in Guiyang. The spatial correlation between the intensity of human activities and habitat quality was weak from 2000 to 2005. Considering the constraints of economic development and the topographic conditions, less amount of land was used for ecological land transfer and construction in Guiyang during this period, and the impact of human economic activities on urban habitat quality was weak as well. The period from 2015 to 2020 is a period featuring the rapid development of urban construction in Guiyang, when human construction activities continued to affect the urban habitat quality, and the land use map spots changed frequently and obviously. The land use change is the main reason for the habitat quality change.

(4) Limitations of the Study. Some limitations exist in our study. For example, land-use change is an uncertain and dynamic process. Due to the heavy workload of data

processing and the difficulty of data collection, the data used in this study covers the period from 2000 to 2020. In future research, data from more stages can be obtained for comparison, so as to explore the spatio-temporal evolution law of human settlement's environment quality and its influencing factors from more micro levels. The study can be enriched by obtaining air pollution volatility indices and other natural factors in certain sectors of the study area. This will be the focus of our future research.

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References

1. Liu, N.; Zhou, Y.; Cheng, W. Analysis on the change of Yubei District construction land in Chongqing. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *783*, 012092. [CrossRef]
2. Pang, X.; Lee, X. Temporal variations of atmospheric carbonyls in urban ambient air and street canyons of a Mountainous city in Southwest China. *Atmos. Environ.* **2010**, *44*, 2098–2106. [CrossRef]
3. Zheng, P.; He-Ping, L.; Yue-Ting, G.; Qing, L. Influence of land cover change on land surface temperature in the mountainous city. geographical research. *Geogr. Res.* **2009**, *28*, 673–684.
4. Xu, F.; Baoligao, B.; Wang, X.; Yao, Q. Integrated River Restoration in a Mountainous City and Case Study. *Procedia Eng.* **2016**, *154*, 787–793. [CrossRef]
5. Carlson, T.N.; Arthur, S.T. The impact of land use—Land cover changes due to urbanization on surface microclimate and hydrology: A satellite perspective. *Glob. Planet. Change* **2000**, *25*, 49–65. [CrossRef]
6. Peng, J.; Du, Y.; Liu, Y.; Hu, X. How to assess urban development potential in mountain areas? An approach of ecological carrying capacity in the view of coupled human and natural systems. *Ecol. Indic.* **2016**, *60*, 1017–1030. [CrossRef]
7. Hanski, I. Habitat Loss, the Dynamics of Biodiversity, and a Perspective on Conservation. *Ambio* **2011**, *40*, 248–255.
8. Lahiji, R.N.; Dinan, N.M.; Liaghati, H.; Ghaffarzadeh, H.; Vafaeinejad, A. Scenario-based estimation of catchment carbon storage: Linking multi-objective land allocation with InVEST model in a mixed agriculture-forest landscape. *Front. Earth Sci.* **2020**, *14*, 637–646. [CrossRef]
9. Román, M.O.; Justice, C.; Csiszar, I.; Key, J.R.; Devadiga, S.; Davidson, C.; Wolfe, R.; Privette, J. Pre-launch evaluation of the NPP VIIRS Land and Cryosphere EDRs to meet NASA's science requirements. In Proceedings of the 2011 IEEE International Geoscience and Remote Sensing Symposium, Vancouver, BC, Canada, 24–29 July 2011.
10. Karnieli, A.; Agam, N.; Pinker, R.T.; Anderson, M.; Imhoff, M.L.; Gutman, G.G.; Panov, N.; Goldberg, A. Use of NDVI and Land Surface Temperature for Drought Assessment: Merits and Limitations. *J. Clim.* **2010**, *23*, 618–633.
11. Zhan, D.S.; Zhang, W.Z.; Yu, J.H.; Meng, B.; Dang, Y.X. Analysis of influencing mechanism of residents' livability satisfaction in Beijing using geographical detector. *Prog. Geogr.* **2015**, *34*, 966–975.
12. Svoray, T.; Ben-Said, S. Soil loss, water ponding and sediment deposition variations as a consequence of rainfall intensity and land use: A multi-criteria analysis. *Earth Surf. Process. Landf.* **2010**, *35*, 202–216. [CrossRef]
13. Li, K.; Cao, J.; Adamowski, J.F.; Biswas, A.; Zhou, J.; Liu, Y.; Zhang, Y.; Liu, C.; Dong, X.; Qin, Y. Assessing the effects of ecological engineering on spatiotemporal dynamics of carbon storage from 2000 to 2016 in the Loess Plateau area using the InVEST model: A case study in Huining County, China. *Environ. Dev.* **2021**, *39*, 1–15. [CrossRef]
14. Zhang, X.; Zhou, J.; Li, G.; Chen, C.; Li, M.; Luo, J. Spatial pattern reconstruction of regional habitat quality based on the simulation of land use changes from 1975 to 2010. *J. Geogr. Sci.* **2020**, *30*, 90–109. [CrossRef]
15. Zhou, T.; Chen, W.X.; Li, J.F.; Liang, J.L. Spatial relationship between human activities and habitat quality in Shennongjia Forest Region from 1995 to 2015. *Acta Ecol. Sin.* **2021**, *41*, 6134–6145. (In Chinese)

16. He, J.; Huang, J.; Li, C. The evaluation for the impact of land use change on habitat quality: A joint contribution of cellular automata scenario simulation and habitat quality assessment model. *Ecol. Model.* **2017**, *266*, 58–67. [CrossRef]
17. Liu, J.; Dou, S.; Aehh, B. Cost-effectiveness analysis of different types of payments for ecosystem services: A case in the urban wetland ecosystem. *J. Clean. Prod.* **2020**, *249*, 119325.
18. Liang, F.C.; Liu, L.M. Quantitative analysis of human disturbance intensity of landscape patterns and preliminary optimization of ecological function regions: A case of Minqing County in Fujian Province. *Resour. Sci.* **2011**, *33*, 1138–1144. (In Chinese)
19. Li, Y.F.; Luo, Y.C.; Liu, G.; Ouyang, Z.Y.; Zheng, H. Effects of Land Use change on ecosystem services, a case study in Miyun reservoir watershed. *Acta Ecol. Sin.* **2013**, *33*, 726–736. (In Chinese)
20. Li, L.; Zhu, L.Q.; Zhu, W.B.; Xu, S.B.; Li, Y.H.; Ma, H. The correlation between ecosystem service value and human activity intensity and its trade-offs —Take Qihe River basin for example. *China Environ. Sci.* **2020**, *40*, 365–374. (In Chinese)
21. Zhang, T.; Ge, L. On Moran's I coefficient under heterogeneity. *Comput. Stat. Data Anal.* **2015**, *95*, 83–94.
22. Anselin, L.; Rey, S.J. *Modern Spatial Econometrics in Practice: A Guide to Geoda, Geodaspace and Pysal*; GeoDa Press LLC: Urbana, IL, USA, 2014.
23. Brunsdon, C.; Fotheringham, S.; Charlton, M. Geographically Weighted Regression. *J. R. Stat. Soc. Ser. D* **1998**, *47*, 431–443. [CrossRef]
24. Kardel, F.; Wuyts, K.; Babanezhad, M.; Wuytack, T.; Potters, G.; Samson, R. Assessing urban habitat quality based on specific leaf area and stomatal characteristics of Plantago lanceolata L. *Environ. Pollut.* **2010**, *158*, 788–794. [CrossRef]
25. Balasooriya BL, W.K.; Samson, R.; Mbikwa, F.; Boeckx, P.; Van Meirvenne, M. Biomonitoring of urban habitat quality by anatomical and chemical leaf characteristics. *Environ. Exp. Bot.* **2009**, *65*, 386–394. [CrossRef]
26. Kardel, F.; Wuyts, K.; Babanezhad, M.; Wuytack, T.; Adriaenssens, S.; Samson, R. Tree leaf wettability as passive bio-indicator of urban habitat quality. *Environ. Exp. Bot.* **2012**, *75*, 277–285. [CrossRef]
27. Zhou, C.; Yan, L.; Yu, L.; Wei, H.; Guan, H.; Shang, C.; Bao, J. Effect of Short-term Forest Bathing in Urban Parks on Perceived Anxiety of Young-adults: A Pilot Study in Guiyang, Southwest China. *Chin. Geogr. Sci.* **2019**, *29*, 139–150. [CrossRef]

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Evolution Characteristics and Formation Mechanism of Production-Living-Ecological Space in China: Perspective of Main Function Zones

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Abstract: The main function zone (MFZ) is the major strategy of China's economic development and ecological environment protection. Clarifying the logical relationship between "MFZ strategy" and "territorial spatial layout" is vital to construct regional economic layout and territorial spatial supporting system of high-quality development. However, few studies have revealed the evolution process and formation mechanism of the production-living-ecological space (PLES) structure of China's MFZ over a long period of time. To bridge the gap, based on the land use dataset in China from 1980 to 2020, this study analyzed the evolution patterns of PLES in China's MFZs using multiple methods and measured the formation mechanism of PLES in different types of MFZs with the GeoDetector model. Results showed that the spatial structure of China's national territory has evolved drastically in the past 40 years, showing significant horizontal regional differentiation and vertical gradient differentiation. Ecological space has been continuously decreasing, while production space and living space have been continuously increasing, and the evolution of PLES varied significantly in different MFZs. During the study period, the gravity center of PLES in China all moved westward. The spatial distribution pattern of production space and living space was from northeast to southwest, and the ecological space was from east to west. The evolution of China's territorial spatial structure was subject to the combined effects of natural and socio-economic factors, exhibiting significant differences in different MFZs. Land use intensity had the most prominent influence on the formation of PLES, followed by elevation. The influences of different factors on PLES structure were strengthened mainly through two types of nonlinear enhancement and dual-factor enhancement. This study can provide scientific support for the optimal management and high-quality development of territorial space in China.

Keywords: main function zone; territorial space; production-living-ecological space; influencing factors; formation mechanism; China

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1. Introduction

The past 40 years has witnessed remarkable achievements in China's socio-economic development and has also brought about drastic changes in territorial spatial pattern [1,2]. The long-standing lack of spatial layout planning in China has led to disordered territorial spatial development, tightening resource constraints, and imbalanced regional development issues in the process of rapid urbanization in China [3–5]. In 2021, the *Outline of the People's Republic of China 14th Five-Year Plan for National Economic and Social Development and Long-Range Objectives for 2035* put forward the further implementation of regional major strategy, regional coordinated development strategy, main function zone (MFZ) strategy to improve the system of regional harmonious development mechanism, and achieve high-quality development of the regional economic layout and the supporting system for the territorial spatial development [6]. How to build high-quality development of regional economic layout and territorial spatial support system has become the current focus of attention [5,7]. The planning of MFZ is a major innovation of coordinated regional development in China. It is an innovative spatial control method proposed to solve the problems of disordered territorial spatial development and imbalanced regional development under China's rapid economic growth [8,9]. The MFZ was first proposed in China's 11th Five-Year Plan [8]. Since then, MFZ has evolved from planning to regional strategy to national basic system and has currently become the overall plan of China's "one blueprint to the end" [9,10]. According to the *National Plan for Main Function Zones* issued by the State Council and the *Plan for China's Main function Zoning* (*V1.0*), the MFZs are divided into optimized development zone, key development zone, restricted development zone, and prohibited development zone according to their development modes [11,12]. The restricted development zones are divided into main agricultural production zone and key eco-function zone. As prohibited development zone is a kind of functional zone superimposed on the other three functional zones, the area of which is relatively small compared with the other three functional zones, it is not considered in this study [13].

Pieces of previous research have been conducted on the MFZ, mainly focusing on the conceptual theory [10,14–16], zoning [17], structural analysis [15], monitoring and evaluation [5,18], simulation [19–21], coordinated development [5,7,22], pattern optimization [23–26], influence mechanism [5,27], and supporting policies [28]. As the strategic background of national planning, the MFZ is the prospect of the overall pattern of China's territorial spatial protection and development in the future [11,14], which can guide the quantity distribution and spatial layout of production-living-ecological space (PLES) through territorial spatial planning, three-zones and three-lines management and control [11]. However, previous literature on the evolution of the spatial structure of the MFZ mainly analyzed its structural evolution based on socio-economic development (e.g., per capita GDP, population, urbanization) [29,30], ecological function [31], and construction land [13,32]. Few studies have revealed the evolution process and formation mechanism of the PLES structure of China's MFZ over a long period of time. Thus, a systematical review of the evolution of China's PLES structure over a long period of time is an important basis for exploring the optimization strategy of the pattern of MFZ and improving the development strategy and spatial governance system of China's territorial space [33].

PLES is the carrier and path of territorial spatial optimization, which can not only reflect the development and utilization orientation of national strategy at the level of territorial space but also mirror the public's real demands for PLES [16]. Land is the carrier of ecological protection and high-quality development, and the coordinated development of PLES will promote such protection and development [5]. The geographical space classification system of PLES is a comprehensive land spatial zoning method and the related research is mainly focused on China [34]. In China, the classification of PLES is based on the theory of multi-functionality of land use in Europe [35]. Thus, land use change is a direct reflection of PLES change. Previous studies on PLES mainly focused on PLES theory [16], classification [36], pattern evolution [17,37,38], optimization coordination, and conflict regulation [39,40], whereas few studies explored the structural evolution characteristics of PLES based on MFZ. PLES inherits the strategic positioning in territorial spatial planning under the MFZ strategy and is reflected in the quantity and spatial layout of PLES [41]. MFZs differ significantly in economic development, development intensity, resource and environmental carrying capacity, development potential, and development direction. Therefore, it is particularly necessary to understand the driving mechanism of the MFZ structure of different types of MFZs, which will help to promote the formation of a spatial development pattern with effective main function constraints and orderly territorial space development. Previous studies have explored the driving mechanism of natural factors and socio-economic conditions on territorial spatial differentiation in river basins and mountainous areas [4,41], but research on the process of PLES change and regional differentiation mechanism of national MFZ is still insufficient.

China is a vast country with significant regional differences in natural environment, resource endowment, stage, and characteristics of socio-economic development. It is vital to explore the evolution process of PLES structure and regional differentiation mechanism of China's MFZ over a long period of time for the construction of high-quality regional economic layout and territorial spatial support system [42]. Therefore, based on the land use data in China in 1980, 1990, 2000, 2010, and 2020, this study introduced land spatial transfer matrix, landscape pattern metrics, and standard deviation ellipse to measure the evolution characteristics of PLES structure of China's MFZ. Meanwhile, with the help of GeoDetector model, the formation mechanism of the regional differentiation of PLES in four types of MFZs is explored. Specifically, the study aims to (1) Identify the spatio-temporal evolution patterns of PLES in China from the perspective of MFZ. (2) Explore the formation mechanism of PLES in China. (3) Provide theoretical reference and decision-making basis for the development of national space and the optimization of MFZ.

2. Data Sources and Methods

2.1. Data Sources

The data of 1 × 1 km land use data in China in 1980, 1990, 2000, 2010, and 2020 were obtained from Resources and Environmental Science and Data Center of Chinese Academy of Sciences (RESDC) (http://www.resdc.cn/, accessed on 12 July 2022). Based on Landsat TM/ETM and Landsat 8 remote sensing images, this dataset was generated by Liu et al. through manual visual interpretation with 5-year interval [43]. Land use types include 6 first-level types and 25 second-level types. A distance of 1 km resolution DEM, annual precipitation, and annual mean temperature data were also obtained from RESDC. The 2000, 2010, and 2020 collections of China's population density data are supplied by the WorldPop website (https://www.worldpop.org/, accessed on 12 July 2022), with a resolution of 100 × 100 m. The data of MFZ used in this study were derived from the National Planning for MFZ issued by The State Council and the *Plan for China's Main Function Zoning* (*V1.0*) [11]. To fully reveal the evolution process and formation mechanism of PLES in different MFZs, this study combined optimized development zone, key development zone, major agricultural production zone, and key eco-function zone (Figure 1).

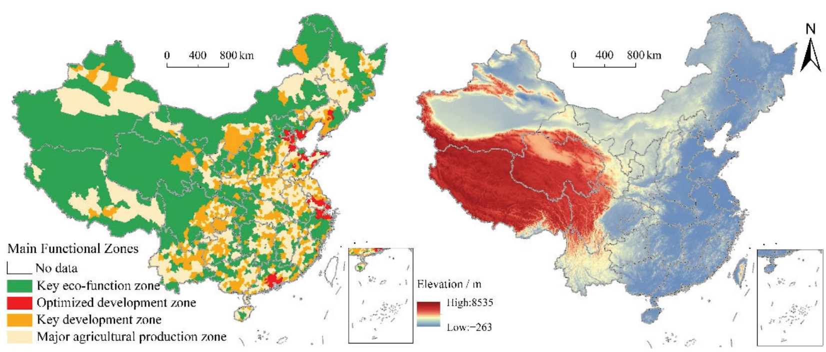

Figure 1. Spatial distribution of MFZ and elevation in China.

2.2. Classification System of Production-Living-Ecological Space

Building a scientific and reasonable classification system of PLES is the premise and basis for studying the structural evolution of PLES [44]. Territorial spatial pattern is a comprehensive reflection of the interaction and coupling between natural ecological process and humanistic social system [45], and territorial space is a multi-functional complex [18,34,46,47]. Scholars have conducted a large number of studies on the classification of PLES, mainly based on the dominant functions of different land use types [5,44]. Based on previous studies, this study took the multi-function of territorial space as the entry point, combined with the land use classification system of Chinese Academy of Sciences and *Current Land Use Classification* (GB/T21010-2007), classified the PLES in China, and constructed the classification system of PLES in China for specific reference [5,48–50] (Table 1).

Table 1. Land use types based on dominant function.

Land Use Classification Based on Dominant Function and Production-Living-Ecological Land Types		National Land Use Classification System
	First-Level Type	**Second-Level Type**
Production space	Agricultural production space Industrial and mining production space	Paddy field, dry land Mining and transportation land
Ecological space	Forestland ecological space	Forestland, shrub area, wood land, other forest land
	Grassland ecological space	High coverage grassland, medium coverage grassland, low coverage grassland
	Water ecological space	River and canals Lakes Reservoir, pit, and ponds bottom land
	Other ecological space	Swampland, bare soil Bare rock
Living space	Urban living space Rural living space	Urban land Rural residential land

2.3. Methods

2.3.1. National Spatial Transfer Matrix

The national spatial transfer matrix takes the land use transfer area as the matrix, reflecting the structure and current situation of the dynamic change of land use [51]. Transfer matrix is usually used to analyze and estimate the rate of land use change and quantitatively describe the structural characteristics of land use [49]. The specific equation is as follow:

$$S_{ij} = \begin{vmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ s_{31} & s_{32} & \cdots & s_{3n} \\ \cdots & \cdots & \cdots & \cdots \\ s_{n1} & s_{n2} & \cdots & s_{nn} \end{vmatrix} \tag{1}$$

where, S_{ij} is the area of category i territorial spatial type at the early stage of the study converted to category j territorial spatial type at the late stage of the study; n is the number of types of territorial spatial utilization.

2.3.2. Landscape Pattern Metrics

Landscape pattern metrics can well represent landscape dynamics and functions [52,53]. The evolution patterns of territorial space in spatial form are subject to different aspects of landscape pattern, such as the area, density, and proximity. Meanwhile, landscape structure, function, and change are scale dependent [54]. Thus, scale effects must be incorporated when selecting specific indicators to characterize different aspects. With reference to relevant studies [55–58] and the actual situation of the study scale of this research, five landscape pattern indices, namely percentage of landscape (PLAND), patch cohesion index (COHESION), patch density (PD), largest patch index (LPI), and mean Euclidean nearest neighbor distance (ENN_MN), were selected from the aspects of proximity, area edge, and aggregation dispersion to measure the evolution process of landscape patterns in the recent 40 years in China.

2.3.3. Standard Deviation Ellipse

Standard deviation ellipse method can quantitatively and accurately reveal the spatial distribution characteristics of geographical and socio-economic elements, such as centrality, spatial range, and evolution direction, through the parameters of ellipse center, long axis, short axis, azimuth angle, and flattening [59,60]. In this study, standard deviation ellipse was used to identify the gravity center position and its spatial movement trend of territorial spatial type area. The specific equations are as follows:

$$\overline{X}_w = \sum_{i=1}^{n} w_i x_i \Big/ \sum_{i=1}^{n} w_i \tag{2}$$

$$\overline{Y}_w = \sum_{i=1}^{n} w_i y_i \Big/ \sum_{i=1}^{n} w_i \tag{3}$$

$$\theta = \arctan\left[\left(\sum_{i=1}^{n} x_i'^2 - \sum_{i=1}^{n} y_i'^2\right) + \sqrt{\left(\sum_{i=1}^{n} x_i'^2 - \sum_{i=1}^{n} y_i'^2\right)^2 + 4\left(\sum_{i=1}^{n} x_i' y_i'\right)^2}\,\right] \Big/ 2\sum_{i=1}^{n} x_i' y_i' \tag{4}$$

$$\delta_x = \sqrt{\sum_{i=1}^{n} \left(x_i' \cos\theta - y_i' \sin\theta\right)^2 \Big/ n}\,,\ \delta_y = \sqrt{\sum_{i=1}^{n} \left(x_i' \sin\theta - y_i' \cos\theta\right)^2 \Big/ n} \tag{5}$$

where $\left(\overline{X}_w, \overline{Y}_w\right)$ is the weighted average center; (x_i, y_i) is the geometric center coordinate of county unit i; w_i is the weight; θ is azimuth; δx and δy are, respectively, the standard deviation along the major axis and the minor axis.

2.3.4. GeoDetector Model

To reveal the evolution mechanism of PLES structure in different MFZs in China, this study intended to use the Geodetector model to quantitatively detect the regional differentiation of PLES and its driving forces [61,62]. This method can effectively detect the influence of various factors and identify the strength of interaction among multiple factors [63]. The specific equation is as follow:

$$P_{D,H} = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^{L} N_h \sigma_h^2 \tag{6}$$

where $P_{D,H}$ is the detection power indicator of factors influencing the differentiation of PLES, and it values 0~1. If the independent variable has stronger explanatory power to the dependent variable, the value of $P_{D,H}$ will be higher. N and N_h are the number of sample units in the study area and the number of sample units in the sub-level area, respectively. L is the number of layers or partitions of independent variables or dependent variables; σ^2 and ${\sigma_h}^2$ are the variances of the whole region and the sub-region. GeoDetector mainly includes four detectors, namely factor detection, interaction detection, risk area detection, and ecological detection. This study focused on the formation mechanism of PLES detection, so factor detection and interaction detection are selected for quantitative elaboration and analysis. The types of interaction between two factors can be divided into the following five categories (Table 2).

Referring to previous studies, territorial spatial evolution is formed under the comprehensive action of natural and socio-economic factors [4,49,64]. In this study, six influencing factors, including land use intensity (X_1), normalized difference vegetation index (NDVI, X_2), population density (X_3), annual average temperature (X_4), annual average precipitation (X_5), and average elevation (X_6) were selected from two aspects of natural factors and socio-economic factors. Socio-economic factors mainly include X_1 and X_3, among which X_1 can effectively measure the intensity of human activities [65]. X_3 is used to represent the pressure of population pressure on territorial space development and utilization [66]. X_2 was used to characterize the effect of vegetation growth on PLES structure. X_4 and X_5

are used to represent the influence of climate factors on the evolution of territorial spatial structure, while X_6 is used to represent the impact of topographic factors on territorial spatial evolution [4,49,64]. The PLES and influencing factors in 2000, 2010, and 2020 were spatialized by ArcGIS 10.3 software, and the PLES and influencing factors index database of different MFZs of county units in China was constructed.

Table 2. Interaction types of Geodetector model.

Criterion	Interaction
$q(X_1 \cap X_2) < \min[q(X_1), q(X_2)]$	The interaction of X_1 and X_2 factors weakens the nonlinearity
$\min[q(X_1), q(X_2)] < q(X_1 \cap X_2) < \max[q(X_1), q(X_2)]$	The interaction of X_1 and X_2 factors weakens the single-factor nonlinearity
$q(X_1 \cap X_2) > \max[q(X_1), q(X_2)]$	The interaction of X_1 and X_2 factors enhances the dual-factor
$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	The X_1 and X_2 factors are independent
$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	The interaction of X_1 and X_2 factors enhances the nonlinearity

3. Results

3.1. Spatio-Temporal Evolution Pattern of Territorial Space in China from 1980 to 2020

From 1980 to 2020, ecological space played an absolutely dominant role in China's territorial space, accounting for a significantly higher proportion than production space and living space. During the study period, the proportion of ecological space continued to decrease from 79.87% in 1980 to 78.40% in 2020. Production space and living space continued to increase, with production space increasing from 18.67% in 1980 to 19.30% in 2020 and living space from 1.46% in 1980 to 2.29% in 2020 (Figure 2). There are significant differences in the proportion of PLES in different types of MFZs. Specifically, ecological space of different types of MFZs showed a reduction in the overall trend. Among them, the ecological space area of restricted development zone (key eco-function zone) accounts for the highest proportion (nearly 90%), followed by restricted development zone (major agricultural production zone), accounting for about 66%, and the ecological space of optimized development zone accounts for the lowest proportion, less than 30%.

During the study period, the production space of different types of MFZs varied greatly. The proportion of production space in optimized development zone was the highest (>50%) and showed a gradual decline trend, followed by the proportion of production space in key development zone (>36%), which also showed a continuous decline trend. The proportion of production space in restricted development zone (key eco-function zone) is <10%, and the proportion of production space in restricted development zone (major agricultural production zone) is approximately 30%, both showing a continuous increase trend. During the study period, the living space of different types of MFZs showed an overall increasing trend. The living space proportion of restricted development zone (key eco-function zone) was the lowest (<0.60%), followed by restricted development zone (major agricultural production zone), which accounted for <4%; while the living space proportion of optimized development zone was the highest, which increased from 9.90% in 1980 to 22.28% in 2020.

Owing to its vast territory, complex terrain, and diverse climate, China's territorial space utilization types are significantly different. Production space and living space showed similar spatial distribution patterns during the study period, mainly distributed in the east of Hu line (Figure 3). Specifically, production space and living space are mainly distributed in the Sichuan Basin, North China Plain, Guanzhong Plain, Northeast Plain, the Middle-Lower Yangtze River Plain, and the Pearl River Delta Region. In addition, there is more production space and living space in the surrounding areas of provincial capital cities, urban agglomeration areas, and major transportation routes. Ecological space is concentrated in the west of Hu line and mountainous areas in the east of Hu line, such as the Lesser Khingan Mountains, Changbai Mountains, T'ai-hang Mountains, Dabie Mountains, Wushan Mountains, Xuefeng Mountains, Nan Mountains, and Wuyi Mountains. Besides, the vertical gradient of China's territorial space is obviously differentiated (Figure 4). A total of 27.60% of the total territorial space is concentrated below 500 m, accounting for 15.81%

within 500~1000 m, 17.88% within 1000~1500 m, and 6.68% within 1500~2000 m. The proportion of territorial space above 4000 m is 20.00%. From 1980 to 2020, the proportion of PLES at different elevations did not change significantly. With the increase in elevation, the proportion of living space continued to decrease, the proportion of production space first decreased, then increased, and then decreased, whereas the proportion of ecological space first increased, then decreased, and then increased. Specifically, the proportion of production space in the range of 0~1200 m continued to decrease and gradually increased in the range of 1200~1600 m, and then showed an overall decreasing trend. The change trend of ecological space showed the opposite. Below 100 m, production space was more than 50%, while ecological space was over 30%. The ecological space between 100 and 200 m accounted for >50%, while the production space accounted for >40%. In China, the proportions of 0~2°, 2~5°, 5~8°, 8~15°, 15~25°, and >25° are 40.89%, 16.95%, 10.51%, 15.77%, 10.88%, and 5.01%, respectively. It can be found that the territorial space is mainly concentrated below 5° (Figure 5). From 1980 to 2020, the proportion of PLES in different slopes had little change. The proportion of production space and living space decreased with the increase in slope, while the proportion of ecological space increased.

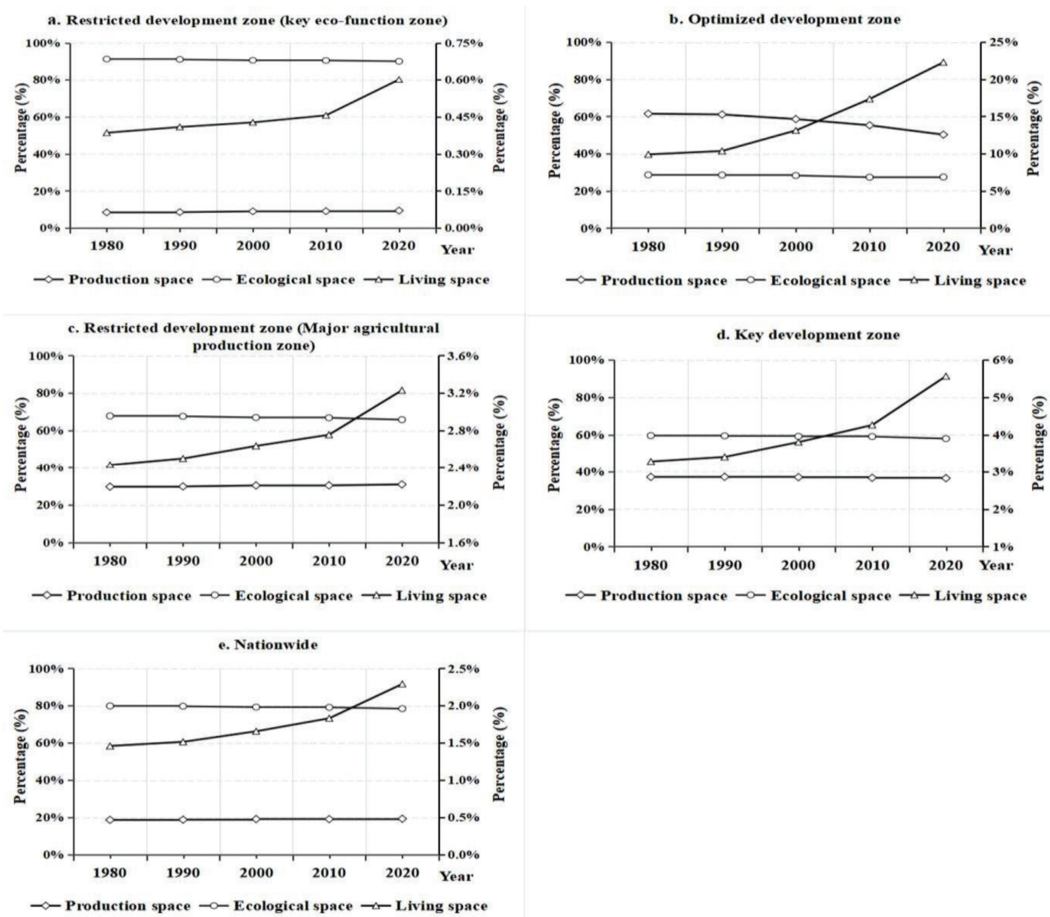

Figure 2. Proportion of PLES in major functional zones in China (%). Note: Production space and ecological space correspond to the main axis (**left**); living space corresponds to the sub-axis (**right**).

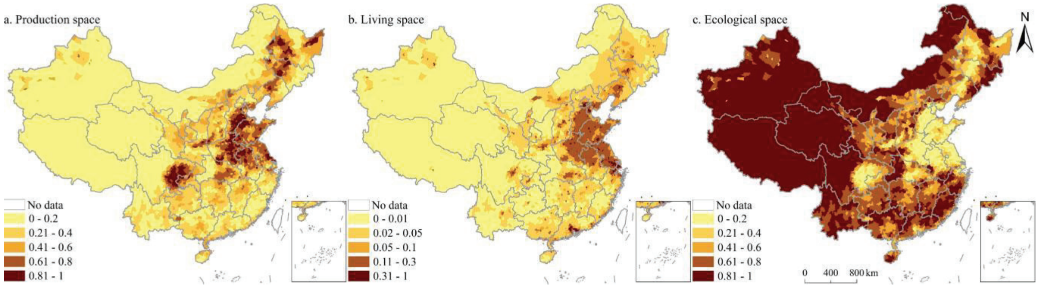

Figure 3. Spatial distribution of PLES at county level in China in 2020.

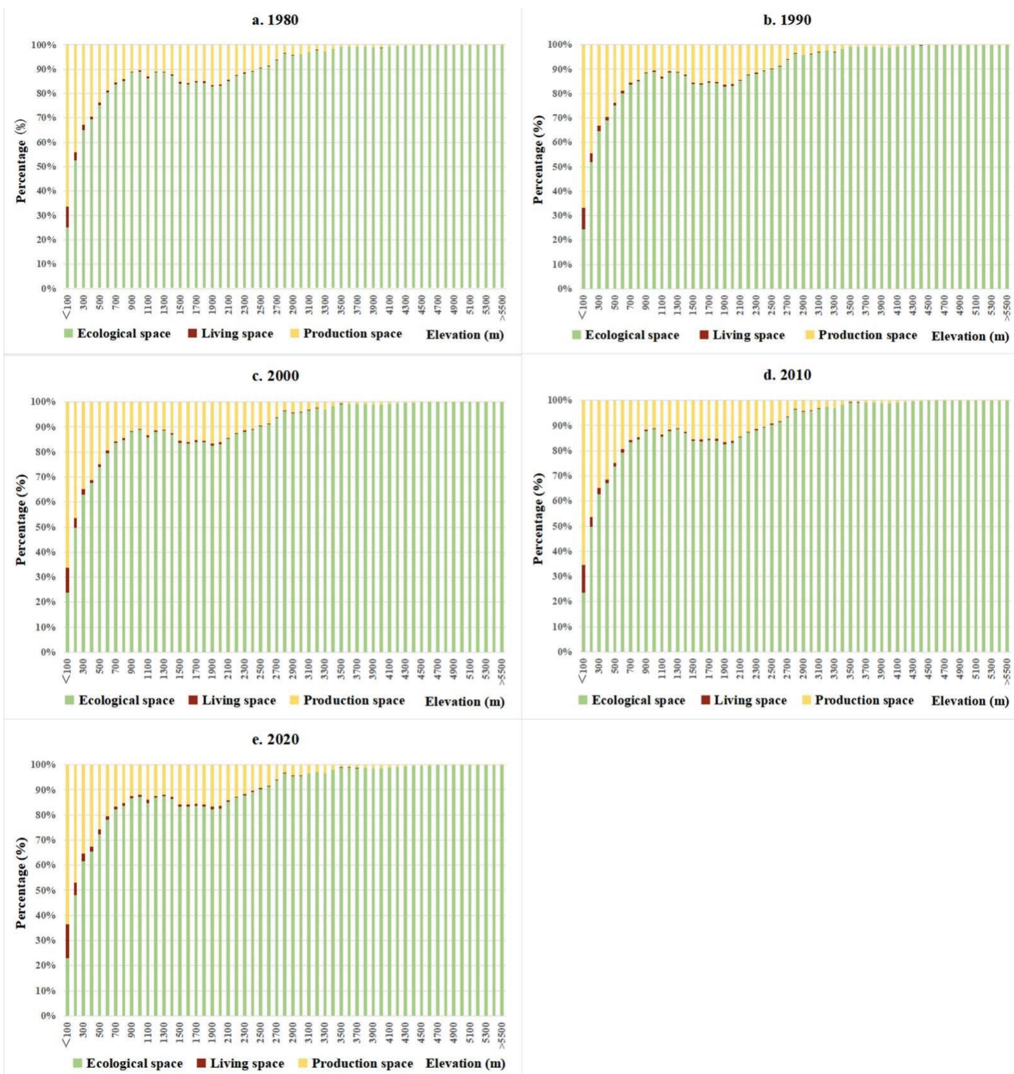

Figure 4. Changes in the proportion of PLES in different elevations in China from 1980–2020.

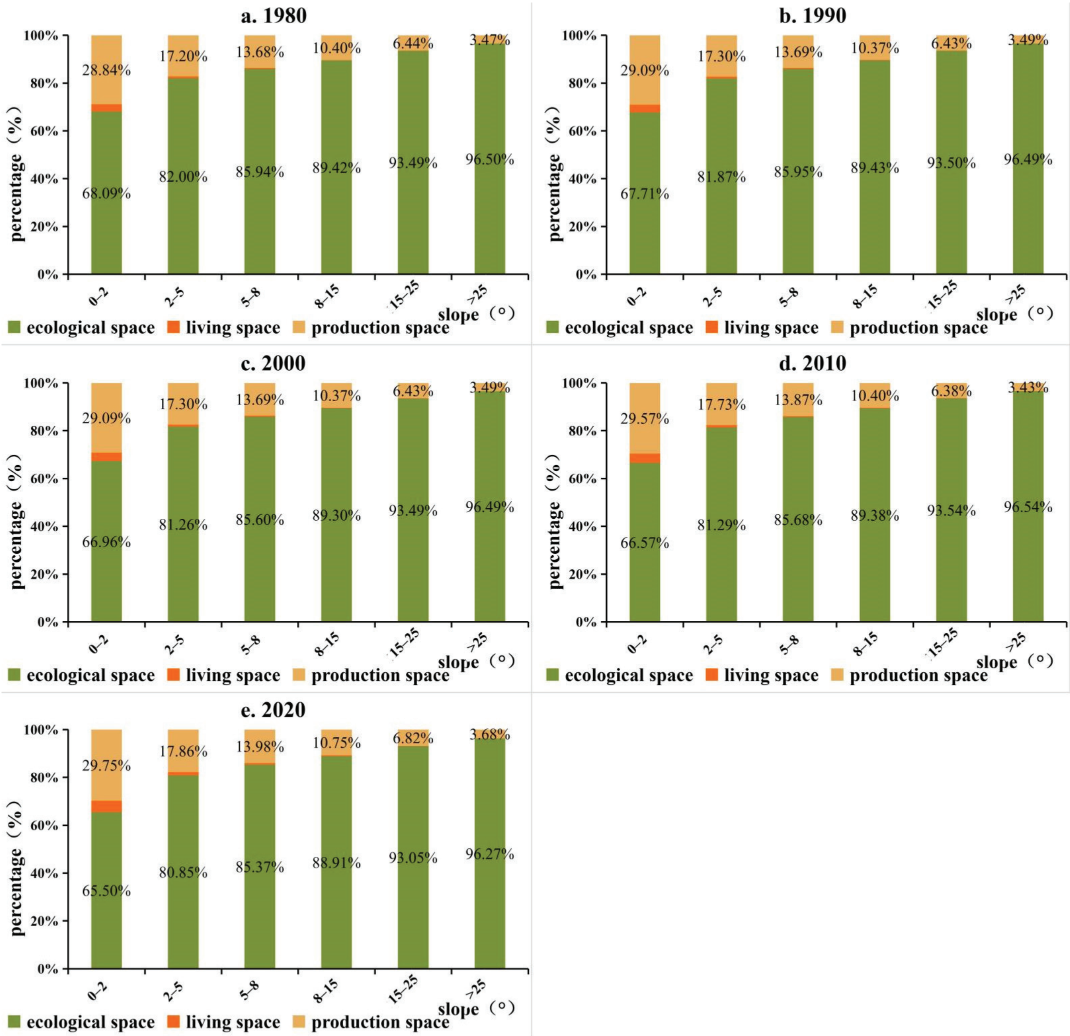

Figure 5. Changes in the proportion of PLES in different slopes in China from 1980–2020.

3.2. Spatial Transfer Matrix of Production-Living-Ecological Space in China from 1980 to 2020

Based on the conversion of PLES between 1980 and 2020, this study visualized land use transition matrices of four periods by using Sankey diagram (Figure 6). From 1980 to 1990, the range of grassland ecological space and agricultural production space to forestland ecological space was 25,325.47 km^2 and 251,574.11 km^2, respectively. The area of grassland ecological space converted to other space was the largest, reaching 681,424.70 km^2. Meanwhile, the area of other space converted to grassland ecological space was also the largest, reaching 672,171.73 km^2. The area of agricultural production space converted to other space reached 578,143.31 km^2. The conversion of industrial and mining production space to other space was the smallest, and the area of other space to forestland ecological space was also relatively large, reaching 543,864.98 km^2. From 1990 to 2000, the conversion of forestland ecological space to agricultural production space, forestland ecological space to grassland ecological space, and other ecological space to grassland ecological space were relatively evident, accounting for 21.95%, 21.34%, and 18.19% of the national spatial transformation area, respectively. From 1990 to 2000, the area of grassland ecological space converted to other space was the largest, reaching 695,586.91 km^2, followed by agricultural production space and forestland production space converted to other space, reaching 582,231.59 km^2 and 555,507.73 km^2. The grassland ecological space converted from other space was the largest, reaching 668,095.14 km^2, followed by the agricultural production space and forestland ecological space converted from other space, reaching 611,079.11 km^2 and 543,198.54 km^2, respectively.

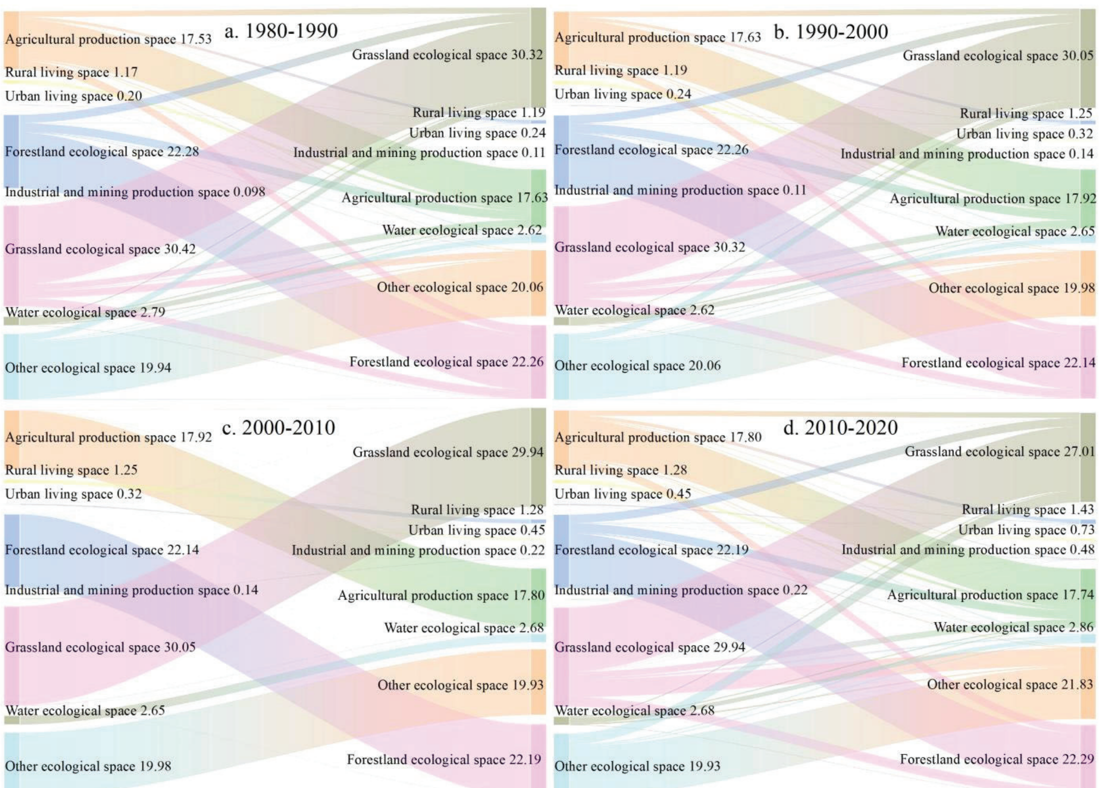

Figure 6. Sankey diagram of territorial space transfer matrix (Unit: 10^5 km^2).

From 2000 to 2010, grassland ecological space turned into agricultural production space, agricultural production space turned into urban living space, and grassland ecological space turned into forestland ecological space, accounting for 11.94%, 9.51%, and 7.94% of the transformation area of territorial space from 2000 to 2010, respectively. From 2010 to 2020, the transition between other ecological space and grassland ecological space was the most intense, accounting for 28.73% of the national spatial transformation area from 2010 to 2020, followed by grassland ecological space to forestland ecological space, accounting for 9.73% of the national spatial transformation area. From 2010 to 2020, the area of grassland ecological space converted to other space was 1,066,650.67 km^2, followed by the agricultural production space converted to other space, reaching 607,092.58 km^2. From 2010 to 2020, the area of other space converted to grassland ecological space was the largest, reaching 7,760,669.25 km^2, followed by other space to other ecological space and agricultural production space, 615,643.26 km^2 and 603,473.00 km^2, respectively.

3.3. Landscape Pattern of Production-Living-Ecological Space in China from 1980 to 2020

During the study period, the proportions of industrial and mining production space, urban living space, and rural living space continued to increase, while the water ecological space decreased from 1980 to 1990 and continued to increase from 1990 to 2020. From 1980 to 2000, the agricultural production space increased continuously, and then decreased continuously in the following 20 years. On the contrary, the forestland ecological space decreased continuously from 1980 to 2000 and increased continuously in the following 20 years. During the study period, grassland ecological space continued to decrease, while other ecological space showed a general decline trend. The COHESION index of ecological space was significantly higher than that of living space and production space, and the COHESION index of rural living space was the lowest (Figure 7b). During the study period, the COHESION index of urban living space and rural living space continued to increase, indicating that the agglomeration degree of living space increased significantly, while the ecological space of water area continued to decrease, and the COHESION index of industrial and mining production space increased first and then decreased, while other types of territorial space had little change. The LPI of forestland ecological space, grassland ecological space, and other ecological space was significantly higher than that of other territorial space types, and the proportion of industrial and mining production space, urban living space, and rural living space was relatively low (Figure 7c). The PD index of agricultural production space and grassland ecological space was higher than that of industrial and mining production space and urban living space (Figure 7d). The PD of industrial and mining production space, urban living space, rural living space, and forestland ecological space increased during the study period. The ENN_MN of industrial and mining production space and urban living space is relatively larger, followed by rural living space and water ecological space (Figure 7e).

3.4. Changes in the Direction of Territorial Expansion in China from 1980 to 2020

Based on Equations (2)–(5), this study drew the standard deviation ellipse of PLES in China from 1980 to 2020, which was used to analyze the overall patterns of China's territorial spatial distribution and its spatial movement direction (Figure 8). Production space and living space form a northeast–southwest spatial distribution pattern, and ecological space form an east–west spatial distribution pattern. From 1980 to 2020, the standard deviation ellipse area of China's production space increased, and the growth in the Y-axis direction was significantly higher than that in the X-axis direction, indicating that the production space expanded significantly along the Y-axis direction, namely the northwest to southeast direction. The gravity center of production space shifted 50.931 km to the northwest from 1980 to 2000, and 66.426 km to the northwest from 2000 to 2020 (Table 3). During the study period, the standard deviation ellipse area of living space increased, and the growth in the Y-axis direction was significantly higher than that in the X-axis direction, indicating that the living space expanded significantly along the Y-axis direction, namely the northwest to southeast direction. From 1980 to 2010, the gravity center of living space shifted 55.550 km to the southwest, and 51.639 km to the northwest from 2010 to 2020. During the study period, the standard deviation ellipse area of ecological space was small, and the center of ecological space gravity shifted 25.224 km to southwest China from 1980 to 2020.

3.5. Mechanism of Regional Differentiation in China from 2000 to 2020

3.5.1. Detection of Territorial Spatial Regional Differentiation Mechanism

Based on Equation (6), this study explored the mechanism of territorial spatial regional differentiation in the whole country and four types of MFZs. The results showed that the evolution of PLES structure in China was influenced by natural and socio-economic factors. In general, X_1 had the most prominent influence on the formation of PLES, while other influencing factors had significant differences in different regions. Specifically, from a national scale, the impact of X_1 on PLES gradually increased during the study period, and the similar impact of X_2 on PLES also gradually increased. The impact of X_3 on ecological space was greater than that of living space and production space, while the impact of X_4, X_5, and X_6 on ecological space was stronger than that of production space and living space. In major agricultural producing areas, the impact of X_2 on living space was significantly lower than that of production space and ecological space. Similar to the national scale, the impact of X_3 on ecological space was higher than that of living space and production space. The impact of X_4 on living space was stronger than that of production space and ecological space, while the impact of X_5 on living space was lower than that of production space and ecological space. The impact of X_6 on PLES was lower than that of X_1, and the impact of X_6 on production space was lower than that of living space and ecological space.

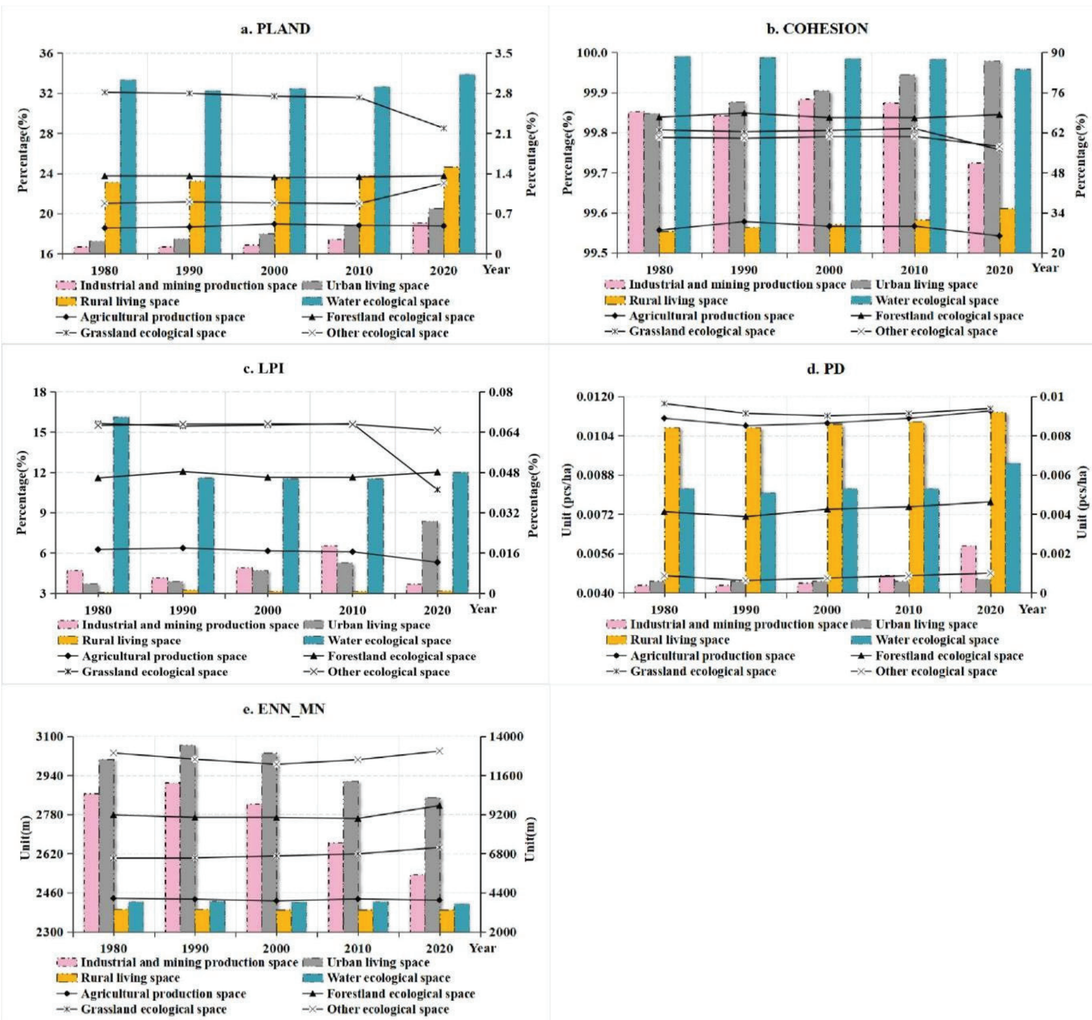

Figure 7. Landscape pattern index of territorial space in China during 1980–2020.

In the optimized development zone, the impact of each influencing factor on PLES fluctuated greatly in different years. Specifically, the impact of X_2 and X_3 on production space and living space in 2000 was significantly higher than that in 2010 and 2020, while the impact of X_2 and X_3 on ecological space in 2010 and 2020 was significantly higher than that in 2000. The impact of X_4 on ecological space was higher than that of production space and living space, the impact of X_5 on production space was significantly higher than that of living space and ecological space, and the impact of X_6 on living space was the biggest. In key development zone, the impact of X_2 on production space and living space was significantly higher than that of ecological space, and the impact of X_3 on ecological space was significantly higher than that of living space and production space. The impact of X_4 and X_5 on living space was significantly lower than that of production space and ecological space. The impact of X_6 on ecological space was significantly higher than that of living space and production space. In key eco-function zone, the impact of X_2 on PLES increased gradually, while the impact of X_3 on production space and ecological space gradually decreased, and the impact on living space gradually increased. The impact of X_4 and X_5 on production space were higher than those of ecological space and living space, and the impact of X_6 on ecological space was significantly higher than those of production space and living space.

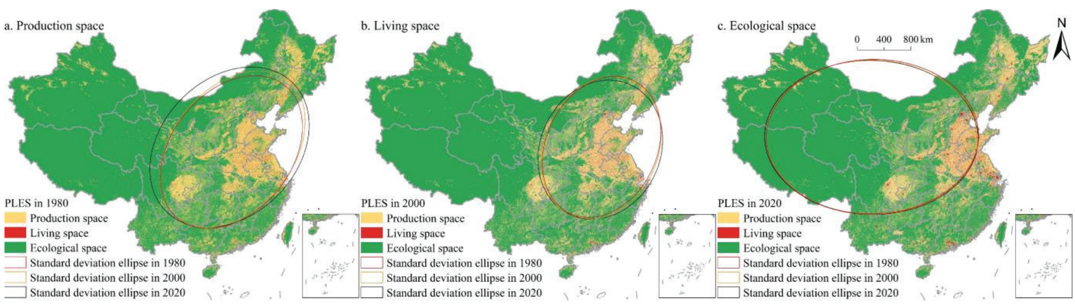

Figure 8. Standard deviation ellipse of PLES pattern in China during 1980–2020.

Table 3. Standard deviation ellipse parameter of PLES pattern during 1980–2020.

Year	Ecological Space				Production Space				Living Space			
	Latitude and longitude of Central Point	Major Axis/km	Minor Axis/km	Azimuth Angle	Major Axis/km	Minor Axis/km	Azimuth Angle	Major Axis/km	Major Axis/km	Minor Axis/km	Azimuth Angle	Major Axis/km
1980	35.20° N; 113.39° E	1267.67	894.70	36.41	35.81° N 115.58° E	1091.73	824.22	23.55	36.82° N 100.99° E	1583.86	1144.9	85.95
1990	35.31° N; 113.48° E	1280.55	892.98	36.49	35.86° N 115.55° E	1103.07	852.33	23.65	36.80° N 100.94° E	1571.62	1142.22	86.57
2000	35.59° N; 113.64° E	1309.96	896.53	36.61	35.65° N 115.49° E	1095.45	845.51	21.39	36.74° N 100.83° E	1569.92	1142.87	87.48
2010	35.700° N; 113.49° E	1315.49	934.95	38.04	35.32° N 115.49° E	1086.94	844.13	18.80	36.72° N 100.85° E	1568.43	1141.37	87.38
2020	35.85 N; 113.10 E	1341.54	1012.80	41.90	35.44° N 115.29° E	1062.34	893.53	23.51	36.69° N 100.81° E	1591.54	1142.16	88.04

3.5.2. Evolution Mechanism of Territorial Space

The results of interactive detection by GeoDetector model showed that the evolution of China's territorial spatial pattern was formed by the combined effects of natural and socio-economic factors through nonlinear enhancement and dual-factor enhancement, with the nonlinear enhancement the dominant, showing the synergistic enhancement effect. By comparing the interaction factor values of different zones, it could be found that the interaction between X_1 and other factors was significantly stronger than the interaction between other factors (Figure 9). The increase in X_1 would accelerate the evolution of territorial space. Therefore, the interaction degree between X_1 and various factors is the most complex. The evolution of China's territorial space was influenced by the integration of natural and socio-economic factors. In different regions, there were significant differences in natural environment background, resource and environment carrying capacity, location characteristics, environmental capacity, existing development density, economic structure characteristics, population agglomeration, and participation in international division of labor. However, it could be found that the intensity of interaction between X_6 and other factors in different MFZs was second only to X_1. As an important natural element, X_6 can effectively limit the range of X_2 and affect the evolution characteristics of territorial spatial structure.

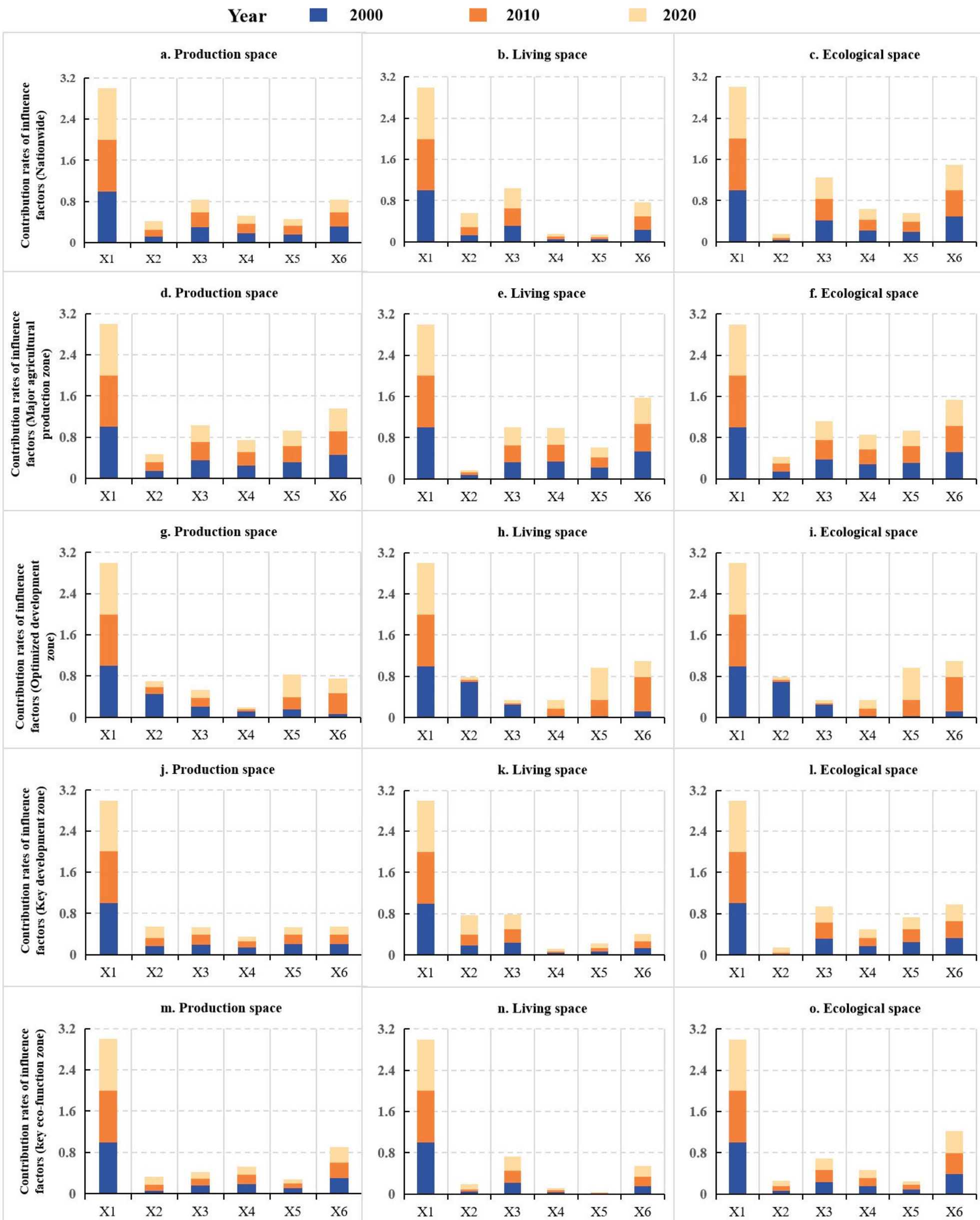

Figure 9. Contribution rates of influence factors from 2000 to 2020. Notes: Variables X_1–X_6 in the figure represent land use intensity, NDVI, population density, average annual temperature, average annual precipitation, and average elevation, respectively.

4. Discussion

As a big strategic background, the MFZ carries the national will and transmits it to all kinds of planning, and finally guides the layout of PLES through the three-zones and three-lines [4,49,64]. The quantitative relationship and spatial layout of PLES are the application guidance of national strategy at the level of territorial space, and also the real appeal of the public for affluent life, efficient production, and ecological living conditions [5,34,67,68]. Meanwhile, it is also a response to the sustainable development goals of the United Nations [69]. In Europe, land-use functions are classified into three main functions: social, economic, and environmental functions [35]. In China, the classification of PLES is based on the theory of multi-functionality of land use in Europe [34]. For example, Liu et al. scored different land use types according to the primary and secondary functions of the land [44], while Liao et al. established a PLE land classification system for southwestern China [70]. These studies provide the research basis for the classification of PLES in this study.

Based on the remote sensing data of land use monitoring in China and a series of theories and methods of territorial spatial evolution analysis, through the construction of PLES classification system, this study analyzed the evolution patterns of PLES structure of China's MFZs in the past 40 years. In addition, the GeoDetector model was used to detect the mechanism of territorial spatial regional differentiation of different MFZs. Studies consistently consider that natural and socio-economic factors jointly influence the evolution of territorial spatial structure, most notably human activity [22]. However, the evolution of territorial spatial structure is also affected by national strategic policies and public appeals. Meanwhile, the demarcation of China's MFZ is based on the differences in economic development level, development intensity, resource and environment carrying capacity, development potential, and development direction within the region. The delineation of optimized development zone, key development zone, restricted development zone, and prohibited development zone will certainly affect the quantity and layout of PLES, and the public demand will also appeal to PLES. Thus, future research needs to further strengthen the research on the impact of national macro strategies and public appeals on the evolution of territorial spatial structure. Besides, it is vital to scientifically explore the evolution process and formation mechanism of PLES in China's MFZs in the past 40 years, and to effectively connect and provide feedback on the PLES between MFZs, territorial spatial planning, and three-zones and three-lines. Based on the analysis of the evolution process of China's territorial space over a long period of time and the detection results of regional differentiation mechanism, this study puts forward the following suggestions.

Firstly, the development of the optimized development zone need to focus on improving and upgrading the quality and the transformation of production and living space. However, at present, the living space expansion rate of the optimized development zone in China is the fastest among all MFZs. In the future, it is necessary to further optimize living space, improve supporting functional facilities, and control urban sprawl, and promote more scientific and reasonable layout of living space.

Secondly, key development zone is important carrier to support the country's future economic development and population agglomeration. This study found that the production space of the key development zone in the last 40 years has decreased, while the increase in living space is not significant. In the future, it is necessary to further improve the urban infrastructure and public services and promote the population and economy to cluster in the urban agglomeration and the core area of the main axis.

Thirdly, the main agricultural producing zone is an important area to guarantee the supply safety of agricultural products in China. The production space of major agricultural producing zone in the past 40 years only increased by 1.22%. In the future, we need to step up efforts to comprehensively improve territorial space and restore the ecological environment, strengthen agricultural infrastructure, improve the distribution and structure of agricultural production, and increase the intensity of development in major agricultural production zone.

Lastly, restricted development zone is an important guarantee for ecological security in China. However, in the past 40 years, the production space and living space in China's key eco-function zone have increased by 0.98% and 0.22%, respectively, while the ecological space has decreased by 1.20%. In the future, it is necessary to further restrict large-scale and high-intensity industrialization and urbanization in territorial space development and optimize the ecosystem pattern.

5. Conclusions

Based on China's land use data from 1980 to 2020, this study explored the evolution process and the formation mechanism of the PLES structure of China's MFZs in the past 40 years by combining the theories and methods of territorial spatial pattern evolution, such as territorial spatial transfer matrix, landscape pattern index, standard deviation ellipse, and GeoDetector model. The results are as follows:

(1) During the study period, China's ecological space was absolutely dominant, and its proportion continued to decrease, while the production space and living space continued to increase. There were significant differences in the proportion of PLES in different types of MFZs.
(2) During the study period, the conversion between land types was frequent, among which the conversion between grassland and other land use spaces was the most frequent. From 1980 to 2000 and 2000 to 2010, the largest conversion was grassland ecological space to other space, and from 2000 to 2010, it was the grassland ecological space to agricultural production space; while from 2010 to 2020, other land use space converted to grassland ecological space was the largest.
(3) During the study period, the COHESION index of ecological space was significantly higher than that of living space and production space, and the COHESION index of rural living space was the lowest. The PD index of agricultural production space and grassland ecological space was high, while the ENN_MN of industrial and mining production space and urban living space was relatively large.
(4) The spatial distribution pattern of production space and living space was northeast to southwest, and the spatial distribution pattern of ecological space was east to west. There was a gradual shift of the PLES to the west during the study period.
(5) The land use intensity had the most prominent influence on the formation of PLES, and the intensity of other influencing factors varied significantly in different regions. The evolution of China's territorial spatial pattern was a synergistic enhancement effect of natural factors and socio-economic factors through nonlinear enhancement and dual-factor enhancement.

It is expected that the results of this study and the proposed policy recommendations can provide scientific support for the optimal management and high-quality development of territorial space in China and other regions with similar dominant functions.

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References

1. Liu, Y.S.; Zhou, Y. Territory spatial planning and national governance system in China. *Land Use Policy* **2021**, *102*, 105288. [CrossRef]
2. Gong, P.; Li, X.C.; Zhang, W. 40-Year (1978–2017) human settlement changes in China reflected by impervious surfaces from satellite remote sensing. *Sci. Bull.* **2019**, *64*, 756–763. [CrossRef]
3. Liu, J.J.; Wang, J.; Zhai, T.L.; Li, Z.H.; Huang, L.Y.; Yuan, S.H. Gradient characteristics of China's land use patterns and identification of the east-west natural-socio-economic transitional zone for national spatial planning. *Land Use Policy* **2021**, *109*, 105671. [CrossRef]
4. Song, Y.Y.; Xue, D.Q.; Xia, S.Y.; Mi, W.B. Change characteristics and formation mechanism of the territorial spatial pattern in the Yellow River Basin from 1980 to 2018, China. *Geogr. Res.* **2021**, *40*, 1445–1463.
5. Li, J.S.; Sun, W.; Li, M.Y.; Meng, L.L. Coupling coordination degree of production, living and ecological spaces and its influencing factors in the Yellow River Basin. *J. Clean. Prod.* **2021**, *298*, 126803. [CrossRef]
6. China. Outline of the 14th Five-Year Plan for National Economic and Social Development of the People's Republic of China and the Vision for 2035. 2021. Available online: https://www.gov.cn/xinwen/2021-03/13/content_5592681.htm (accessed on 12 July 2022).
7. Yang, Y.Y.; Bao, W.K.; Liu, Y.S. Coupling coordination analysis of rural production-living-ecological space in the Beijing-Tianjin-Hebei region. *Ecol. Indic.* **2020**, *117*, 106512. [CrossRef]
8. State Council (SC). Announcement on Issuing the National Main Functional Zone Plan. 2010. Available online: https://www.gov.cn/zhengce/content/2015-08/20/content_10107.htm (accessed on 8 June 2011).
9. Wang, Y.F.; Fan, J. The core-periphery structure of major function zones in China. *Acta Geogr. Sin.* **2019**, *74*, 710–722. [CrossRef]
10. Wang, Y.F.; Guo, R.; Fan, J. Evolution analysis of China's spatial development structure and pattern optimization of major function zones. *Bull. Chin. Acad. Sci.* **2020**, *35*, 855–866. [CrossRef]
11. Fan, J. Draft of major function oriented zoning of China. *Acta Geogr. Sin.* **2015**, *70*, 186–201. [CrossRef]
12. Wei, W.; Xia, J.N.; Hong, M.Y.; Bo, L.M. The evolution of "Three-Zone Space" in the Yangtze River Belt under major functional zoning strategy from 1980 to 2018. *Urban Plan. Forum* **2021**, *3*, 28–35. [CrossRef]
13. Liu, J.Y.; Liu, W.C.; Kuang, W.H.; Ning, J. Remote sensing-based analysis of the spatiotemporal characteristics of built-up area across China based on the plan for major function-oriented zones. *Acta Geogr. Sin.* **2016**, *71*, 355–369. [CrossRef]
14. Fan, J. A Research on the importance and significance of major function oriented zoning based upon the analysis on the restrictive factors of regional coordinative development. *Bull. Chin. Acad. Sci.* **2007**, *22*, 194–201. [CrossRef]
15. Wang, Y.F.; Fan, J. Spatial analysis of national-provincial pole-axis structure based on major function zoning in China. *Geogr. Res.* **2019**, *38*, 1651–1663. [CrossRef]
16. Lin, G.; Jiang, D.; Fu, J.Y.; Zhao, Y. A Review on the overall optimization of production–living–ecological space, theoretical basis and conceptual framework. *Land* **2022**, *11*, 345. [CrossRef]
17. Xie, X.T.; Li, X.S.; Fan, H.P.; He, W.K. Spatial analysis of production-living-ecological functions and zoning method under symbiosis theory of Henan, China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 69093–69110. [CrossRef] [PubMed]
18. Fu, J.C.; Zhang, S.L. Functional assessment and coordination characteristics of production, living, ecological function—A case study of Henan Province, China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 8051. [CrossRef] [PubMed]
19. Liao, G.T.; He, P.; Gao, X.S.; Lin, Z.Y.; Huang, C.Y.; Zhou, W.; Deng, O.P.; Xu, C.H.; Deng, L.J. Land use optimization of rural production–living–ecological space at different scales based on the BP–ANN and CLUE–S models. *Ecol. Indic.* **2022**, *137*, 108710. [CrossRef]
20. Tao, Y.Y.; Wang, Q.X.; Zou, Y. Simulation and analysis of urban production–living–ecological space evolution based on a macro–micro joint decision Model. *Int. J. Environ. Res. Public Health* **2021**, *18*, 9832. [CrossRef] [PubMed]
21. Wu, J.X.; Zhang, D.N.; Wang, H.; Li, X.C. What is the future for production-living-ecological spaces in the Greater Bay Area? A multi-scenario perspective based on DEE. *Ecol. Indic.* **2021**, *131*, 108171. [CrossRef]
22. Zhang, X.S.; Xu, Z.J. Functional coupling degree and human activity intensity of production–living–ecological space in underdeveloped regions in China: A case study of Guizhou Province. *Land* **2021**, *10*, 56. [CrossRef]
23. Wang, D.; Fu, J.Y.; Jiang, D. Optimization of production–living–ecological space in national key poverty-stricken city of Southwest China. *Land* **2022**, *11*, 411. [CrossRef]
24. Yu, R.; Qin, Y.; Xu, Y.T.; Chuai, X.W. Study on the optimization of territory spatial "Urban–Agricultural–Ecological" pattern Based on the improvement of "Production–Living–Ecological" function under carbon constraint. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6149. [CrossRef] [PubMed]
25. Fu, X.X.; Wang, X.F.; Zhou, J.T.; Ma, J.H. Optimizing the production-living-ecological space for reducing the ecosystem services deficit. *Land* **2021**, *10*, 1001. [CrossRef]
26. Chen, H.J.; Yang, Q.Y.; Su, K.C.; Zhang, H.Z.; Lu, D.; Xiang, H.; Zhou, L.L. Identification and optimization of production-living-ecological space in an ecological foundation area in the upper reaches of the Yangtze River: A case study of Jiangjin District of Chongqing, China. *Land* **2021**, *10*, 863. [CrossRef]
27. Deng, Y.X.; Yang, R. Influence mechanism of production-living-ecological space changes in the urbanization process of Guangdong Province, China. *Land* **2021**, *10*, 1357. [CrossRef]

28. Sheng, K.R.; Fan, J. Fundamental institution function of major function oriented zoning for China's land development and protection. *Bull. Chin. Acad. Sci.* **2016**, *31*, 44–50. [CrossRef]
29. Lin, L.Q.; Li, N.; Li, G.Y.; Wu, S.D.; Wang, Q.; Lin, H.L.; Dong, Z.; Huang, Y.J. Urban construction land-use efficiency evaluation based on the plan for major function-oriented zones in Fujian Province. *J. Nat. Resour.* **2018**, *33*, 1018–1028. [CrossRef]
30. Shen, Y.; Zhang, J.; Shi, L. Research on the influence of main functional area policy on regional economic growth gap. *Chin. Soft Sci.* **2020**, *4*, 97–108.
31. Xia, H.; Zhang, W.S.; Peng, H.; Li, L.; Huang, P.P.; Xia, J.J. Evaluation of ecological functions of urbanized areas based on the plan for major functional areas in China. *Sci. Geogr. Sin.* **2020**, *40*, 882–889. [CrossRef]
32. Xue, J.F.; Chen, W.; Cao, Y.H. The definition of urban concentrated areas and the relations with the national main function areas of China. *Geogr. Res.* **2013**, *32*, 146–156. [CrossRef]
33. Fan, J. Perspective of China's spatial governance system after 19th CPC National Congress. *Bull. Chin. Acad. Sci.* **2017**, *32*, 396–404. [CrossRef]
34. Duan, Y.M.; Wang, H.; Huang, A.; Xu, Y.Q.; Lu, L.H.; Ji, Z.X. Identification and spatial-temporal evolution of rural "production-living-ecological" space from the perspective of villagers' behavior—A case study of Ertai Town, Zhangjiakou City. *Land Use Policy* **2021**, *106*, 105457. [CrossRef]
35. Kienast, F.; Bolliger, J.; Potschin, M.; de Groot, R.S.; Verburg, P.H.; Heller, I.; Wascher, D.; Haines-Young, R. Assessing landscape functions with broad-scale environmental data: Insights gained from a prototype development for Europe. *Environ. Manag.* **2009**, *44*, 1099–1120. [CrossRef] [PubMed]
36. Bai, R.; Shi, Y.; Pan, Y. Land-use classifying and identification of the production-living-ecological space of island villages—A case study of islands in the western sea area of Guangdong Province. *Land* **2022**, *11*, 705. [CrossRef]
37. Zhao, Y.Q.; Cheng, J.H.; Zhu, Y.G.; Zhao, Y.P. Spatiotemporal evolution and regional differences in the production-living-ecological space of the urban agglomeration in the middle reaches of the Yangtze River. *Int. J. Environ. Res. Public Health* **2021**, *18*, 12497. [CrossRef]
38. Wei, L.Y.; Zhang, Y.J.; Wang, L.Z.; Mi, X.Y.; Wu, X.Y.; Cheng, Z.L. Spatiotemporal evolution patterns of "production-living-ecological" spaces and the coordination level and optimization of the functions in Jilin Province. *Sustainability* **2021**, *13*, 13192. [CrossRef]
39. Wang, Q.; Wang, H.J. Dynamic simulation and conflict identification analysis of production–living–ecological space in Wuhan, Central China. *Integr. Environ. Assess. Manag.* **2022**. [CrossRef]
40. Xi, F.R.; Wang, R.P.; Shi, J.S.; Zhang, J.D.; Yu, Y.; Wang, N.; Wang, Z.Y. Spatio-temporal pattern and conflict identification of production–living–ecological space in the Yellow River Basin. *Land* **2022**, *11*, 744. [CrossRef]
41. Wei, W.; Zhang, R. Exploration on the optimization path of land space based on main functional areas, spatial planning, and three living space. *Urban. Archit.* **2019**, *16*, 45–51. [CrossRef]
42. Fan, J.; Wang, Y.F.; Liang, B. The evolution process and regulation of China's regional development pattern. *Acta Geogr. Sin.* **2019**, *74*, 2437–2454. [CrossRef]
43. Kuang, W.H.; Zhang, S.W.; Du, G.M.; Yan, C.Z.; Wu, S.X.; Li, R.D.; Lu, D.S.; Pan, T.; Ning, J.; Guo, C.Q.; et al. Remotely sensed mapping and analysis of spatio-temporal patterns of land use change across China in 2015–2020. *Acta Geogr. Sin.* **2022**, *77*, 1056–1071. [CrossRef]
44. Liu, J.L.; Liu, Y.S.; Li, Y.R. Classification evaluation and spatial-temporal analysis of "production-living-ecological" spaces in China. *Acta Geogr. Sin.* **2017**, *72*, 1290–1304. [CrossRef]
45. Kuang, W.H. Issues regarding on spatial pattern change of national land space and its overall implementation on beautiful vision in new era. *Resour. Sci.* **2019**, *41*, 23–32. [CrossRef]
46. Zou, L.L.; Liu, Y.S.; Wang, J.Y.; Yang, Y.Y. An analysis of land use conflict potentials based on ecological-production-living function in the southeast coastal area of China. *Ecol. Indic.* **2021**, *122*, 107297. [CrossRef]
47. Tao, Y.Y.; Wang, Q.X. Quantitative recognition and characteristic analysis of production-living-ecological space evolution for five resource-based cities: Zululand, Xuzhou, Lota, Surf Coast and Ruhr. *Remote Sens.* **2021**, *13*, 1563. [CrossRef]
48. Yang, Q.K.; Duan, X.J.; Wang, L.; Jin, Z.F. Land use transformation based on ecological-production-living spaces and associated eco-environment effects: A case study in the Yangtze River Delta. *Sci. Geogr. Sin.* **2018**, *38*, 97–106. [CrossRef]
49. Kong, D.Y.; Chen, H.G.; Wu, K.S. The evolution of "Production-Living-Production" space eco-environmental effects and its influencing factors in China. *J. Nat. Resour.* **2021**, *36*, 1116–1135. [CrossRef]
50. Yuan, S.F.; Tang, Y.Y.; Shentu, C.N. Spatiotemporal change of land use transformation and its eco-environmental response: A case of 126 counties in Yangtze River Economic Belt. *Econ. Geogr.* **2019**, *39*, 174–181. [CrossRef]
51. Chen, W.C.; Chi, G.Q.; Li, J.F. Ecosystem services and their driving forces in the middle reaches of the Yangtze River urban agglomerations, China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 3717. [CrossRef]
52. Dadashpoor, H.; Azizi, P.; Moghadasi, M. Land use change, urbanization, and change in landscape pattern in a metropolitan area. *Sci. Total Environ.* **2019**, *655*, 707–719. [CrossRef]
53. Wei, L.; Luo, Y.; Wang, M.; Su, S.L.; Pi, J.H.; Li, G.E. Essential fragmentation metrics for agricultural policies, Linking landscape pattern, ecosystem service and land use management in urbanizing China. *Agric. Syst.* **2020**, *182*, 102833. [CrossRef]
54. Pickett, S.; Cadenasso, M.L. Landscape ecology: Spatial heterogeneity in ecological systems. *Science* **1995**, *269*, 331–334. [CrossRef] [PubMed]

55. Liu, J.; Jin, X.; Xu, W.; Sun, R.; Han, B.; Yang, X.; Gu, Z.; Xu, C.; Sui, X.; Zhou, Y. Influential factors and classification of cultivated land fragmentation, and implications for future land consolidation: A case study of Jiangsu Province in eastern China. *Land Use Policy* **2019**, *88*, 104185. [CrossRef]
56. Xu, W.; Jin, X.; Liu, J.; Zhou, Y. Analysis of influencing factors of cultivated land fragmentation based on hierarchical linear model: A case study of Jiangsu Province, China. *Land Use Policy* **2021**, *101*, 105119. [CrossRef]
57. Liang, J.; Pan, S.; Chen, W.; Li, J.; Zhou, T. Cultivated land fragmentation and its influencing factors detection: A case study in Huaihe River Basin, China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 138. [CrossRef] [PubMed]
58. Chen, W.C.; Chi, G.Q.; Li, J.F. The spatial aspect of ecosystem services balance and its determinants. *Land Use Policy* **2020**, *90*, 104263. [CrossRef]
59. Rogerson, P.A. Historical change in the large-scale population distribution of the United States. *Appl. Geogr.* **2021**, *136*, 102563. [CrossRef]
60. Wang, N.; Fu, X.D.; Wang, S.B. Spatial-temporal variation and coupling analysis of residential energy consumption and economic growth in China. *Appl. Energy* **2022**, *309*, 118504. [CrossRef]
61. Wang, J.F.; Zhang, T.L.; Fu, B.J. A measure of spatial stratified heterogeneity. *Ecol. Indic.* **2016**, *67*, 250–256. [CrossRef]
62. Zhu, L.J.; Meng, J.J.; Zhu, L.K. Applying Geodetector to disentangle the contributions of natural and anthropogenic factors to NDVI variations in the middle reaches of the Heihe River Basin. *Ecol. Indic.* **2020**, *117*, 106545. [CrossRef]
63. Polykretis, C.; Alexakis, D.D. Spatial stratified heterogeneity of fertility and its association with socio-economic determinants using Geographical Detector: The case study of Crete Island, Greece. *Appl. Geogr.* **2021**, *127*, 102384. [CrossRef]
64. Shi, Z.Q.; Deng, W.; Zhang, S.Y. Spatial pattern and spatio-temporal change of territory space in Hengduan Mountains region in recent 25 years. *Geogr. Res.* **2018**, *37*, 607–621. [CrossRef]
65. Chen, W.C.; Zeng, J.; Li, N. Change in land-use structure due to urbanisation in China. *J. Clean. Prod.* **2021**, *321*, 128986. [CrossRef]
66. Chi, G.Q.; Ho, H.C. Population stress: A spatiotemporal analysis of population change and land development at the county level in the contiguous United States, 2001–2011. *Land Use Policy* **2018**, *70*, 128–137. [CrossRef] [PubMed]
67. Feng, C.C.; Zhang, H.; Xiao, L.; Guo, Y.P. Land use change and its driving factors in the rural–urban fringe of Beijing: A Production–Living–Ecological perspective. *Land* **2022**, *11*, 314. [CrossRef]
68. Wang, A.Y.; Liao, X.Y.; Tong, Z.J.; Du, W.L.; Zhang, J.Q.; Liu, X.P.; Liu, M.S. Spatial-temporal dynamic evaluation of the ecosystem service value from the perspective of "production-living-ecological" spaces: A case study in Dongliao River Basin, China. *J. Clean. Prod.* **2022**, *333*, 130218. [CrossRef]
69. Fleming, A.; Wise, R.M.; Hansen, H.; Sams, L. The sustainable development goals: A case study. *Marine Policy* **2017**, *86*, 94–103. [CrossRef]
70. Liao, G.T.; He, P.; Gao, X.S.; Deng, L.J.; Zhang, H.; Feng, N.N.; Zhou, W.; Deng, O.P. The production-living-ecological land classification system and its characteristics in the Hilly Area of Sichuan Province, Southwest China based on identification of the main functions. *Sustainability* **2019**, *11*, 1600. [CrossRef]

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Are Farmers in National Park Communities Willing to Reallocate Their Lands? A Situational Analysis

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Abstract: Limited by China's mixed land ownership model, which is divided into collective and state ownership, national parks' strict ecological protection measures of restricting land use patterns and intensity are subject to the decisions made by collective landowners and contract operators, namely, rural households in national park communities. The disposition and intention of community farmers regarding collective land ownership is related to the nature conservation effect of the national park. In the context of national park land functions for ecological conservation, environmental education, leisure and recreation, scientific research, and "nest eggs" (basic living guarantees), the research on the influencing factors of farmers' intentions to reallocate their land (expropriated or transferred) will provide a basis for a National Parks Administration (NPA) to develop supporting policies for collective land reallocation in different functional zones and to prevent community conflicts. The research took Shennongjia National Park as an example and, combined with literature analysis, used the Structural Equation Model (SEM) to explore the influencing factors of community farmers' land reallocation intentions and drew the following conclusions: farmers' intentions to leave their land for nature conservation purposes and for urbanization purposes are different. In the five land function situations above, farmers' perceptions of land function in national parks did not directly affect their land reallocation intentions, while their trust in the land management ability of NPA was a complete mediator. Farmers' preferences for the economic value of land had no significant moderating effect on land reallocation intentions. Farmers' characteristics have a moderating effect on different land function situation models. Older and less educated farmers are more likely to receive livelihood compensation rather than monetary compensation after leaving their land. Therefore, some management suggestions are put forward, such as strengthening the capacity for building national park land and other natural resources management, adapting to the collective land policy in different function zones, and paying attention to the livelihood compensation of community farmers after they leave the land.

Keywords: community farmers; land reallocation intentions; Shennongjia National Park; structural equation model; situational analysis

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1. Introduction

Establishing a new natural reserve system with national parks as the main body was proposed by the report of the 19th National Congress of the Communist Party of China (CPC) in 2017, noting that China's natural reserve system construction has entered the era of national parks. Land protection measures must be sensitive to the rudiments of these land tenure arrangements. National parks fulfill the important function of protecting national ecological security through strict restriction of land use mode and intensity. The ownership of natural resources such as land directly affect the protection effect [1–4]. Collective Land Ownership and State Land Ownership are the two most dominant forms of land tenure in China and are similar to the complex mosaic of land tenure of rangelands in the United States and other countries [5]. Collective Land Ownership means that the ownership of the land belongs to the village collective, but the farmer households have the contract and management rights to the land and are the actual controllers of the collective land.

If strict protection measures are implemented on the premise that all land under protection is owned by the state, the resistance to strict protection will undoubtedly be greatly reduced. However, this is not the reality. Strategies to amalgamate China's Protected Lands into the national parks structure face dichotomous difficulties. As most lands are under Collective Ownership and the large numbers in the indigenous population [6], strict land management protection measures are bound to be counterproductive and encounter resistance under these conditions of diverse land tenure.

The Overall Plan for the Establishment of a National Park System (2018) calls for "*ensuring that natural resource assets owned by the state occupy a dominant position and are managed with feasibility*". This is to be realized using three distinct strategies, covering the following:

1. Creating a unified, standardized, and highly efficient National Park Management Structure/System,
2. Prioritizing protection of ecological and natural assets, and
3. Prioritizing public and social welfare.

This tripartite objective will result in two important transformations in land management within the new national parks structure. Firstly, the state will expropriate all Collective Lands, and secondly, according to Wang, et al. (2014) [7], it will undertake stringent land use policies that may potentially deprive local communities of important extended living spaces. Under the circumstance that the natural ecosystem and the community in the protected area have been deeply interbedded in China, if all the land is "universally" acquired by the state, although conducive to the realization of the goal of the "unified, standardized, and highly efficient" treatment of the national park, it is not feasible in management. The reasons are as follows.

First, the "one size fits all" expropriation of these lands limits the space for community development, essentially depriving community residents of their sources of livelihood [8]. When an alternative livelihood is not replaced in time, it is easy to cause community conflicts, possibly leading to the destruction of the ecological environment in the community [9]. This has been learned from previous "isolated island" protection practices. Therefore, whether this action can promote the improvement of the efficiency of ecological protection is still debatable. Second, gaps created between the implementation of the national park structure and the possible disruptions in the traditional community socio-economic and cultural activities that are aligned to the land will need to be filled early in the process. It is necessary to defend and protect traditional cultural and social practices. Finally, there are concerns regarding the move of establishing the National Parks System and its ability to eventually promote ecological conservation. This is especially disquieting since there will the need for legislation to expropriate collective lands by the state, which is likely to require some sort of compensation involving land tenure arrangements. This will undoubtedly cause significant pressure on the state's economic resources, due to the sheer number of people involved [10]. Land compensation also places great economic pressure upon the government [8], so the exploration of community protected areas is also required [11]. Accordingly, how to deal with collective land ownership has become an important issue in the pilot process of the national park system.

The Guidance on Establishing a Nature Reserve System with National Parks as the Main Body (2019) was published jointly by the General Office of the CPC Central Committee and the State Office. The Guidelines proposed by the report postulate that, given the principles of volunteerism and compensation, the state should explore strategies to safeguard the rights and interests of property owners. This should also involve approaches that realize the diverse protectionist policies of the collective land tenure arrangements and the social and cultural dynamics of the indigenous and rural populations. These protectionist policies are proposed to be realized in the various natural protected areas by means of lease, relocation and replacement, purchase and cooperation. Formulating strategies unique to each functional zone will eliminate the “one size fits all” approach and leave room for better land management. According to the current functional zoning of national parks, strictly protected areas adhere to the state ownership of land and the orderly expropriation of collective land; the collective land in the general control area is allowed to explore various land circulation methods, such as leasing and redeeming, while the National Park Administration (NPA), on behalf of the state, is responsible for obtaining the management (protection) easement for all the land, limiting the extensive land use mode and intensity [8].This diversified land ownership model not only strictly implements the principle of the national park ecological protection first but also takes into account the needs of community development, so it is a feasible way to solve community conflicts.

In this research, collective land expropriation, transfer, lease, replacement, and other forms of abandoning the original land use and intensity are defined as “land reallocation”. In all forms of land reallocation, the national park will enforce the conservation easement of all collective land to ensure that the use of collective land will not be abused after reallocation to a third party [12]. Of the 10 national parks areas currently across China, approximately 50% have at least one third of the land falling under some Collective Land Ownership regime. As such, the interest of farmers whose land tenure is classified as unclear and collective must be strategically considered, whether their lands are expropriated by the state or allowed to be transferred, to minimizes the farmers’ displacement and disenfranchisement. The NPA must also consider the attitude and perception that the farmers, who are under Collective Land Ownership, have towards land expropriation and relocation. The management of these farmers will determine the overall success of the national parks project [7]. Detecting the willingness and overall attitude of farmers under Collective Land Ownership to abandon their rights to land will undoubtedly complicate the process of establishing China’s national parks project. Consequently, there is a need to determine the factors influencing land surrender and reallocation intentions. Determining the responses to these and other Collective Land Ownership concerns will be an important basis for the formulation of policy and planning for the establishment of national parks. Resolving these concerns will reduce potential community conflicts and foster farmers’ willingness to participate in the project. At the same time, the current academic research on willingness to leave land and its influencing factors almost all focus on the research on land reallocation intentions from the perspective of rural labor transfer or the economy under the background of urbanization [13,14]. In the context of protected nature areas, research on farmers’ willingness to leave land is relatively lacking in situations where the functions of national park land are for ecological protection, environmental education, scientific research, leisure and recreation, “nest eggs”, and so on.

In conclusion, it is an urgent task to clarify the land reallocation intentions of rural households in national park communities under different land function situations. Therefore, the research took Shennongjia National Park as an example, using questionnaire and semi-structured interviews to explore community farmers’ land reallocation intentions and their influencing factors in national parks under different land function situations. We use the Structural Equation Model (SEM) method to investigate the mechanism and causal relationship between farmers perceptions of park land function, farmers’ trust in park land management abilities, farmers’ land economic value preferences, household characteristics, and land reallocation intentions. The research results provide a scientific, reasonable, and effective basis for the Collective Land Ownership disposition of the national parks.

2. Literature Review and Research Hypothesis

2.1. Research Hypothesis

The research attempts to answer three questions: first, what are the factors that influence farmers’ land reallocation intention (LRI) under different situations of land functions in national parks? The integrated approaches of a literature review and the understanding of the reality of China were used to find out the influencing factors of farmers’ land reallocation intentions in national parks. Community farmers’ perceptions about the land function of national parks, land management ability of NPA, characteristics of farmers, and farmers' preferences of land economic value were taken as influencing factors for land reallocation intention. Second, how do the influencing factors affect the land reallocation intention? The Structural Equation Model (SEM) is used to reveal the mechanism of action. Third, is there a difference in the land reallocation intentions for the purpose of urbanization vs. that for nature conservation? A comparative study was applied to infer the differences of farmers' land reallocation intentions against the background of nature conservation and urbanization.

Therefore, based on practical experience and existing research literature, this study proposed the following hypotheses:

Hypothesis 1 (H1). *Community farmers' perceptions of national park land function (PNPLF) affect their land reallocation intention (LRI).*

According to cognitive behavioral theory, farmers' land reallocation intentions are affected by their perception of land functions [15,16]. Land function is different from land value [17], but a large amount of the literature does not clearly distinguish between land function and land value. This research considers that land value is the economic manifestation of land function. To some extent, land value assessment can urge landowners to pay attention to ecological protection, scientific research, cultural carriers, and other functions of land. Farmers' land values have a certain degree of influence on land reallocation intentions. Wang et al. (2018) hold that the consistent relationship between farmers' cognition and behavior regarding farmland ownership adjustment is an important content of theoretical research on farmland ownership adjustment [18]. There is also much research on the relationship between land function perception and land reallocation intention. For example, Xu (2014) studied the relationship between land function preferences and farmland reallocation and proved that farmers' different preferences for land functions had different degrees of influence on the transfer intention [19].

Land functions are expanding with the development of society and the change of demand. Agricultural land had multiple functions [20]. At the practical level, the function of farmland depends on the nation demand for land use. Land function is situational, and different land use situations determine the various land functions. Therefore, the land function of national parks in China is different from general agricultural land. The primary function of farmland is mainly a supply function, including a production function and carrier function. The former refers to food production and cash crop planting, while the latter mainly refers to the carrying of traditional culture and values, which is a non-economic factor [21]. In the context of China, as the land has been dominated by farming culture since ancient times, land is also the source of livelihood for farmers and the basic guarantee for their pension, employment, medical care, and life necessities [22]. Therefore, agricultural land has the "nest egg" function, which means a basic living guarantee. The land ownership policy of national parks cannot deprive farmers of basic living security, and the land "nest egg" function still needs to be realized within the scope of national parks. Moreover, according to the Guidelines for the National Park Function Zoning, which is a Forestry Industry Standard of the People's Republic of China (LY/T2933-2018), the functional zoning of national parks is divided into strictly protected zones, ecological conservation zones, traditional utilization zones, and environmental education zones. Consequently, land functions of national parks should also include ecological conservation, recreation, scientific research, environmental education, and so on. To sum up, the hypothesis is proposed as follows: land functions that include the ecological conservation function (ECF), nest egg function (NEF), leisure and recreation function (LRF), scientific research function (SRF) and environmental education function (EEF) will affect the land reallocation intention (LRI).

Hypothesis 2 (H2). *Farmers' trust in the land management ability (TLMA) of the national parks administration is the mediating factor between the perception of land function and land reallocation intention.*

Studies have shown that farmers' willingness to transfer land will be affected by the credibility of the government. Farmers with high trust in the government have higher willingness to transfer land. For example, Wang et al. (2017) and Pu et al. (2018) concluded through case studies that farmers with high trust in the government have higher willingness to transfer agricultural land [23,24]. On the premise of high trust in the government, the probability of mass conflicts in the process of land expropriation will be low [25,26]. The failure of government behavior to meet public psychological expectations is the main reason for reducing government credibility [27]. The promotion of management or governance ability to credibility has been verified in relevant studies [28].

In the context of national parks, the NPA manages and operates the national parks on behalf of the central government, and its management ability is one of the main factors affecting credibility. When the land management ability of NPA is not sufficient to meet the expectations of community farmers, or the community farmers are full of doubts about the land management ability of NPA, this is likely not only to affect the community farmers' trust in NPA but also the farmers' land reallocation willingness. Therefore, TLMA is taken as a mediator, and we discuss its influence mechanism on LRI.

Hypothesis 3 (H3). *Farmers' land preferencse for economic value (PEV) in the national park have a moderating effect on LRI.*

The preference for the economic value of land will lead to large differences in farmers' willingness to relocate from land [16]. Based on the survey data of farmers in Shuyang County, Jiangsu province, Zhao et al. (2012) concluded that the direct economic value of land (grain production, etc.) was negatively correlated with farmers' willingness to leave their land, while the indirect economic value, such as the expectation of land transfer (rent per unit area), was positively correlated with their land reallocation intention [15]. Yang et al. (2013) conducted a questionnaire survey among rural households in suburban villages and suburban villages in Hongta District, Yuxi City, Yunnan, China and found that rural households' awareness of land compensation function was lower than that in suburban villages, which would affect farmers' willingness to transfer land to some extent [29]. Xu (2014) conducted an empirical study on peasant households' willingness to transfer land in developed and undeveloped regions and proved that peasant households in developed regions preferred the property function of land, and the economic value of land was relatively high [19]. The land reallocation could bring them higher economic income and guarantee their living standards. Therefore, peasant households in developed regions had a strong desire to leave their land. However, farmers in undeveloped areas prefer the land production function, and the economic income brought by land reallocation is not high, so the land reallocation intention in undeveloped areas is low [16]. Previous research has shown that the economic development level will affect farmers' cognition of the land's economic function. When land brings considerable indirect economic income, such as rent and compensation, farmers tend to transfer land and have a stronger desire to reallocate land. However, in the case of natural ecological protected areas, how farmers' preference for the economic value of land affects their willingness to leave the land remains to be verified. Therefore, this study proposes the hypothesis that farmers' land economic value preference has a moderating effect on land reallocation intention in national parks.

Hypothesis 4 (H4). *The household characteristics (HC) of the national park community have a moderating effect on the LRI.*

The research defines the characteristics of farmers as individual characteristics and family characteristics [30]. In the existing literature on farmers' reallocation intention, individual factors of farmers include their education level, age, and gender [30,31]. The type of landowner is related to the way the land is used [32], and thus the characteristics of the farmers must be considered. The characteristics of peasant households include household resources (whether they have off-farm employment skills) [15,31] and the percentage of agricultural income making up their total income [33]. The higher the proportion of agricultural income in the total household income, the lower the willingness to engage in land transfer [16]. Farmers' willingness to leave land is closely related to off-agricultural employment to a large extent [15].

In conclusion, combined with the national park context, the research proposes the hypothesis that the characteristics of farmers in the national park community have a moderating effect on farmers' willingness to leave the land. Characteristics of farmers include age, education, household income, and off-farm employment skills.

2.2. Theoretical Model Construction

Based on the four research hypotheses proposed above, we constructed a theoretical model of influencing factors of farmers' land reallocation intention in national parks (Figure 1). Although the theoretical model is based on the research results of influencing factors of farmland ownership adjustment under the background of rapid urbanization, it also considers the land function demands of national park ecological protection, leisure and recreation, scientific research, environmental education, basic living guarantees, and the role of farmers' trust in the land management ability of NPA.

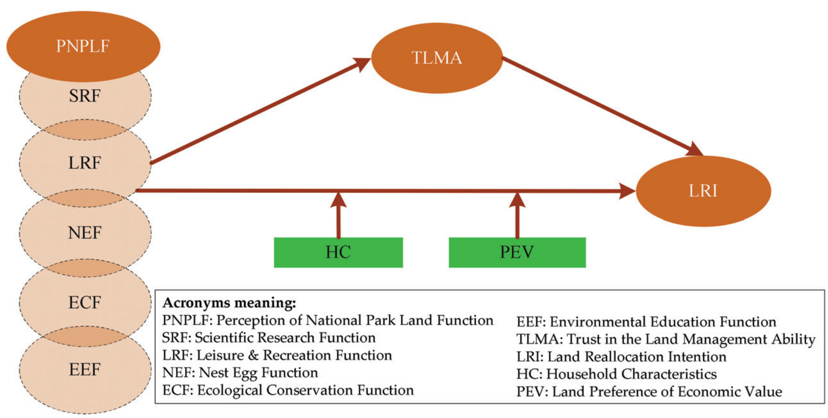

Figure 1. The conceptual model.

3. Overview of the Research Area

The system pilot area of Shennongjia National Park, which is also a World Natural Heritage Area, is located in the southwest of Shennongjia Forest district, Hubei province, covering an area of 1169.88 km^2, accounting for 35.97% of the total area of Shennongjia Forest district. The national park includes Jiuhu Town, Xiaguping Town, Muyu Town, Hongping Town, and Song Luo township. According to the General Plan of Shennongjia National Park (hereafter referred to as The Plan), the state-owned land area of the park system pilot area is 1005.79 km^2, and the collective land area is 164.09 km^2. During the system pilot period (2016–2020), the southern land of Shennongjia Forest district was entrusted to Shennongjia National Park. After the end of the pilot period (2021–2025), the trust area will be officially included in the Shennongjia National Park. The total area of the national park will be increased to 1325.06 km^2, of which the collective land area will be increased to 307.37 km^2, accounting for 23.2% of the total area of the national park. The general situation of land ownership in Shennongjia National Park is shown in Figure 2. During the vision planning period (2026–2030), the area of the park will be extended to the whole Shennongjia area, and Hubei Padong Golden Monkey National Nature Reserve and Hubei Longmen River National Forest Park will also be included in the vision planning area of the park.

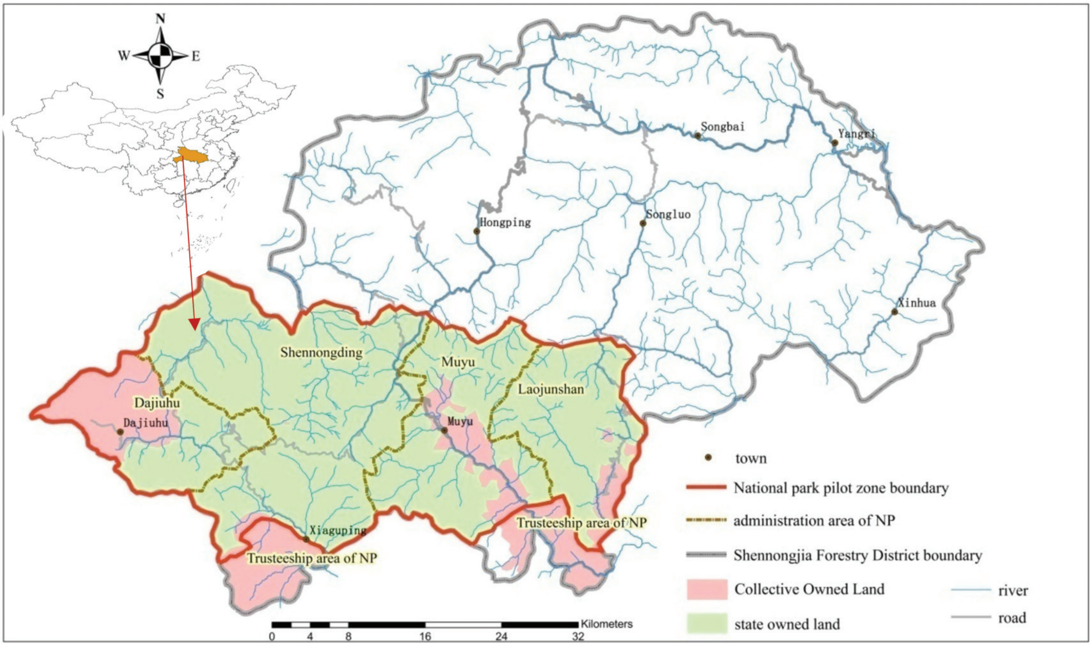

Figure 2. Land ownership of Shennongjia National Park.

The gradual expansion of Shennongjia National Park in different stages of development in The Plan is a temporary solution to the current tense relationship between people and land. In the pilot phase, the zoning of Shennongjia National Park deliberately avoided collectivized land and densely populated areas. Shennongjia Forest district has a population of nearly 80,000, and the relationship between people and land is complicated. Hongping Town and Songluo Township in the north of the park are more densely populated, with more development activities and complex land ownership, so they were partly excluded from the scope of the national park during the pilot period. Xiaguping township and the southern area of Muyu Town were designated as the national park trust area. Among them, 92.33% of the trust area is collective land, which can avoid community conflicts and financial pressure caused by land ownership. However, according to the long-term planning of Shennongjia National Park, the area of the park will be gradually expanded in the future, and the areas mentioned above with complicated land property rights will be gradually assigned to the national park, and the land ownership problem will gradually become prominent. In this context, this study not only provides a basis for making policies on the transfer or reallocation of collectively owned land in the current pilot areas but also lays a foundation for making land policies in the future expansion of national parks.

4. Methodology

4.1. Survey Questionnaire Design

On the basis of literature analysis, and in combination with the situational design questionnaire for national parks, the research contains 32 observed variables. Among them, 27 observed variables were combined into 7 latent variables (shown in Table 1). The 7 latent variables are as follows: farmers' perception of land ecological conservation function (ECF), land environment education function (EEF), leisure and recreational function (LRF), "nest egg" function (NEF), scientific research function (SRF), land reallocation intentions (LRI), and farmers' trust in the land management ability (TLMA) of the NPA. The other 5 observed variables covered the farmers' preference of economic value (PEV) and the 4 characteristics of farmers: age, education, family income, and off-farm employment skills. Except for the 4 household characteristic variables, all other observed variables were measured by a 5-level Likert scale.

Table 1. The *CR* and *AVE* of the scale based on CFA.

Latent Variable	**Items**		***Std* (λ)**	***SMC* (θ)**	***Cronbach' Alpha* (α)**	***CR***	***AVE***
Ecosystem Conservation Function (ECF)	A6	Forest, grassland, and other land ecosystems are the main ecosystems on the earth.	0.714	0.509	0.930	0.930	0.655
	A7	Humans are not the only owners of the land. The land is also home to plants and animals.	0.794	0.631			
	A8	Land is the foundation of the growth of all living things and the space carrier of natural ecosystem.	0.870	0.756			
	A9	Land is the carrier of traditional culture, and the destruction of land ecology will affect the inheritance of traditional culture.	0.753	0.567			
	A10	National parks are nature protected areas, and their land use should be based on ecological protection.	0.859	0.738			
	A11	The land can be used for vegetation growth to regulate climate, purify the environment, and reduce noise pollution.	0.832	0.692			
	A12	The conservation of the land ecology in national parks preserves development opportunities for future generations.	0.832	0.691			
Nest Eggs Function (NEF)	A13	Land can provide a minimum livelihood for family members.	0.723	0.523	0.857	0.862	0.678
	A14	Land gives family members pension security.	0.874	0.764			
	A15	Land can provide unemployment insurance for family members.	0.864	0.746			
Leisure & Recreation Function (LRF)	A16	National park land is the carrier of natural and cultural tourism resources.	0.786	0.617	0.884	0.880	0.647
	A17	National park land provides space for human recreation and leisure activities.	0.752	0.565			
	A18	The recreation and leisure industry of a national park can provide employment chances for the local community and promote incomes of local families.	0.828	0.685			
	A19	The development of national park tourism industry can activate tradition culture, and the tradition culture can be inherited.	0.848	0.719			

Table 1. *Cont.*

Latent Variable		Items	*Std* (λ)	*SMC* (θ)	*Cronbach' Alpha* (α)	*CR*	*AVE*
Scientific Research Function (SRF)	A20	The land ecosystem is the vital research subject in the science area.	0.784	0.615	0.881	0.876	0.703
	A21	The land science research works try to balance the relationship between development and conservation and provide the basis for wise land use.	0.821	0.674			
	A22	Land science knowledge is the significant content of environment education.	0.905	0.819			
Environmental Education Function (EEF)	A23	Environment education in a national park can enable people to understand the land ecosystem and increase environment protect knowledge.	0.900	0.810	0.917	0.917	0.786
	A24	Environment education in a national park can promote people's awareness of environment protection.	0.875	0.766			
	A25	Environment education in a national park can cause people to engage in environment protection behavior.	0.884	0.782			
Trust in Land Management Ability (TLMA)	A26	The national park service knows better how to preserve the land ecological environment.	0.797	0.634	0.851	0.853	0.593
	A27	The national park service knows better how to wisely explore and use land.	0.812	0.659			
	A28	The national park service can obtain land ownership with important ecological functions.	0.752	0.565			
	A29	The national park service has the power to regulate the use of all land within the park.	0.716	0.512			
Land Reallocation Intention (LRI)	A30	If monetary compensation is reasonable, I am willing to transfer land property to the national park.	0.799	0.638	0.858	0.858	0.669
	A31	If national parks provide alternative livelihoods, I am willing to transfer land property to the national park.	0.875	0.765			
	A32	I prefer livelihood security to monetary compensation in terms of land reallocation.	0.777	0.604			

4.2. Questionnaire Distribution

Questionnaires were distributed to Xiaguping, Muyu, and Dajiuhu in Shennongjia National Park. In total, 170 questionnaires were distributed in two periods, which covered July 2019 and then July 2020. In total, 281 questionnaires on network communication were collected from December 2020 to February 2021 through the Shennongjia National Park Administration and Shennongjia poverty alleviation work QQ group. The departments of Shennongjia National Park Administration, including the Community Affairs, Policies, and Publicity and Education Division frequently communicate with community farmers in their daily work. The staff in the above-mentioned departments shared the QR code or link for the online questionnaire to the farmers when they were working in the villages, and the farmers filled in the questionnaire online and submitted it directly. In addition, as the Shennongjia National Park has a large number of farmers scattered living in the mountains more than 1000 m above sea level, it was difficult for researchers to collect questionnaires on a large scale. As a result, in our research, the staff in the Shennongjia poverty alleviation work QQ group assisted in issuing questionnaires to reduce costs and improve work efficiency. Finally, a total of 451 questionnaires were issued in this study. Among these, 121 questionnaires were collected from Xiaguping, 213 from Dajiuhu, and 117 from Muyu. In order to avoid the high redundancy in the questionnaire, the researchers only collected one questionnaire for each peasant household.

4.3. The Questionnaire Response

All questionnaire responses were reviewed, and invalid questionnaires were deleted. The identification of invalid questionnaires followed these criteria: first, for the network recovered questionnaires, we judged whether the questionnaires were from the same IP address according to the submission time (the questionnaires filled from the same IP address were invalided and deleted). Second, the standard deviation of all samples was tested, and each sample with a standard deviation of 0 or close to 0 was deleted. Finally, questionnaires with missing values were marked invalid, and the missing values were deleted or supplemented with the mean value, which did not exist in all questionnaires collected in this study. In accordance with the above principles, 61 invalid questionnaires were removed from the recovered questionnaires, and a total of 390 questionnaires were finally used in the research. The effective rate of the questionnaire was 86.47%.

5. Research Results and Analysis

5.1. CFA Test of Scale Reliability and Validity

5.1.1. Composite Reliability and Convergence Validity

Mplus7.4 was used to perform Confirmatory Factor Analysis (CFA) for the seven latent variables in the oblique models to obtain the standard indicator loading estimate and *Squared Multiple Correlations* (*SMC*) of observe variables. Then, the Composite Reliability (*CR*) and Average of Variance Extracted (*AVE*) of latent variables were calculated. In this research, *AVE* is represented by the Convergence Validity (*CV*). Traditionally, the most common indicator of calculating the scale or testing reliability is *Cronbach's Alpha* (α), where, in congeneric tests with unrelated errors, the α underestimates the reliability except for tests where τ is equivalent [34], and when the error is positively correlated, the α coefficient will overestimate the reliability. After the application of the CFA method, *CR* and *AVE* were used to calculate the internal consistency reliability [35,36]. The calculation formulas are shown in Formulas (1) and (2):

$$CR = \frac{(\sum\lambda)^2}{\left[(\sum\lambda)^2 + \sum(1-\theta)\right]} \tag{1}$$

$$AVE = \frac{(\sum\lambda^2)}{[(\sum\lambda^2) + \sum(1-\theta)]} \tag{2}$$

where λ is the standardized factor loading estimate value, and θ is *SMC*. The composite reliability and convergence validity of latent variables in the scale are shown in Table 1. SPSS22.0 was used to calculate the *Cronbach's Alpha* (α) of the scale.

First, the higher the *CR* value, the higher the internal consistency, where 0.7 is the acceptable threshold. Fornell and Larcker (1981) suggested a value of 0.6 or above as acceptable. Table 1 shows that the minimum *CR* value and *Cronbach's Alpha* (α) of the latent variables in the scale are 0.853 and 0.851, respectively, which are ideal, indicating that the internal consistency of all latent variables is high. *AVE* then shows how much variation explained by potential variables is from measurement error. If *AVE* is higher, the percentage of variation explained by latent variables is higher, and the relative measurement error is smaller, which implies that the questionnaire has higher reliability and convergence validity. The ideal value should be greater than 0.5 [37], with 0.36~0.5 as the acceptable threshold. Table 1 shows that the AVE value of latent variable is at least 0.593, which is close to ideal.

Finally, the standardized factor load estimation values of all observed variables in the scale were all greater than 0.7, and *SMC values* were all greater than 0.5, which was ideal.

5.1.2. Discriminant Validity

There are various methods to verify Trauernichant validity, such as mean variation extraction [37], competitive model comparison [38], and the confidence interval method of correlation coefficients [39]. If the correlation between latent variables is below the absolute value of 0.7, the *AVE* method can be used for evaluation. If the correlation between latent variables is above the absolute value of 0.7, it is recommended to use the confidence interval method for estimation [40]. The correlation values of some latent variables in Table 2 were greater than 0.7, and the confidence interval method was used to test the discriminant validity of the scale by repeating the sampling 2000 times and calculating the 95% Confidence Interval (CI) of the correlation coefficient. If by calculating $\Phi \pm 2\sigma$, the bias-corrected and percentile method to calculate the correlation coefficient between the latent variables of the CI does not contain a value of 1.0, this shows good discriminant validity [31,33,39]. As shown in Table 2, the CI of the correlation coefficient calculated by the above three methods didn't contain 1.0. Therefore, the latent variables set in this research have good discriminant validity.

Table 2. Discriminate validity results.

Pairs of Correlation			Estimate	S.E.	$\Phi \pm 2\sigma$		95% CI					
							Bias-Correct			Percentile		
					Lower	Upper	Lower	Upper	p	Lower	Upper	p
NEF	↔	LRF	0.513	0.052	0.409	0.617	0.362	0.654	0.001	0.351	0.649	0.001
NEF	↔	SRF	0.448	0.055	0.338	0.558	0.295	0.597	0.001	0.286	0.587	0.001
NEF	↔	EEF	0.485	0.052	0.381	0.589	0.341	0.628	0.001	0.327	0.621	0.001
NEF	↔	TLMA	0.495	0.054	0.387	0.603	0.342	0.626	0.001	0.340	0.625	0.001
NEF	↔	LRI	0.502	0.053	0.396	0.608	0.357	0.644	0.001	0.357	0.644	0.001
NEF	↔	ECF	0.348	0.058	0.232	0.464	0.158	0.521	0.001	0.158	0.521	0.001
LRF	↔	SRF	0.866	0.024	0.818	0.914	0.788	0.930	0.001	0.779	0.924	0.001
LRF	↔	EEF	0.887	0.020	0.847	0.927	0.817	0.940	0.001	0.813	0.938	0.001
LRF	↔	TLMA	0.766	0.034	0.698	0.834	0.671	0.850	0.001	0.660	0.845	0.001
LRF	↔	LRI	0.710	0.039	0.632	0.788	0.587	0.812	0.001	0.586	0.811	0.001
LRF	↔	ECF	0.765	0.031	0.703	0.827	0.605	0.877	0.001	0.607	0.878	0.001
SRF	↔	EEF	0.850	0.024	0.802	0.898	0.769	0.921	0.001	0.762	0.915	0.001
SRF	↔	TLMA	0.730	0.037	0.656	0.804	0.603	0.845	0.000	0.584	0.834	0.000
SRF	↔	LRI	0.592	0.047	0.498	0.686	0.437	0.718	0.001	0.437	0.716	0.001
SRF	↔	ECF	0.734	0.033	0.668	0.800	0.580	0.830	0.002	0.597	0.839	0.001
EEF	↔	TLMA	0.782	0.031	0.720	0.844	0.670	0.868	0.001	0.660	0.859	0.001
EEF	↔	LRI	0.709	0.038	0.633	0.785	0.584	0.818	0.001	0.579	0.815	0.001
EEF	↔	ECF	0.688	0.036	0.616	0.760	0.532	0.803	0.001	0.534	0.804	0.001
TLMA	↔	LRI	0.819	0.032	0.755	0.883	0.713	0.898	0.001	0.701	0.896	0.001
TLMA	↔	ECF	0.603	0.045	0.513	0.693	0.438	0.741	0.001	0.437	0.740	0.001
LRI	↔	ECF	0.547	0.048	0.451	0.643	0.367	0.679	0.001	0.376	0.685	0.001

5.2. Model Validation

5.2.1. Model Fitting Degree

Mplus7.4 was used to verify the five scenario models of ECF, EEF, LRF, SRF, and NEF, and the fitting indicators are shown in Table 3. According to the judgment criteria, in five situations, except when the land has the function of environmental education (EEF), the model fitting indicator is not satisfactory, and other models all meet the fitting standard.

Table 3. Test of fitting degree of SEM.

Fit Indicator	Criteria	Scenario Model				
		ECF	NEF	LRF	SRF	EEF
X^2	The smaller, the better	184.999	70.389	116.632	85.064	156.971
$\frac{X^2}{df}$	<3	2.569	2.271	2.926	2.744	5.064
CFI	≥0.9	0.960	0.977	0.962	0.970	0.940
TLI	≥0.9	0.950	0.966	0.948	0.957	0.913
RMSEA	≤0.08	0.074	0.066	0.081	0.078	0.118
SRMR	≤0.08	0.050	0.047	0.044	0.041	0.054

5.2.2. Path Coefficient and Significance

Table 4 shows the non-standardized coefficient and significance of the influencing factors model of farmers' land reallocation in different situations. Farmers' perception of five types of land functions and the direct influence of land reallocation intention is not significant.

Table 4. Unstandardized path coefficients and significance of the model.

Scenario	Path			Estimate (Regression Weight)	S.E.	Est./S.E.	Two-Tailed p-Value
ECF	TLMA	←	ECF	0.495	0.109	4.451	***
	LRI	←	TLMA	0.998	0.156	6.415	***
	LRI	←	ECF	0.134	0.096	1.399	0.162
NEF	TLMA	←	NEF	0.429	0.093	4.635	***
	LRI	←	TLMA	1.018	0.158	6.426	***
	LRI	←	NEF	0.138	0.095	1.455	0.146
LRF	TLMA	←	LRF	0.690	0.109	6.312	***
	LRI	←	TLMA	0.882	0.187	4.718	***
	LRI	←	LRF	0.240	0.172	1.397	0.162
SRF	TLMA	←	SRF	0.616	0.095	6.460	***
	LRI	←	TLMA	1.068	0.214	5.003	***
	LRI	←	SRF	−0.015	0.175	−0.086	0.932
EEF	TLMA	←	EEF	0.603	0.107	5.637	***
	LRI	←	TLMA	0.877	0.195	4.502	***
	LRI	←	EEF	0.206	0.160	1.292	0.196

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The above research results do not show the research conclusion that the perception of land function directly affects the land reallocation intention but indirectly affects the land reallocation intention through the mediating variable of TLMA. Hypothesis 1 and Hypothesis 2 were found to hold. Table 5 shows that the mediating effect of TLMA is obviously different in the five situations, and the situations where the mediating effect is from strong to weak are SRF (0.658), LRF (0.609), EEF (0.529), ECF (0.494), and NEF (0.437). The data show that when the land is used for scientific research, leisure, or environmental education, it is necessary for farmers to gain enough trust in the land management ability of NPA for them to leave the land. The reason is that scientific research, leisure, and environmental education in national parks are not land functions in the common sense, and farmers have limited knowledge of the land functions of the above national parks, requiring the NPA to make more efforts to gain farmers' trust in their land management capabilities. In actuality, when the main function of land is ecological protection or living security, it is necessary to gain less trust in the land management ability of NPA, and farmers will then leave the land for it. The Chinese government initiated two nation-wide conservation policies in the late 1990s: the Natural Forest Conservation Program and the Grain-To-Green Program [41]. The Shennongjia Forest district is also involved in the two projects, and as a result, natural forest harvesting has been completely stopped. Farmers' awareness of ecological protection has a long history, and the concept of reforestation in mountains and changing production has already taken shape. Farmers have benefited a great deal from the tourism industry, and their livelihood does not depend entirely on the consumption of natural resources. Therefore, farmers trust the government's land management ability in terms of ecological protection and the ability to guarantee their basic livelihood.

Table 5. Path coefficient and significance of PEV moderating effect model.

Scenario model	Path			Estimate (Regression Weight)	S.E.	Est./S.E.	Two-Tailed *p*-Value
ECF	LRI	←	TLMA	0.977	0.147	6.628	***
	LRI	←	ECF	−0.084	0.262	−0.322	0.747
	LRI	←	**ECF * PEV**	−0.034	0.036	−0.929	0.353
	LRI	←	PEV	0.187	0.280	0.669	0.504
	TLMA	←	ECF	0.519	0.111	4.691	***
NEF	LRI	←	TLMA	0.940	0.160	5.883	***
	LRI	←	NEF	0.023	0.117	0.199	0.843
	LRI	←	**NEF * PEV**	0.020	0.083	0.237	0.813
	LRI	←	PEV	0.323	0.187	1.731	0.083 (*)
	TLMA	←	NEF	0.449	0.094	4.783	***
LRF	LRI	←	TLMA	0.873	0.182	4.796	***
	LRI	←	LRF	0.049	0.359	0.138	0.891
	LRI	←	**LRF * PEV**	−0.047	0.042	−1.119	0.263
	LRI	←	PEV	0.183	0.368	0.498	0.618
	TLMA	←	LRF	0.711	0.108	6.567	***
SRF	LRI	←	TLMA	1.032	0.205	5.042	***
	LRI	←	SRF	−0.380	0.312	−1.217	0.224
	LRI	←	**SRF * PEV**	−0.068	0.039	−1.747	0.081 (*)
	LRI	←	PEV	0.457	0.355	1.287	0.198
	TLMA	←	SRF	0.636	0.096	6.651	***
EEF	LRI	←	TLMA	0.846	0.185	4.585	***
	LRI	←	EEF	0.070	0.217	0.321	0.748
	LRI	←	**EEF * PEV**	−0.030	0.035	−0.868	0.385
	LRI	←	PEV	0.190	0.226	0.839	0.401
	TLMA	←	EEF	0.627	0.111	5.647	***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3. Test of Moderating Effect

5.3.1. Moderating Effect of PEV

The purpose of this research was to investigate whether PEV is the moderator between the perceptions of land function and land reallocation intention by using Latent Moderated Structural Equations (LMSE). LMSE model analysis results are shown in Table 5. In the scenario model of NEF, ECF, EEF, and LRF, the interaction term of PEV and land function has no significant influence on LRI, so the variable PEV has no significant moderating effect on LRI. In the scenario model of SRF, the PEV negatively affects LRI only at the significance level of 10%. The analysis results reject Hypothesis 3.

The conclusions presented by the analysis above are not consistent with the previous research [19] against the background of urbanization, which holds that the higher the PEV is, the stronger the LRI is. A study in India shows that states with more rental-market activity feature less misallocation and reallocate land more efficiently over time [42]. The Shennongjia National Park, the case of this study, is located in Shennongjia Forest district, Hubei Province. Since the implementation of the Natural Forest Conservation Program and the Grain-To-Green Program in this administrative region in the late 1990s, ecological protection policy has been put into practice for almost 20 years and has become solidified in farmers' ideology. This land is located in a mountainous area, and the topographic and geomorphic conditions with a large slope are not suitable for large-scale urbanization development, so the land does not show economic value under the background of urbanization. It is unrealistic and difficult for farmers to obtain high economic returns through land transfer or expropriation. As a result, in the four situations where land functions are ecological conservation, "nest eggs", leisure and recreation, and environmental education, the moderating effect of PEV on farmers' LRI is not significant. This conclusion is in line with the conclusions of Yang et al. (2013) and Xu et al. (2014) that farmers in underdeveloped areas and distant suburbs do not have a strong perception of the economic value of land [19,29]. Under the condition that the land function is for scientific research, farmers have a low perception of the local economic value of land, which is also the actual situation in such cases, so farmers are inclined to transfer land under these circumstances. However, when the economic value of the land is high, farmers will keep the land, and the NPA must gain enough trust from farmers to improve the willingness of farmers to leave the land. This shows that when national parks realize the function of scientific research, NPA play an important role in LRI. It also implies that farmers do not quite understand and recognize the scientific research function of national parks.

5.3.2. Moderating Effect of HC

Multiple group analysis is used to explore whether group variables (farmer characteristics) have the function of moderating the theoretical model. The software AMOS21.0 was used for multi-group analysis of the samples. According to age, education level, household income, and off-farm employment skills, the sample was divided into high and low groups to measure the differences in LRI between the two groups, as shown in Table 6.

Table 6. Grouping according to sample characteristics.

Characteristics		Grouping Criterion	Low Group	High Group
Personal characteristics	Age	The low group is under 25 years of age; age 25 and above is the high group.	247	143
	Education	Tertiary education and above are in the high group; below college education level is the low group.	136	254
Household	Household income	Ministry of Agriculture: In 2017, the per capita disposable income of rural residents is about 13,000 yuan. Based on the three members of a nuclear family, incomes of 40,000 yuan and above are classified as the high group. The low group earns 40,000 yuan or less.	202	188
	Off-farm employment skills	Non-agricultural employment skills were sorted into the high group; skills without off-farm employment were sorted into the low group.	121	269

The purpose of this study was to test whether the model path has unique structure invariance between different groups by conducting the test for partial invariance through AMOS21.0. According to the research literature of Wen et al. (2005), Zhao (2007), and Xu (2010), we followed the steps listed below [43–45].

First, the data were grouped according to the characteristics of farmers. Second, we set the two models, namely the Unconstrained Model and Structural Weights Model: the Unconstrained Model was not limited to any parameters, while the Structural Weights Model defined two groups in which the latent variable path regression coefficient was equal. The above two models form the Nested Model, and we determined the signifcance of $\Delta\chi^2$ in Δdf. As if $\Delta\chi^2$ reached a significant level ($p < 0.01$, $p < 0.05$ or $p < 0.1$), this indicated that the model path had no causal structural invariance in different groups; that is, the group variables (characteristics of farmers) had a moderating effect on the model. The model's χ^2/df, CFI, TLI, RMSEA, SRMR are basically within the ideal range, with a good fitting degree. The significance of the comparison results of the Nested Model is shown in Table 7.

Table 7. The significant of Nested Model comparisons (*p*-value).

Scenario \ Characteristics	Age	Education	Income	Off-Farm Skill
NEF	0.009 (***)	0.003 (***)	0.006 (***)	0.009 (***)
ECF	0.013 (**)	0.132	0.000 (***)	0.326
LRF	0.213	0.002 (***)	0.256	0.024 (**)
SRF	0.078 (*)	0.001 (***)	0.042 (**)	0.230
EEF	0.408	0.406	0.165	0.094 (*)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

By combining the path coefficient of multiple groups and data in Table 7, the following results were obtained. The unreported path coefficients were insignificant.

Age has a significant moderating effect on the scenario models of NEF, ECF, and SRF. In the NEF scenario model, the mediating effect was 0.215 in the high group and 0.656 in the low group, and the direct effect was 0.188 in the high group. The mediating effect of the ECF scenario model was 0.224 in the high group and 0.521 in the low group, and the direct effect was 0.159 in the low group. The mediating effect of the SRF scenario model was 0.372 in the high group and 0.649 in the low group. It can be seen that the LRI of the low group is stronger. Against the background of China's current urbanization, the rural hollowing out phenomenon is becoming increasingly serious—the elderly and children were left behind on the land, and the young migrant workers were more likely to give up land—especially when the land functions only for nest eggs, ecological conservation, and scientific research, land does not directly bring economic benefits. The low age group of farmers were not attracted by land, and they were more likely to give up land. On the other hand, due to the lack of off-farm skill learning ability, high group farmers were more inclined to stay on the land to obtain basic security. When the land function is leisure and recreation and environmental education, age does not have a significant moderating effect on the model. In the LRF scenario model, the mediator effect of the low group was 0.791, the direct effect was 0.298, and the mediating effect of the high group was 0.459. In the EEF scenario model, the mediating effect of the low group was 0.571, the mediating effect of the high group was 0.324, and the direct effect was 0.422. As recreation and ecological education can bring direct economic benefits to local communities and promote community development, communities have a higher degree of support for the construction of national parks, which is reflected in the willingness of farmers to hand over their land to the NPA regardless of their age level.

Education shows a very significant moderating effect on the scenario models of NEF, LRF, and SRF. Forest persistence was positively affected by increases of basic education percentage [46]. In the NEF scenario model, the direct and mediating effects of the low group are significant, the sum of which is 0.410, while the mediating effects of the high group are only slightly significant, at 0.644. In the LRF scenario model, the LRI of the low group is only affected by the mediation path, with a mediation effect of 0.436. The direct and mediating effects of high group farmers on LRI were 0.335 and 0.683, respectively, and the sum of the effects was 1.018. In the SRF scenario model, the LRIs of farmers in the low group and the high group were only affected by the mediation path, and the mediating effect was 0.319 and 0.703, respectively. Thus, it can be seen that farmers with a higher education level have a better understanding of the functions of land for nest eggs, leisure and recreation, and scientific research in national parks and are more willing to leave the land in order to realize these functions. In addition, they will consider whether the NPA has enough ability to manage these lands well when they leave the land.

Family income has a significant moderating effect on the scenario models of NEF, ECF, and SRF. In the NEF scenario model, the direct effect of the low group was 0.230, the mediating effect was 0.545, and the sum of the effects was 0.775. In the high group, only the mediating effect was significant, at 0.315. In the ECF scenario model, farmers' LRIs were only affected by the mediation path, and the mediating effects of the low group and the high group were 0.565 and 0.223, respectively. Thus, when the land function is for nest eggs and ecological conservation, the added value of land cannot be reflected, and the direct benefits brought by it are low. Farmers in the low-income family group are more inclined to give up the land and seek for a more sustainable kind of livelihood. In the SRF scenario model, farmers' cognition of the land's scientific research function can only affect the LRI through the mediating variable, and the mediating effects of the low group and the high group are 0.586 and 0.662, respectively. This reveals that farmers will give up their land only if they have enough trust in the NPA, and farmers in high income families are more willing to give up land. This also shows that farmers do not quite understand the scientific research function of national parks, and the NPA needs to strengthen the publicity of the scientific research function of national parks.

Off-farm employment skills have a significant moderating effect on the scenario models of NEF, LRF, and EEF. The mediating effect and direct effect of the EEF scenario model were both present. The mediating effect of the low group was 0.411, the direct effect was 0.342 and the sum was 0.753. In the high group, the mediating effect was 0.523, the direct effect was 0.177, and the sum was 0.700. The sum of the two groups of effects was basically the same. When the land function was environmental education, there was no significant difference in LRI, regardless of off-farm employment skills. However, in the NEF scenario model, farmers only generated land reallocation intentions through the mediation path, with the mediating effect of 0.550 in the low group and 0.391 in the high group. In the LRF scenario model, the LRI of the low group was not significant, while the LRI was generated by the high group only through the mediating path, with a mediating effect of 0.583. This indicates that when the land function is for leisure and recreation and life security, farmers will only give up the land if they have enough trust in the NPA. At the same time, when the land function is leisure and recreation, farmers with off-farm employment skills are more likely to give up the land. These farmers will make use of their off-farm employment skills to benefit by participating in leisure and recreation, such as catering, accommodation, and other reception businesses or providing guide services. When the land function is life security, farmers without off-farm employment skills are more likely to give up their land. This may not be consistent with common sense, but it is common practice in China. The natural resources of the protected land are strictly protected, and the function of farmers to ensure a minimum standard of living through farming activities on the land cannot be guaranteed in some core protected areas. As a result, a lack of off-farm employment skills means that farmers cannot get income from the land, which will only aggravate their poverty level. So, farmers without off-farm employment skills are more likely to give up their land. The Chinese government is addressing the above problem through the relocation of poverty alleviation, ecological migration, and other measures. There is a robust negative effect of land reallocation on the amount of time that villagers devote to off-farm work [47].

5.4. Characteristics of Farmers and Compensation Form of Land Reallocation

In this study, three observed variables (A30, A31, and A32) were used to measure the latent variable LRI. A32 is a five-level quantification of the degree to which "I prefer livelihood security to monetary compensation in terms of land reallocation". The results of the comparative mean analysis and the ANOVA test are shown in Table 8.

Table 8. The compensation for land reallocation according to the characteristics of farmers.

Characteristics		Mean	N	Ratio (%)	Standard Deviation	ANOVA Intergroup Significance
Age	18–25	3.95	247	47.18	1.023	0.024 **
	26–35	4.24	51	9.74	1.051	
	36–45	4.41	62	11.79	1.024	
	46–55	4.37	22	4.10	0.806	
	>56	4.5	8	1.54	0.837	
Education	Without education	4	4	0.77	1	0.019 **
	Primary school	4.57	9	1.79	0.787	
	Junior high school	4.36	48	9.23	0.99	
	High school	4.36	74	14.10	0.93	
	Junior college and above	3.95	254	48.46	1.045	
Off-farm employment skills	No	4.13	121	23.08	1.019	0.903
	Yes	4.08	269	51.28	1.034	
Income (yuan per year)	3000–5000	4.06	48	9.23	1.068	0.559
	5000–10,000	4.1	55	10.51	1.114	
	10,000–20,000	3.88	66	12.56	1.033	
	20,000–30,000	4.17	32	6.15	1.007	
	>30,000	4.16	188	35.90	0.994	
total		4.09	390	100	1.026	–

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The data showed that the quantitative score of observation variable A32 was 4.09, and farmers were more willing to get livelihood compensation. At the same time, off-farm employment skills and household income do not have a significant impact on the willingness to take livelihood compensation; age and education level had a significant influence on the willingness to take livelihood compensation among the groups, and farmers with an advanced age and lower education level were more likely to be eligible for livelihood compensation.

6. Conclusions

First, farmers' cognition of the land functions in national parks affects their land reallocation intention through mediation variables, and farmers' trust in the land management ability of NPA is a complete mediator between farmers' land function cognition and their willingness to leave the land. In the five land function scenario models of scientific research, leisure and recreation, environmental education, ecological protection, and livelihood security, the mediating effect value of the variable of farmers' trust in NPA's land management ability decreased gradually. The results showed that rural households did not understand the non-conventional functions of national parks, such as scientific research, recreation, and environmental education. Therefore, when land is used for scientific research, recreation, and environmental education, the NPA needs to gain sufficient trust from farmers in order to improve farmers' willingness to leave land.

Second, PEV has no significant positive moderating effect on the relationship between land functions (ECF, EEF, NEF, LRF, SRF) and land reallocation intention (LRI). According to the actual situation in the case study, if farmers perceive that the economic value of the land is low in the scenario of SRF, they are inclined to transfer the land. However, when the economic value of the land is higher, the farmers tend to reserve the land. At this time, the NPA must gain high trust from farmers to promote the improvement of farmers' willingness to leave the land. PEV has a negative moderating effect on the relationship between the land function of scientific research and land reallocation intention. This also reveals that farmers' cognition of the scientific research function of national parks is insufficient.

Third, the moderating effects of peasant household characteristics on different situation models are not the same. ① Age has a significant moderating effect on the scenario models of NEF, ECF, and SRF. The land reallocation intention was stronger among the farmers of the younger age group. This is supported by the research of Hu et al. (2018) [48] and Tang et al. (2014) [49]. ② Education shows a very significant moderating effect on the scenario models of NEF, LRF, and SRF. The willingness of highly educated farmers to leave their land is stronger, and with the improvement of education level, the willingness of highly educated farmers to leave their land will increase with the degree of trust in the land management ability of NPA. This conclusion was confirmed in the study of Tang et al. (2014) [49]. ③ Family income has a significant moderating effect on the scenario models of NEF, ECF, and SRF. Due to the strict ecological protection restrictions, the livelihood of farmers in the low-income family group is not sustainable, and they are more inclined to give up their land. This is consistent with the research conclusion of Hu et al. (2018) [48]. ④ Off-farm employment skills have a significant moderating effect on the scenario models of NEF, LRF, and EEF. When the land function is leisure and recreation, farmers with off-farm employment skills are more inclined to give up their land. When the land function is life security, farmers without off-farm employment skills are more likely to give up their land.

Fourth, compared with material or monetary compensation, land-losing farmers are more willing to receive livelihood compensation, and the less educated and older farmers are more willing to receive livelihood compensation after land reallocation.

Finally, in the context of nature conservation and urbanization in China, there are differences in farmers' willingness to leave the land. ① Against the background of urbanization, when the economic value of land is high, farmers are willing to leave the land to obtain compensation [16], but against the background of nature protection, the economic value of land has no significant moderating effect on the willingness of farmers to leave the land. ② The management ability of NPA is a completely mediating factor for the peasants' land reallocation intention, but the government's land management ability is rarely mentioned in the study of land reallocation intention against the background of urbanization. ③ Farmers without off-farm employment skills in nature reserve communities were more likely to give up their land, while farmers without off-farm employment skills were not found to be likely to do so in the context of urbanization [14,50]. The reason is that, against the background of nature protection, the land use mode and intensity are strictly restricted, and the minimum subsistence security function of the land cannot be ensured, so the farmers have to give up the land to find another livelihood. Farmers with off-farm employment skills can benefit from participation in recreational and ecotourism operations, so they tend to stay on their land.

7. Applications

According to the Guidelines, national parks are divided into two functional zones: the Strictly Protected Zone (SPZ) and Generally Controlled Zone (GCZ). Of these, the SPZ is devoted to carrying out ecological protection and the scientific research function of the land, while the GCZ can be further refined to consider land functions such as leisure and recreation, environmental education, and living guarantees to promote community development. The land function situations in this study can be combined with the functional zoning of national parks in the Guidelines. In order to adhere to the principle of ecological protection first, the collective land in the Strict Protection Zones needs to be nationalized. In order to protect the rights and interests of community development, collective land in zjr GCZ need not be fully expropriated, but the mode and intensity of land use need to be limited and can be transferred to the park management agency or a third party when necessary. In any type of land function scenario, the NPA needs to deal with Collective Land Ownership. To prevent community conflicts, this study proposes the following collective land management recommendations.

The capacity for the building of national parks to manage natural resources such as land needs to be strengthened. The construction of park natural resource management capacity is the key to realize the strict collection of collective land in protected areas and the transfer of collective land in general controlled areas.

A national park community communications and support department should be established within the NPA with the purpose of strengthening the communication between the national park and the community and popularizing the background and significance of the park construction in the community to improve the cognition of the community farmers of the basic functions of the national park. The key points of the work are to strengthen farmers' cognition of the scientific research function of national parks, to increase communication with young and highly educated people with off-farm employment skills and a low living guarantee whose land is located in the general control zone in order to gain their trust in the NPA, to help community farmers to improve their off-farm employment skills and raise their household income, and finally to increase investment in basic community education needs. The NPA should work with schools in the compulsory education stage in the park community to carry out national park education and improve young people's awareness of the functions of national parks to foster a positive emotional connection with national parks.

Attention should be paid to the compensation method of community farmers' land reallocation. In the process of acquiring land control rights, the NPA should give preference to livelihood compensation for farmers who are older or less educated, so that farmers can acquire lasting "nest eggs". In the process of the ecological migration of the original Dajiuhu Village in Shennongjia National Park, the NPA leased the collective land located in SPZ (Dajiuhu Wetland) for 30 years. For the Dajiuhu immigrants who have moved to Pingqian Town, the NPA has guided the immigrants to engage in accomodation, catering, and other service industries in Pingqian Town through systematic tourism training. The NPA has also given preferential interest rates for loans to the accomodation operators of ecological migrants. At present, Pingqian Town is another important tourist node in Shennongjia National Park besides Muyu Town. It has been proved that Shennongjia National Park pays attention to farmers' demands for livelihood compensation in the disposal of the Collective Land Ownership of protected land and obtains community support through diversified land compensation methods, realizing a win–win situation of ecological protection and community development.

8. Limitation and Prospect

The statistical data of the samples in this research show that farmers with a college education or a graduate degree and young farmers account for a large proportion of the samples, which may be due to the large proportion of questionnaires collected through the Internet. The penetration rates of smart phones and the Internet are higher among farmers who are young or have a high education. Limited by objective factors, the sample data collection rate from the field household survey was not high, which is the limitation of this research.

At present, among the 10 national parks in China, the collective land of Sanjiangyuan, Qilian Mountain, Northeast Hubao, Puda Cuo, and Hainan tropical rain forest accounts for less than 20%, and the largest proportion of the collective land area is 80.73% in Qianjiangyuan, followed by 74.74% in Wuyi Mountain, 64.42% in Nanshan Mountain, and 28.59% in Giant Panda. In this case, the collective land of Shennongjia National Park (including the area of the trust area) accounts for 23.2%, which is at a medium level. The research on the difference of the reallocation intention of collective land in different types and regions of national parks can be taken as a future research direction. Especially after the end of the national park system pilot project, China's national parks will continue to expand. By then, the comparative study on the land reallocation intentions of community farmers of collective land in national parks in southern, northern, and central China will provide a scientific basis for differentiated land ownership policies in protected areas.

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References

1. Mortimer, M.J. Private property rights and selective private forest conservation: Could a Nordic hybrid policy address a United States problem? *Environ. Manag.* **2008**, *41*, 640–653. [CrossRef] [PubMed]
2. Roy, A.K.; Alam, K.; Gow, J. Community perceptions of state forest ownership and management: A case study of the Sundarbans Mangrove Forest in Bangladesh. *J. Environ. Manag.* **2013**, *117*, 141–149. [CrossRef] [PubMed]
3. Quintana, J.; Morse, S. Social interactions and resource ownership in two private protected areas of Paraguay. *J. Environ. Manag.* **2005**, *77*, 64–78. [CrossRef] [PubMed]
4. Kubacka, M.; Ywica, P.; Subirós, J.V.; Bródka, S.; Macias, A. How do the surrounding areas of national parks work in the context of landscape fragmentation? A case study of 159 protected areas selected in 11 EU countries. *Land Use Policy* **2022**, *113*, 105910. [CrossRef]
5. Robinson, N.P.; Allred, B.W.; Naugle, D.E.; Jones, M.O. Patterns of rangeland productivity and land ownership: Implications for conservation and management. *Ecol. Appl.* **2019**, *29*, e1862. [CrossRef]
6. Su, Y.; Wang, L. Relative Concepts, Policy Background and Technological Difficulty of Pilot National Park System in China. *Environ. Prot.* **2015**, *43*, 17–23.
7. Wang, Q.; Ma, Y. Study on community participation mechanism in natural heritage protection and development. *J. Jiangxi Univ. Sci. Technol.* **2014**, *35*, 24–28.
8. Gao, Y.; Deng, Y. The Solution to the Constraint of Land Ownership in National Parks Under the Concept of Land Property Bundle. *Environ. Prot.* **2019**, *47*, 50–56.
9. Seijo, F.; Godoy, M.M.; Guglielmin, D.; Ciampoli, C.; Ebright, S.; Picco, O.; Defosse, G. Conflicting Frames about Ownership and Land Use Drive Wildfire Ignitions in a Protected Conservation Area. *Environ. Manag.* **2020**, *65*, 448–462. [CrossRef]
10. Fligg, R.A.; Ballantyne, B.; Robinson, D.T. Informality within Indigenous land management: A land-use study at Curve Lake First Nation, Canada. *Land Use Policy* **2022**, *112*, 105786. [CrossRef]
11. Crain, B.J.; Sanchirico, J.N.; Kroetz, K.; Benefield, A.E.; Armsworth, P.R. Species protection in areas conserved through community-driven direct democracy as compared with a large private land trust in California. *Environ. Conserv.* **2020**, *47*, 30–38. [CrossRef]
12. Wang, Y.; Su, H.; Su, Y.; Luo, M. Conservation easement-inspired adaptive management methods for natural protected areas: A case study on Qianjiangyuan National Park pilot. *Biodivers. Sci.* **2019**, *27*, 88–96.
13. Zhang, X. The Interactive Relationship between Urbanization and Rural Land Circulation: Challenges and Solution. *Reform Econ. Syst.* **2018**, *4*, 90–95.
14. Li, Z.; Wu, L.; Li, M. Research on the Influencing Factors of Land Circulation under the Perspective of Urbanization: Based on the Survey Data of the Peasant Households from Five Cities in Anhui Provinces. *J. Chongqing Technol. Bus. Univ.* **2018**, *35*, 20–26.
15. Zhao, G.; Li, F. Non-agricultural Employment, Social Security and Farmer's Land Transfer: An Empirical Analysis Based on 476 Farmers in 30 Towns and 49 Villages. *China Popul. Resour. Environ.* **2012**, *22*, 102–110.
16. Xu, M. Land Value, Social Security and Farmers' Willingness to Transfer Land—Structural Equation Model Analysis Based on Survey Data in Jiangsu Province. *Innovation* **2016**, *10*, 116–128.
17. Rui, Y. Research on Farmers' Land Attitude in Country Changes Ilustrated by the Example of Xiqu Village in Ningxia. Master's Thesis, Lanzhou University, Lanzhou, China, 2017.
18. Wang, M.; Wang, W. Consistency of farmers' cognition and behavior in the adjustment of land ownership under farmland consolidation. *Resour. Sci.* **2018**, *40*, 53–63.
19. Xu, M. A Comparative Analysis on Rural Land Transfer in Developed Areas and Less Developed Areas from Security Models and Land Function. *J. South China Agric. Univ.* **2014**, *13*, 1–10.
20. Song, X.; Huang, Y.; Wu, Z.; Ouyang, Z. Does cultivated land function transition occur in China? *J. Geogr. Sci.* **2015**, *25*, 817–835. [CrossRef]
21. Mei, S. Review on Characteristics and Influences of Farmers' Land Usufruct Abdication. *Agric. Econ. Manag.* **2017**, *3*, 18–26.

22. Zhu, L.; Qu, L.; Chen, W.; Yuan, X.; Liu, C.; Hu, W. Influencing factors and improvement of farmer satisfaction under land expropriation compensation in Wuhan. *Resour. Sci.* **2018**, *40*, 299–309.
23. Wang, Y.; Zhang, G.; Han, J.; Wang, X.; Zhao, Z.; He, F. Government trust and farmers' willingness to transfer farmland in mountainous areas. *Rural Econ. Sci. Technol.* **2017**, *28*, 148–149.
24. Pu, S.; Yuan, W. Study on the Influence of Government Trust on the Will of Farmland Transfer and Its Mechanism on the Background of Rural Revitalization. *J. Beijing Adm. Coll.* **2018**, *4*, 28–36.
25. Guo, C.; Shi, M. On the Conflict of Land Expropriation and the Reconstruction of the Administrative Ability of Local Government. *Manag. Obs.* **2015**, *10*, 27–28.
26. Xu, H. The Study of the Land Expropriation-Based Group Events under the Perspective of Government Trust. Master's Thesis, China University of Mining & Technology, Xuzhou, China, 2016.
27. Hetherington, M.J. The political relevance of political trust. *Am. Political Sci. Rev.* **1998**, *92*, 791. [CrossRef]
28. Weng, L.; Tao, Z. Research on the influencing factors of local government credibility. *Theor. Investig.* **2019**, *3*, 44–49.
29. Yang, Y.; Liu, W.; Wu, X. Research on Farmers' Cognition of Land Functions Based on an Empirical Survey in Yunan. *Sci. Technol. Manag. Land Resour.* **2013**, *30*, 36–41.
30. Xu, H.; Guo, Y.; Wu, G.; Jin, J. Analysis on Influencing Factors of Migrant Workers Willingness of Land Transfer under the Perspective of Intergenerational Difference:An Empirical Study Based on Questionnaires of 613 Migrant Workers in Tianjin City. *Resour. Sci.* **2012**, *34*, 1864–1870.
31. Liu, T.; Kong, X. Family Resource, Personal Endowment and the Farmers' Urban Migration Preference. *China Popul. Resour. Environ.* **2014**, *24*, 73–80.
32. Sorice, M.G.; Kreuter, U.P.; Wilcox, B.P.; Fox, W.R. Changing landowners, changing ecosystem? Land-ownership motivations as drivers of land management practices. *J. Environ. Manag.* **2014**, *133*, 144–152. [CrossRef]
33. Tang, J.; Chen, Y.; Zhang, R. Analysis of differences in farmers' land values. *Resour. Environ. Arid Area* **2015**, *29*, 13–18.
34. Raykov, T.; Penev, S. Structural equation modeling and the latent linearity hypothesis in social and behavioral research. *Qual. Quant.* **1997**, *31*, 57–78. [CrossRef]
35. Bentler, P.M.; Satorra, A.; Yuan, K.H. Smoking and Cancers: Case-Robust Analysis of a Classic Data Set. *Struct. Equ. Modeling A Multidiscip. J.* **2009**, *16*, 382–390. [CrossRef]
36. Raykov, T. Behavioral scale reliability and measurement invariance evaluation using latent variable modeling. *Behav. Ther.* **2004**, *35*, 299–331. [CrossRef]
37. Fornell, C.; Larcker, D.F. Structural equation models with unobservable variables and measurement error: Algebra and statistics. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
38. Anderson, J.; Gerbing, C.; David, W. Structural equation modeling in practice: A review and recommended two-step approach. *Psychol. Bull.* **1988**, *103*, 411. [CrossRef]
39. Torkzadeh, G.; Koufteros, X.; Pflughoeft, K. Confirmatory Analysis of Computer Self-Efficacy. *Struct. Equ. Modeling A Multidiscip. J.* **2003**, *10*, 263–275. [CrossRef]
40. Ping, R.A. On assuring valid measures for theoretical models using survey data. *J. Bus. Res.* **2004**, *57*, 125–141. [CrossRef]
41. Li, Y.; Vina, A.; Yang, W.; Chen, X.; Zhang, J.; Ouyang, Z.; Liang, Z.; Liu, J. Effects of Conservation Policies on Forest Cover Change in Giant Panda Habitat Regions, China. *Land Use Policy* **2013**, *33*, 42–53. [CrossRef]
42. Misallocation in Indian Agriculture. Available online: https://ideas.repec.org/p/nbr/nberwo/29363.html (accessed on 9 July 2022).
43. Wen, Z.; Hou, J.; Zhang, L. A comparison of moderator and mediator and their application. *Acta Psychol. Sin.* **2005**, *37*, 268–274.
44. Zhao, B. Measurement Equivalence Test and Implementation of AMOS. *Chin. J. Health Stat.* **2007**, *6*, 659–661.
45. Xu, H. The application of SEM Multiple-Group Analysis in applied linguistics research: An illustration with Amos 17.0. *Foreign Lang. Educ. China* **2010**, *3*, 59–67.
46. Beatriz, A.; Daunt, P.; Sanna, T.; Silva, F.; Hersperger, A.M. Urban expansion and forest reserves: Drivers of change and persistence on the coast of So Paulo State (Brazil). *Land Use Policy* **2021**, *101*, 105189.
47. Fan, Z.; Zhang, Y.; Tian, G. The Effect of Land Reallocation on Off-Farm Employments in Rural China. *Front. Econ. China* **2019**, *14*, 27.
48. Hu, Y.; Li, L.; Ren, N.; Wang, Z. The influence factors of rural land circulation intention in poverty-stricken mountainous areas based on binary logistic model: From the survey samples of 19 provincial-level poverty-stricken Mountain counties in Hebei province. *Chin. J. Agric. Resour. Reg. Plan.* **2018**, *39*, 137–143, 211.
49. Tang, H.; Shi, G. Farmers' stratum differentiation and preference for land property rights. *Agric. Technol. Econ.* **2014**, *9*, 38–45.
50. Zhang, Z.; Zhou, H. Off-farm Employment, Insurance Selection and Land Transfer. *China Land Sci.* **2017**, *31*, 42–52.

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Analysis of the Dynamic Relationship between Green Economy Efficiency and Urban Land Development Intensity in China

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Abstract: The improvement of green economic efficiency (GEE) should be realized under reasonable urban land development intensity (ULDI). Improving GEE can also help alleviate the negative externalities of excessive or unreasonable ULDI. Clarifying the interactive response mechanism between GEE and ULDI is a key link in regional sustainable development. Therefore, this paper uses the super-efficiency slack-based model (SBM) method, panel entropy method, and panel vector auto regression model to comprehensively analyze the interactive response relationship between GEE and ULDI in 283 prefecture-level cities in China from 2003 to 2019. This paper finds that: (1) during the research period, both the GEE and ULDI showed a relatively obvious upward trend, which is manifested in the fact that ULDI increased year by year while GEE overall increased in volatility. The growth and evolution trend of ULDI and GEE has the characteristics of interaction and coordination; (2) there is a two-way interactive Granger causality between ULDI and GEE, showing a positive interactive response effect; and (3) both ULDI and GEE have positive inertial growth and self-enhancement mechanisms. In the long run, GEE has a greater impact on the change of ULDI.

Keywords: green economic efficiency; urban land development intensity; interactive response

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1. Introduction

The complex interaction between economic development and urban land use has always been the focus of global sustainable development. Although there is a big gap between developed and developing countries [1], they are both faced with the problem that economic growth is not sustainable because of the rigid restriction of the total amount of urban land resources [2]. The whole world chooses to implement green economic development and higher intensity urban land use to solve the unsustainable problem of the traditional economic development model. Since the 20th century, China's economic development achievements have attracted worldwide attention. However, the reality is that China's traditional economic development model of high pollution and extensive utilization still exists [3,4]. Economic development is strongly dependent on the development and utilization of land resources [5], and the problems of high-intensity or unreasonable urban land use, such as the disorderly expansion of urban construction land, structural imbalance, and overall low level of resource allocation efficiency, are becoming increasingly prominent [6,7]. Realizing the benign interaction between urban land development and green economic development is a strategic task and an important path for China, which is in the transition stage to green and low-carbon development, both at present and for a long time in the future. At the same time, studying the interaction between green economic development and urban land use intensity, and summarizing China's experience in the above aspects, can provide path reference and experience for other developing countries to achieve sustainable development.

Green economic efficiency (GEE) reflects the economic efficiency of a country or region after comprehensive consideration of resource depletion and environmental impact, and is directly related to the green economy development in the future [8]. In the research on the measurement of GEE, existing studies incorporated the cost of environmental pollution control into the production function as an undesired output, and used the Solow residual value method to measure green economy productivity to judge whether a country or region could achieve green economic development [9–11]. With the continuous deepening of the index system and method innovation research on GEE, scholars have selected indicators based on the traditional indicator system of labor, capital, resource input, economic expected output, and environmental pollution discharge as undesired output [12], adding consideration for the input and output of factors such as technology and smog [13]. The parametric method and the non-parametric method are two methods to measure green economy efficiency. Among them, the parameter method is used to measure the GEE by setting the specific form of the production function, and the more commonly used method is the stochastic frontier analysis method (SFA) [14]. Nonparametric methods mainly refer to data envelopment analysis (DEA) and its derived models [15,16]. The DEA model can measure the GEE under multiple input factors and multiple input–output conditions, but it can easily lead to biased results because it cannot consider the influence of input–output slack variables. In recent years, scholars have mostly used the slack-based model (SBM) based on slack variables proposed by Tone (2001) [17] and the super-efficient SBM model that can make up for the SBM model to measure the efficiency value of multiple decision-making units with a unit of 1 [18].

Urban land development intensity (ULDI) is an index to comprehensively evaluate the status of urban land development and utilization, including the comprehensive characterization of the urban land development scale, urban land development benefits, and urban land development structure [19–22]. In the above definition, the actual performance of urban land development is the expansion of the scale of construction land and the reduction in cultivated land, forest land, water areas, etc. [23,24]. In this process, the same urban land development scale produces different functions and benefits because of different urban land-use structures [25]. Scholars in various countries have reached a general consensus that the ULDI is an important part of the urban space management and control system, and its scientific measurement and evaluation analysis is an important path to optimize the urban land development pattern [19,26]. Under the background of this theoretical research, Chinese scholars have achieved quite rich results in the concept and connotation measurement of ULDI. There are usually two research approaches. The first is to use a single indicator, such as the proportion of regional construction land area to regional land area [27], building density [28], compactness [29], and plot ratio [30,31] to measure ULDI. In recent years, scholars mainly directly use the proportion of the construction land area in the urban area to the total land area in the urban area to measure the urban land development intensity [32]. The second is to construct an index system from multiple levels for comprehensive evaluation according to the characteristics of urban land development. For example, Wang et al. [33] selected indicators from six aspects including construction land development intensity, population density, economy, ecological environment, infrastructure, and public service facility intensity to comprehensively evaluate the ULDI of typical Chinese cities. Liu Yanjun et al. [34] constructed a theoretical analysis framework for ULDI including the level and extent of construction land use, population, and socio-economic bearing intensity in urban areas, and selected corresponding indicators from three aspects of quantity, structure, and benefit to measure ULDI in northeast China. Kong Xuesong et al. [35] selected indicators from three aspects of urban land development density, development benefit, and development degree to measure and evaluate the ULDI of county-level units in Jiangsu Province.

Existing studies have explored the interaction between ULDI and GEE. Some scholars regard construction land scale and land-use structure changes as the dominant characteristics of urban land development [36,37] and focus on discussing the economic, social, and ecological benefits brought about by construction land scale changes and different urban land-use structures [38,39]. Changes in the scale of urban construction land can have a positive impact on the quality of the economy, society, and ecological environment in the development of green economy, but the rapid expansion of urban construction land has adversely affected the urban ecological environment and the lives of urban residents, thereby reducing the GEE [40]. At the same time, the changes in social structure, economic structure, and ecological structure caused by green development economy will ultimately be reflected in the urban land-use structure and its changes [41,42]. Some scholars have also studied the impact of green economic development on the ULDI. Factor agglomeration and efficient allocation are typical features of GEE improvement [43]. The agglomeration economy, technological innovation and investment expansion caused by the agglomeration of factors and the efficient allocation of resources significantly affect the ULDI. Scholars generally agree that industrial agglomeration, industrial structure upgrading, and technological innovation are the direct reasons that affect the optimization of urban land development [44–46]. However, with the continuous agglomeration of factors, there may be a "crowding effect", resulting in problems such as the intensification of the contradiction between man and land and the blind expansion of construction land [47]. Scholars are also concerned about environmental regulation as an effective means for green economic development to influence urban land development [48]. Environmental regulation plays a certain role in alleviating excessive or unreasonable urban land development through structural effects, innovation effects, spillover effects, etc., and improves the efficiency of resource allocation, thereby affecting the intensity of urban land development [49,50].

There is an interaction and mutual influence between ULDI and GEE. The optimization of urban land development can promote green economy development, and economic transformation and green development can also control the total scale of urban land development and optimize the pattern of urban land development. However, the existing research mainly studies the one-way effect of GEE on ULDI or ULDI on GEE. These studies have not given the dynamic relationship between GEE and ULDI, and the research on the interaction and response mechanism between GEE and ULDI is still insufficient. Therefore, the contribution of this paper is to construct the evaluation index system of GEE and ULDI, respectively, and expand the depth and breadth of existing research on the relationship between GEE and ULDI. This paper will take 283 prefecture-level and above cities in China as the research objects and select the sample data from 2003 to 2019. First, the paper uses the super-efficiency SBM model and the panel entropy method to measure GEE and ULDI, respectively, reveal their evolutionary characteristics, and preliminarily determine the relationship between the two. Second, the paper uses the panel vector autoregression (PVAR) model to explore the dynamic interaction mechanism between the two. Finally, policies and suggestions are put forward to better realize the good interaction and sustainable development between ULDI and GEE.

2. Methods and Data

2.1. GEE Evaluation Model

2.1.1. The Super-Efficiency SBM Model

We adopt the super-efficiency SBM model based on undesired output to measure GEE. Charnes and Cooper (1990) [51] first proposed the data envelopment analysis (DEA), and then in 2001, Tone [17] proposed a non-radial slacks-based measure (SBM) model based on the traditional DEA model. In 2002, Tone proposed a super-efficiency SBM model based on the non-radial SBM model with modified slack variables [52]. The super-efficiency SBM model can not only consider slack variables and avoid the bias caused by the selection of radial and angular selections, but also further rank effective research units with an efficiency value greater than or equal to 1. The super-efficiency SBM model that incorporates undesired outputs is widely used by scholars to measure efficiency. It is of great significance especially in the study of ecological efficiency in economic development and economic development efficiency under the constraints of resources and environment [53]. The calculation model is:

$$\min\rho_{SE} = \frac{\frac{1}{m}\sum_{i=1}^{m}(\overline{x}/x_{ik})}{\frac{1}{r_1+r_2}\left(\sum_{j=1}^{r_1}\overline{y^d}/y_{jk}^d + \sum_{q=1}^{r_2}\overline{y^u}/y_{qk}^u\right)} \tag{1}$$

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

In the formula, assume there are n decision making units (DMUs). Each DMU has m inputs, r_1 expected outputs, and r_2 undesirable outputs. x is the elements in the input matrix. y^d is the elements in the desired output matrix. y^u is the elements in the undesired output matrix. ρ is the GEE value obtained from the measure.

2.1.2. Selection of Indicators

Based on the existing research results, the GEE measurement index system is constructed from three aspects: input, expected output, and undesired output (Table 1).

Table 1. GEE evaluation index system.

Target	Index	Category	Indicator Explanation
GEE	input	Labor input	Number of employees (person)
		capital input	Fixed asset investment (RMB 10,000)
		Technology input	Number of green patents (pieces)
		Energy input	Electricity consumption of the whole society (100 million kWh)
	output	expected output	GDP (RMB 10,000)
		undesired output	Industrial wastewater discharge (tons)
			Industrial exhaust emissions (tons)
			Industrial solid waste discharge (tons)
			Carbon emissions (tons)

The input factors in GEE include non-resource input factors and resource input factors. Non-resource input factors mainly consider labor, capital, and technology input. We select the number of employees and capital stock as the corresponding index to measure labor input and capital input. Green technology innovation is an effective way for China's economic transformation to green development to achieve sustainable development goals [54]. In existing research, R&D funding is an index to measure technology input in economic efficiency [55], but not all R&D funding goes to green innovation. Patent applications can reflect the progress of technological innovation [56], among which the green patent number can be used to evaluate the field of green technological innovation [57,58]. Therefore, this paper chooses the number of green patents as an indicator to measure technology input in GEE. The resource input element is mainly represented by the indicator of electricity consumption in the whole society.

The expected output is expressed by the indicator of GDP. The undesired output is generally represented by the comprehensive index of industrial pollution and, taking into account the current "dual carbon" goal vision, carbon emissions are also included in the undesired output.

2.2. ULDI Evaluation Model

2.2.1. Panel Entropy Method

We adopt the panel entropy method to measure ULDI. The entropy method determines the indicator weight according to the size of the information provided by the indicator observations. Entropy is derived from the physical concept of thermodynamics and was introduced to information theory by Shannon in 1948. In information theory, entropy is used to measure uncertainty. The smaller the amount of information, the greater the uncertainty, and the greater the entropy [59]. Based on this characteristic, the entropy value can be calculated to determine the degree of dispersion of an index. The greater the degree of dispersion of the index, the greater the impact on the comprehensive evaluation of the comprehensive index, and the greater the weight given to the index. The entropy value method can determine the index weight according to the degree of variation of the index value, which can avoid the lack of objectivity that is due to the subjective judgment in the subjective weighting method, and can also avoid the lack of information in the principal component analysis method. The entropy value method applied in practice is the most extensive. Moreover, the traditional entropy method to determine the weight can only deal with cross-sectional data, which makes it difficult to compare between different years. In this paper, the time variable is introduced into the improved panel entropy method to assign the index weight. The calculation model is:

The first step is to select indicators. There are m city t years n indicators, then x_{ijk} represents the value of the k-th index in the j-th year of the i-th city. In this paper, x_{ijk} is the index selected to judge the ULDI.

The second step is to standardize the indicators. Due to the differences in dimensions and units of different indicators, the extreme value method is selected to standardize the indicators. After the positive and negative indicators are determined, normalization is performed:

$$x'_{ijk} = \frac{x_{ijk} - x_{\min k}}{x_{\max k} - x_{\min k}} \tag{3}$$

where $x_{\min k}$ represents the minimum values of the k-th index in the j-th year of the i-th city. $x_{\max k}$ represents the maximum values of the k-th index in the j-th year of the i-th city. The x'_{ijk} obtained after the normalization of x_{ijk} represents the relative size in m cities and t years, and the value is between 0 and 1.

The third step is to determine the indicator weight:

$$y_{ijk} = x'_{ijk} / \sum_i \sum_j x'_{ijk} \tag{4}$$

The fourth step is to calculate the entropy value of the k-th indicator:

$$e_{\mathrm{k}} = -\frac{1}{\theta} \sum_i \sum_j y_{ijk} \ln(y_{ijk}) \tag{5}$$

where the constant $\theta > 0$, and θ is only related to the number of samples $m \cdot t$. We generally make $\theta = \ln(m \cdot t)$, then $0 \le e_k \le 1$, ln is the natural logarithm.

The fifth step is to calculate the information utility value of the k-th indicator:

$$g_k = 1 - e_k \tag{6}$$

The sixth step is to calculate the weight of the information utility value of the k-th indicator:

$$w_k = (1 - e_k) / \sum_k (1 - e_k) \tag{7}$$

The seventh step is to calculate the comprehensive score of each city's ULDI:

$$\mathrm{H}_{ij} = \sum_{k} w_k x'_{ijk} \tag{8}$$

2.2.2. Selection of Indicators

Urban land development intensity is a comprehensive characterization of urban land development scale, urban land development benefit, and urban land development structure (Table 2).

Table 2. ULDI evaluation index system.

Target	Category	Indicator Explanation
ULDI	The scale of urban land development	The ratio of construction land area to total land area in the region (%)
	Economic benefits of urban land development	Industrial non-agricultural rate (%) GDP output per land (10,000 RMB/square kilometer)
	Social benefits of urban land development	Per capita disposable income (yuan/person) Per capita residential land area (square meters/person) Per capita road area (square meters/person)
	Ecological benefit of urban land development	green space per capita (square meters/person)
	Urban land development structure	Information entropy of construction land structure

The total scale of urban construction land is the main content of the scale of urban land development, which is represented by the ratio of the area of construction land in the region to the total land area of the region.

The purpose of urban land development is to produce economic, social, and ecological benefits through the development and utilization of land resources to meet the needs of human production and life. In terms of economic benefits, this paper selects the industrial non-agricultural rate and GDP per land to characterize the economic benefits of urban land development. The social benefits are reflected in the support of people's income, settlement, and public services. Three indicators, namely per capita disposable income, per capita residential land area, and per capita road area, are selected. In terms of ecological benefits, regional green space is an important component of ecological space, which can provide ecological assistance for social and economic development by improving the ecological environment. This paper selects the green space per capita as an indicator.

In this paper, the information entropy index of construction land structure is selected as the index to judge the urban land development structure. The urban land development structure is reflected in various construction land types. The actual manifestation of urban land development is the expansion of the number and scale of construction land and the reduction in cultivated land, forest land, water areas, etc. With the changes in the degree of urban land development affected by human social and economic activities, the type of structure of construction land has been further significantly changed. The specific method is to first refer to the Standard for Classification of Urban Land and Planning and Construction Land (GB501372011) and determine that the construction land mainly includes eight types of land. Second, calculate the ratio of various types of construction land to the total area of regional construction land, expressed as $P_{1,2,\ldots,8}$. Finally, according to the entropy formula $-\sum_{i=1}^{8} P_i \ln P_i$, the entropy value of the construction land structure information is calculated.

2.3. Panel VAR Model

We use the panel vector autoregression (PVAR) model to reveal the dynamic interaction mechanism between green economic efficiency and urban land development intensity.

Based on the univariate autoregression (AR) model, Sims proposes a vector autoregression (VAR) model. The vector autoregression model is used for the prediction research of time series variables and the analysis of variables affected by random disturbances by realizing the regression analysis of the current variables on several lag variables of all variables. It is now widely used to analyze the dynamic correlation between multivariate time series variables. However, since the VAR model cannot handle long-term panel data, a PVAR model for panel data analysis was proposed.

The previous studies on the interaction between GEE and ULDI above showed that the relationship between GEE and ULDI is complex. There is a mutual influence between GEE and ULDI, which means that endogenous causality may occur among GEE and ULDI. Therefore, this paper constructs a PVAR model to accurately identify the interaction and response mechanism between GEE and ULDI. The calculation model is:

$$y_{it} = \alpha_1 + \sum_{p=1}^{n} \beta_p y_{it-p} + \gamma x_{it} + \varepsilon_{it} \tag{9}$$

where y_{it} is a multi-dimensional endogenous variable, which is GEE and ULDI; p is a lag period; y_{it-p} is a lag period variable; x_{it} is an exogenous variable; and ε_{it} is the disturbance vector. The disturbance vector is only related to the current variable, independent of lag variables; α is the intercept term; and β and γ are the coefficient.

2.4. Research Samples and Data Sources

This paper takes prefecture-level cities in China as the research sample area. Considering the availability and completeness of data, the sample to be investigated in this paper is ultimately 283 prefecture-level and above cities in China. The study sample period is 2003–2019. Except for the green patent data from the CNRDS China Research Data Service Platform, other data related to index variables are all from the "China Urban Statistical Yearbook", "China Urban Construction Statistical Yearbook", statistical yearbooks over the years, and national economic and social development during the sample period. For very few cities, the missing data in some years were supplemented by interpolation.

3. Results

3.1. Evolutionary Characteristics of ULDI and GEE

As can be seen from Figure 1, the ULDI increased year by year from 0.0309 in 2003 to 0.0820 in 2019. The measurement results show that during the study period, the overall ULDI in China showed a trend of gradual increase over time. The ULDI kept increasing with the rapid advancement of industrialization and urbanization. The GEE increased from 0.6839 in 2003 to 0.8655 in 2019. The measurement results show that during the study period, China's GEE showed a trend of gradual improvement over time. However, the average green economic efficiency in each year has not reached the effective value. From the perspective of time series evolution, China's GEE shows a staged characteristic of a steady rise in fluctuations. From 2003 to 2010, the change of green economic efficiency was dominated by "fluctuations, supplemented by rising" and green economic efficiency did not form a stable upward trend. From 2010 to 2016, GEE showed a steady upward trend. From 2016 to 2019, GEE showed an upward trend after a significant decline in 2017.

The evolutionary characteristics of ULDI and GEE show that both ULDI and GEE showed an upward trend from 2003 to 2019. It shows that the support efficiency of China's urban land development to the improvement of green economic efficiency continues to increase, and urban land development tends to develop in a good operation and adaptation state. However, the changing trends of ULDI and GEE are different. During the sample period, the ULDI was in a relatively steady upward trend year by year, while the GEE showed a fluctuating upward trend of "decrease first and then increase". When the GEE is on the rise, the increase in the ULDI is larger than that when the GEE is on the decline.

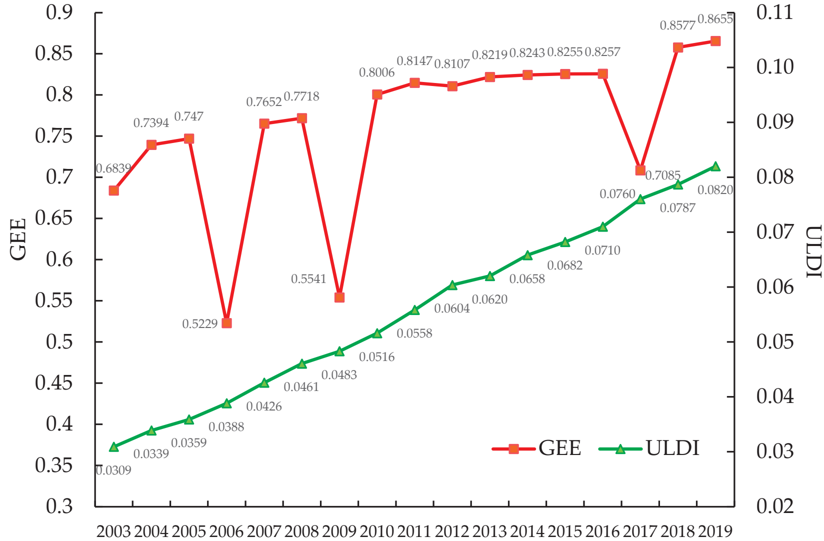

Figure 1. Calculation results and time-series trend characteristics of GEE and ULDI.

3.2. Analysis on the Interactive Response between ULDI and GEE

The PVAR is built in the following four steps [21,60]. First, we used the unit root to test the stationarity of the time-series data, and use the Granger method to test whether there is a causal relationship between GEE and ULDI. Second, we chose the suitable lag order and use the generalized moment method to determine the regression result among GEE and ULDI. The impulse response functions will be tested third.

3.2.1. Stationarity and Causality Tests

Time-series variables need to be tested for their stationarity by unit root, and the PVAR model cannot predict the change law of nonstationary time-series data. The commonly used test methods of Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), and Fisher-type (ADF-Fisher, PP-Fisher) are comprehensively used. The results are shown in Table 3. As can be seen from Table 3, the *p*-values of the LLC, IPS, Fisher-ADF, and Fisher-PP test statistics of green economic efficiency and territorial space development intensity are all 0.0000, and the original data are all stationary data.

Table 3. Unit root test results.

Variables	LLC		IPS		Fisher-ADF		Fisher-PP	
	Statistics	*p*-Value	Statistics	*p*-Value	Statistics	*p*-Value	Statistics	*p*-Value
ULDI	−28.831	0.000	−10.505	0.000	6.524	0.000	24.153	0.000
GEE	−49.157	0.000	−34.443	0.000	47.999	0.000	75.619	0.000

The Granger method is used to test the causality between ULDI and GEE. The results are shown in Table 4. As can be seen from Table 4, the *p*-values of the Granger causality test of ULDI for GEE and GEE for ULDI are both 0.000, indicating that the Granger null hypothesis is rejected. There is a two-way interactive Granger causality between ULDI and GEE.

Table 4. Granger causality test results.

	Null Hypothesis	Z-Bar Tilde	p-Value	Conclusion
ULDI	ULDI is not the Granger reason for GEE	27.690	0.000	Reject the null hypothesis
GEE	GEE is not the Granger reason for ULDI	15.706	0.003	Reject the null hypothesis

3.2.2. PVAR Model Regression Analysis

According to the constructed formula (9), we can use the Stata15.0 software to determine the regression result among GEE and ULDI. The implementing of the PVAR model first needs to determine the optimal lag order. Same as in the existing literature [21], we used Akaike's information criterion (AIC), Baysian information criterion (BIC), and Hannan and Quinn information criterion (HQIC) to select the optimal lag order (Table 5). It can be found from Table 5 that when the lag order is 4, the statistics of AIC, BIC, and HQIC are the minimum. Therefore, 4 is the lag order selected to establish the PVAR (9) model.

Table 5. Results of multi-criteria joint judgement.

Lag	AIC	BIC	HQIC
1	−2.317	−1.463	−2.015
2	−2.551	−1.641	−2.228
3	−2.811	−1.836	−2.464
4	−3.342	−2.291	−2.966
5	−3.308	−2.171	−2.900

We used the generalized method of moments (GMM) method to estimate the PVAR model [60]. The results are shown in Table 6, among which the ULDI equation under "Type" represents the effect of ULDI and GEE on ULDI, and the GEE equation under "Type" represents the effect of GEE and ULDI on GEE, and L1. represents the variable of the first-period lag, L2. represents the variable of the second-period lag, L3. represents the variable of the third-period lag, and L4. represents the variable of the fourth-period lag.

Table 6. Estimation results of PVAR model based on GMM method.

Type	Variable	Coefficient	Variable	Coefficient
ULDI equation	L1.TSDI	0.504 (0.08) ***	L1.GEE	0.063 (0.02) ***
	L2.TSDI	0.049 (0.06)	L2.GEE	0.042 (0.02) **
	L3.TSDI	0.087 (0.06)	L3.GEE	0.070 (0.02) ***
	L4.TSDI	0.059 (0.05)	L4.GEE	0.032 (0.01) ***
GEE equation	L1.GEE	0.044 (0.01) ***	L1.TSDI	0.064 (0.03) **
	L2.GEE	−0.005 (0.01)	L2.TSDI	−0.008 (0.02)
	L3.GEE	0.470 (0.02) ***	L3.TSDI	0.016 (0.02)
	L4.GEE	−0.062 (0.01) ***	L4.TSDI	−0.006 (0.02)

Note: *** and ** show significance at the 1% level and 5% level, respectively. Std. Err. of estimated value is given in parentheses.

As shown in Table 6, in the ULDI equation, the L1., L2., L3., and L4. of both ULDI and GEE have positive influence coefficients on ULDI in the current period. However, the impact of the L1., L2., L3., and L4. of ULDI on the current is only significant in L1. ULDI generally has a large degree of path-dependent inertia in the subsequent development process, but because of the limitation of land resources, this path dependence gradually weakens over time. The positive effect of L1., L2., L3., and L4. of GEE on ULDI is consistently significant. The improvement of GEE is an important reason affecting ULDI and the impact of the improvement of GEE on ULDI has a positive cumulative effect on the time scale.

In the GEE equation shown in Table 6, the L1., L2., L3., and L4. of GEE have alternating positive and negative effects on GEE in the current period. GEE has a large degree of self-adjustment mechanism, and this self-adjustment is manifested as self-promotion. The L1., L2., L3., and L4. of ULDI also showed alternating positive and negative effects on GEE. The influence effect of ULDI on GEE has nonlinear characteristics, which is manifested as a divergent promoting effect on GEE in the early and middle stages of green economic development, and a convergent hindering effect in the short-term and late stages of green economic development. In the long run, the positive effect of ULDI on GEE is greater than the negative effect.

3.2.3. Impulse Response Analysis

We also use the Stata15.0 software based on Equation (9) to analyze the impulse response between ULDI and GEE. We set up 200 Monte Carlo simulations to investigate the impact of random disturbances under unit standard deviation on the dynamic evolution of current and future values of variables to reveal the interactive response mechanism of China's ULDI and GEE in the next 10 years. Figures 2 and 3 show the graph of the impulse response function of ULCI to itself and GEE. Figures 4 and 5 show the graph of the impulse response function of GEE to itself and ULCI.

As shown in Figure 2, ULDI has a positive effect on the impulse response of its own unit, and the impact effect is severe. When it is impacted by its own unit standard deviation, ULDI quickly responds to the peak value in the current period, and then this positive response shows a fluctuating downward trend and converges to 0.

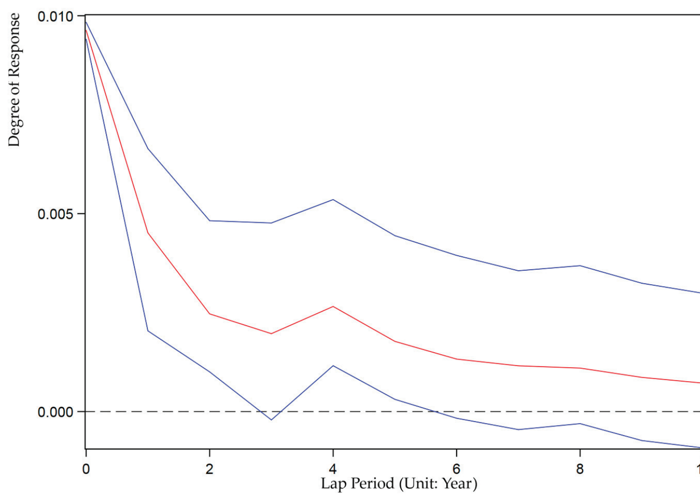

Figure 2. Impulse response of ULDI to ULDI.

As shown in Figure 3, the impulse response of ULDI to GEE is positive. It shows that the current response is 0, and then the positive response speed is accelerated, reaching the highest value in the fourth period, and each period after the fourth period has a relatively stable positive response.

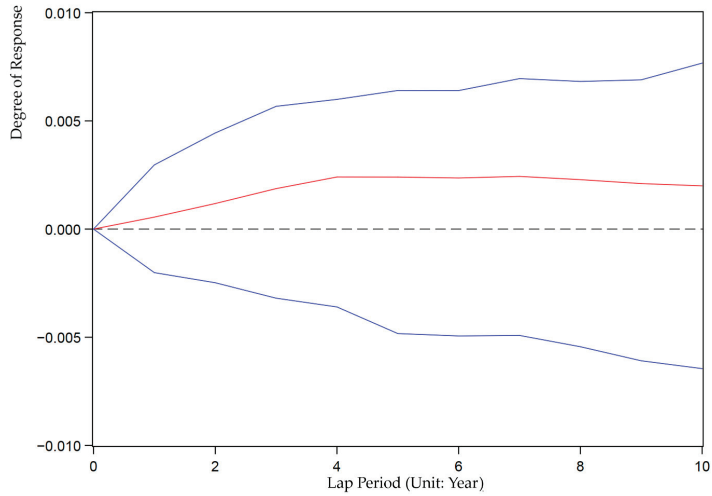

Figure 3. Impulse response of ULDI to GEE.

As shown in Figure 4, when subjected to one standard deviation shock of ULDI, GEE showed a positive response in the 10th period, but its impulse response showed periodic U-shaped fluctuations. It shows that ULDI has a volatile promoting effect on the improvement of GEE. ULDI has always been the driving force for the improvement of GEE, but in this process, it is necessary to continuously improve the efficiency of resource utilization and weaken the restrictive effect of urban land development on the improvement of GEE.

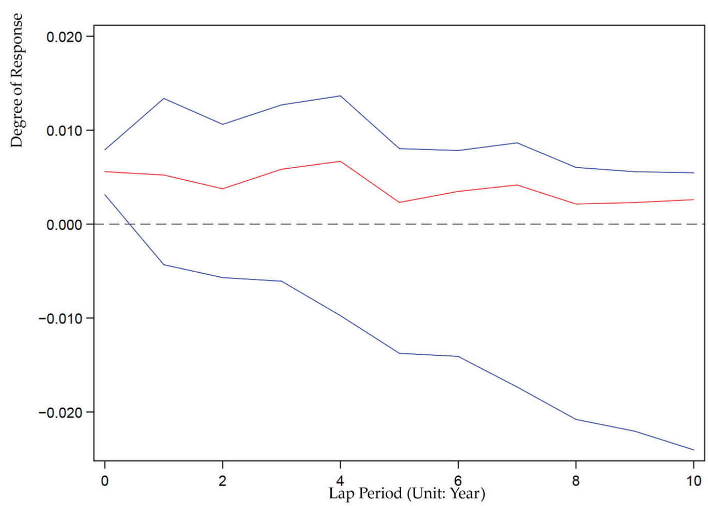

Figure 4. Impulse response of GEE to ULDI.

As shown in Figure 5, when subjected to its own unit standard deviation, GEE also showed a positive response. The specific performance is that it also responds quickly in the current period and reaches the peak value. After that, it showed the characteristics of reciprocating change, of which the positive effect decreases in the first period, tends to be weak in the second period, and increases in the third period.

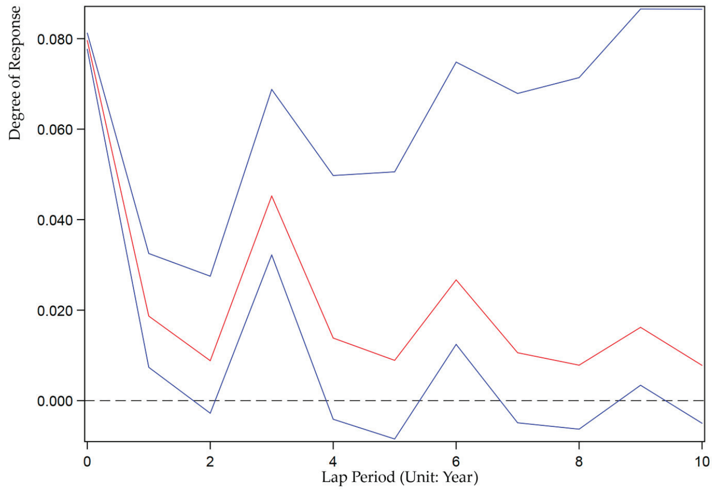

Figure 5. Impulse response of GEE to GEE.

4. Discussion

This paper defines the ULDI including the urban construction land scale, the internal type of urban construction land, and the economic, social, ecological benefits of urban land development. It reflects the current important measures to realize the sustainable development of urban land development in China, that is, to control the disorderly expansion of the scale of construction land in breadth, to optimize the types of urban construction land through internal potential tapping to the limit, and to continuously improve the benefits of urban land development in depth. This provides a reference for other developing countries to pay attention to the ULDI in the process of development.

However, only the internal improvement of ULDI is effective in the short term, but unsustainable in the long run. The rapid growth of China's economy depends on the direct pull of the wide supply of urban land. China is faced with the problem of insufficient capital in the early stage of economic development. China's unique land system, with the compulsory low-cost land acquisition system and the government-monopolized state-owned land transfer system as the core arrangement, ensures a wide supply of land and makes land resource utilization a source of capital for economic development [61]. A large amount of low-cost supply of land has become an important tool for local governments to attract investment and obtain more investment in fixed assets, and promote the development of local industrialization [62,63]. Especially after the reform of the tax-sharing system, local governments have obtained a large amount of land transfer income and tax by increasing the supply of urban development land, bringing a large amount of land fiscal revenue [64]. Land fiscal revenue and land financing mortgage funds have become important sources of funds for local governments to realize infrastructure construction, and further attract the inflow of capital and talents [65]. Land has become a factor of production as important as technology, capital, and labor in the process of economic development, and urban land development as a tool has created a miracle of economic growth in China.

Many problems have begun to emerge from this traditional economic development model accumulated with the extension of the time domain and the frequency domain. First, the economic development model that relies too much on land resource utilization is unsustainable because of the real constraints of a scarcity of land resources. In addition, the development model of land capitalization in which local governments bundle land transfer fees and reserve land mortgage financing has accumulated a lot of financial risks [66]. These further inhibit economic growth and urbanization. Second, environmental problems such as carbon emissions and industrial pollutant emissions are significant. Local governments rely on low-cost land supply to attract a large number of low-end manufacturing industries with high energy consumption and high pollution, which has greatly promoted the process of industrialization. However, in the long run, enterprises with poor prospects and low production capacity squeeze land resources, and the "crowding out effect" of technology-intensive and capital-intensive high-value-added industries reduces industrial output value [67]. Third, bound by the law of diminishing marginal returns, the economic output that can be brought about by an increase in unit land investment is becoming more and more limited, and the engine function of land driving economic growth and regulating economic rhythm begins to decline [68]. Ultimately, China's economy has to face the transformation of old and new economic growth drivers.

China chooses a green way of economic development. From 2003 to 2010, China transformed the traditional economic development model of high pollution and high energy consumption. During this period, China's "Eleventh Five-Year Development" plan has placed emphasis and strategic arrangements on structural adjustment, energy conservation and emission reduction, and coordinated regional development. After comprehensively considering economic growth and resource environmental protection, the GEE has declined. From 2010 to 2016, with technological innovation, industrial restructuring, environmental regulation, and other measures, the GEE began to rise steadily. Since then, China's green economy model has continued to make new achievements. Because there is a direct elastic mechanism of urban land development, unit land input will bring about an increase in output. Therefore, even if China's economy completes the phased transformation of new and old kinetic energy, urban land development as a traditional economic growth kinetic energy still exists, and the scale of urban land development and its growth rate still needs to be maintained at a certain level. Moreover, the green economy development faces the dual goals of increasing total demand and improving efficiency [69]. The increase in aggregate demand for economic development will inevitably lead to and coerce an increase in aggregate supply, that is, an increase in total economic output will inevitably lead to an increase in the scale or marginal output of capital, labor, and land [70]. At the same time, urban land development faces the constraints of limited total land resources and conforms to the law of marginal diminishing returns to land. Only by ensuring the sustainability of ULDI can we achieve the level of total economic output and improve the GEE.

Therefore, our findings confirm that there is a mutual influence and mutual promotion between urban land development and green economic development. Land resources are an indispensable element of economic development. The driving effect of urban land development on economic development will not be significantly adjusted or changed. No matter what kind of economic development mode, the input of urban land resources is required. Under the green economic development model, the development of the green economy presents a strong self-adjustment mechanism, which can adjust itself according to the actual development situation to ensure the sustainable development of the green economy. In addition, through technological innovation, industrial structure transformation, and upgrading, etc. to improve the GEE, it can effectively promote the sustainability of urban land development and achieve a balance between urban land development and protection. To achieve sustainable development goals, whether it is for China or other developing countries, it is not sustainable to rely solely on the optimization within the urban land development system or within the economic development system, but to achieve a benign interaction and collaborative development between urban land development and green economy are promising.

5. Conclusions

This paper has explored the dynamic relationship between ULDI and GEE. It mainly draws the following two conclusions: (1) from 2003 to 2019, China's ULDI and GEE showed a relatively obvious upward trend, and the increase in ULDI in the period of increasing GEE was larger than that in the period of declining GEE. The growth and evolution trend of ULDI and GEE has the characteristics of interaction and coordination. (2) There is a two-way interactive Granger causality between ULDI and GEE. The GMM model estimation results show that both ULDI and GEE have positive inertial growth and self-enhancement mechanisms. The interaction between GEE and ULDI has nonlinear characteristics, which is manifested as a positive cumulative effect on the time scale of the effect of GEE on ULDI, but the effect of ULDI on GEE only has a significant positive enhancement effect in the short term, but this contribution gradually weakened as the number of ULDI lag periods increased. From the results of impulse response analysis, ULDI has a positive response to GEE, which tends to be stable after reaching the highest value in the fourth period and has a significant positive enhancement effect in the long run. The results of impulse response analysis also showed that GEE also had a significant positive response to ULDI, and its impulse response showed a phased "U"-shaped fluctuation trajectory, and ULDI has a fluctuating promoting effect on GEE.

When discussing sustainable development issues from the perspective of urban land use and economic development, it is different from looking at issues from one side. Our novel research perspective is to examine the bidirectional dynamic relationship between GEE and ULDI. The empirical test based on the interaction and response mechanism between GEE and ULDI provides a basis for realizing the path of sustainable development by realizing the urban land development system, the green economic development system, and promoting the good mutual feedback evolution between the two. It can be seen that the development of ULDI can play a positive role in improving GEE. With the expansion of construction land scale, the adjustment of land-use type structure and the improvement of urban land development functions, the green economy development can be continuously promoted. However, when the ULDI reaches a certain level, its influence on GEE will continue to weaken or even have a negative impact. However, at the same time, when GEE is improved through technological innovation, industrial structure transformation, and upgrading, it can continuously optimize the urban land development structure and improve the comprehensive benefits of urban land development, and reduce the dependence of economic development on urban land resources to a greater extent. Similarly, when GEE increases to a certain range, its impact on ULDI will continue to weaken and eventually stabilize. This means that under the support of a certain ULDI, GEE has been improved to a certain level, a new balance has been achieved between ULDI and GEE, and the whole society is in a state of a virtuous circle of sustainable development. However, simply relying on the internal optimization of the urban land development system to improve the ULDI or relying on the internal optimization of the green economic development system to improve GEE is not sustainable. Regional sustainable development plans and policies should be formulated from the perspective of the coordinated development of urban land development and green economy according to their own development conditions.

Admittedly, this study has several limitations. For example, first, there are other indicators and methods for measuring the status quo of urban land development and green economy development. Even the existing index system in this paper also needs to be further supplemented and improved according to the actual situation of each country or city. Second, this study only considers the interactive response between green economic efficiency and urban land development intensity. Studies have shown that resource endowment, population size, and structural characteristics, policies, and regulations have significant impacts on urban land development intensity and green economic efficiency. The current study does not incorporate these factors into the analytical framework. Third, there are significant regional heterogeneities in the resource endowment conditions and social and economic development levels of various countries, and there may be regional differences in the interactive response effect between green economic efficiency and the intensity of national land and space development. Future research will explore the construction of a more scientific index system and method for measuring urban land development intensity and green economic efficiency, and incorporate regional heterogeneity into the study of the relationship between the two. It is also a future research direction to refine the internal dimension of green economic efficiency improvement and the internal dimension of urban land development intensity to reveal the interactive response mechanism between green economic efficiency and urban land development intensity at a deeper level.

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References

1. Syed, S.B.; Dadwal, V.; Rutter, P.; Storr, J.; Hightower, J.D.; Gooden, R.; Carlet, J.; Bagheri Nejad, S.; Kelley, E.T.; Donaldson, L.; et al. Developed-developing country partnerships: Benefits to developed countries? *Glob. Health* **2012**, *8*, 17. [CrossRef]
2. Zhang, L.Y.; Li, Y.; Zhang, J.; Luo, B.; He, J.M.; Deng, S.H.; Huang, X.; Luo, L.; Shen, F.; Xiao, H.; et al. The relationships among energy consumption, economic output and energy intensity of countries at different stage of development. *Renew. Sustain. Energy Rev.* **2017**, *74*, 258–264. [CrossRef]
3. Tan, Z.F.; Chen, K.T.; Ju, L.W.; Liu, P.K.; Zhang, C. Issues and solutions of China's generation resource utilization based on sustainable development. *J. Mod. Power Syst. Clean Energy* **2016**, *4*, 147–160. [CrossRef]
4. Wu, J.; Huang, D.C.; Zhou, Z.X.; Zhu, Q.Y. The regional green growth and sustainable development of China in the presence of sustainable resources recovered from pollutions. *Ann. Oper. Res.* **2020**, *290*, 27–45. [CrossRef]
5. Zhang, M.; Liu, Y.M.; Wu, J.; Wang, T.T. Index system of urban resource and environment carrying capacity based on ecological civilization. *Environ. Impact Assess.* **2018**, *68*, 90–97. [CrossRef]
6. Liu, Y.S.; Fang, F.; Li, Y.H. Key issues of land use in China and implications for policy making. *Land Use Policy* **2014**, *40*, 6–12. [CrossRef]
7. Wang, R.; Zameer, H.; Feng, Y.; Jiao, Z.L.; Xu, L.; Gedikli, A. Revisiting Chinese resource curse hypothesis based on spatial spillover effect: A fresh evidence. *Resour. Policy* **2019**, *64*, 101521. [CrossRef]
8. Ma, L.; Long, H.L.; Chen, K.Q.; Tu, S.S.; Zhang, Y.N.; Liao, L.W. Green growth efficiency of Chinese cities and its spatio-temporal pattern. *Resour. Conserv. Recycl.* **2019**, *146*, 441–451. [CrossRef]
9. Tao, F.; Zhang, H.Q.; Hu, J.; Xia, X.H. Dynamics of green productivity growth for major Chinese urban agglomerations. *Appl. Energy* **2017**, *196*, 170–179. [CrossRef]
10. Gao, K.; Yuan, Y.J. Spatiotemporal pattern assessment of China's industrial green productivity and its spatial drivers: Evidence from city-level data over 2000–2017. *Appl. Energy* **2022**, *307*, 118248. [CrossRef]
11. Xepapadeas, A.; Tzouvelekas, V.; Vouvaki, D. *Total Factor Productivity Growth and the Environment: A Case for Green Growth Accounting*; Beijer International Institute of Ecological Economics: Stockholm, Sweden, 2007.
12. Song, M.L.; Peng, J.; Wang, J.L.; Zhao, J.J. Environmental efficiency and economic growth of China: A Ray slack-based model analysis. *Eur. J. Oper. Res.* **2018**, *269*, 51–63. [CrossRef]
13. Mnif, S. The Impact of Inequality on Growth Driven by Technological Changes: A Panel of Developing Countries. *J. Knowl. Econ.* **2017**, *8*, 127–140. [CrossRef]
14. Zhang, C.Q.; Chen, P.Y. Industrialization, urbanization, and carbon emission efficiency of Yangtze River Economic Belt-empirical analysis based on stochastic frontier model. *Environ. Sci. Pollut. R* **2021**, *28*, 66914–66929. [CrossRef]
15. Cook, W.D.; Seiford, L.M. Data envelopment analysis (DEA)—Thirty years on. *Eur. J. Oper. Res.* **2009**, *192*, 1–17. [CrossRef]
16. Zhang, J.R.; Zeng, W.H.; Shi, H. Regional environmental efficiency in China: Analysis based on a regional slack-based measure with environmental undesirable outputs. *Ecol. Indic.* **2016**, *71*, 218–228. [CrossRef]
17. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
18. Tone, K.; Toloo, M.; Izadikhah, M. A modified slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2020**, *287*, 560–571. [CrossRef]
19. Gong, J.Z.; Chen, W.L.; Liu, Y.S.; Wang, J.Y. The intensity change of urban development land: Implications for the city master plan of Guangzhou, China. *Land Use Policy* **2014**, *40*, 91–100. [CrossRef]
20. Xu, Y.; Tang, Q.; Fan, J.; Bennett, S.J.; Li, Y.J.L.; Planning, U. Assessing construction land potential and its spatial pattern in China. *Landsc. Urban Plan.* **2011**, *103*, 207–216. [CrossRef]

21. Kuang, B.; Lu, X.H.; Han, J.; Fan, X.Y.; Zuo, J. How urbanization influence urban land consumption intensity: Evidence from China. *Habitat. Int.* **2020**, *100*, 102103. [CrossRef]
22. Lambin, E.F.; Rounsevell, M.D.A.; Geist, H.J. Are agricultural land-use models able to predict changes in land-use intensity? *Agric. Ecosyst. Environ.* **2000**, *82*, 321–331. [CrossRef]
23. Zheng, W.; Walsh, P.P. Economic growth, urbanization and energy consumption—A provincial level analysis of China. *Energy Econ.* **2019**, *80*, 153–162. [CrossRef]
24. Fernandez, J.E. Resource consumption of new urban construction in China. *J. Ind. Ecol.* **2007**, *11*, 99–115. [CrossRef]
25. Wang, Y.; Wang, R. Reasons for the increasing information entropy of suburban land use structure during the period of urbanization. *Acta Geograph. Sin.* **2018**, *73*, 1647–1657.
26. Mouratidis, K. Is compact city livable? The impact of compact versus sprawled neighbourhoods on neighbourhood satisfaction. *Urban Stud.* **2018**, *55*, 2408–2430. [CrossRef]
27. Ottensmann, J.R. Urban sprawl, land values and the density of development. *Land Econ.* **1977**, *53*, 389–400. [CrossRef]
28. Tang, B.S.; Yiu, C.Y. Space and scale: A study of development intensity and housing price in Hong Kong. *Landsc. Urban Plan* **2010**, *96*, 172–182. [CrossRef]
29. Yin, F.; Feng, M.; Zhong, F.; Li, X. Research of urban expansion in Siping city based on remote sensing and GIS. *Geo-Inf. Sci.* **2010**, *12*, 242–247. [CrossRef]
30. Geng, B.; Zheng, X.; Fu, M. Scenario analysis of sustainable intensive land use based on SD model. *Sustain. Cities Soc.* **2017**, *29*, 193–202. [CrossRef]
31. Guo, J.; Sun, B.; Qin, Z.; Wong, S.W.; Wong, M.S.; Yeung, C.W.; Shen, Q. A study of plot ratio/building height restrictions in high density cities using 3D spatial analysis technology: A case in Hong Kong. *Habitat Int.* **2017**, *65*, 13–31. [CrossRef]
32. Huang, X.; Huang, X.; Liu, M.; Wang, B.; Zhao, Y. Spatial-temporal dynamics and driving forces of land development intensity in the western China from 2000 to 2015. *Chin. Geogr. Sci.* **2020**, *30*, 16–29. [CrossRef]
33. Wang, S.J.; Fang, C.L.; Wang, Y.; Huang, Y.B.; Ma, H.T. Quantifying the relationship between urban development intensity and carbon dioxide emissions using a panel data analysis. *Ecol. Indic.* **2015**, *49*, 121–131. [CrossRef]
34. Liu, Y.; Yu, H.; Liu, D.; Zhu, L. Spatial differentiation mechanisms of the pattern evolution of construction land development intensity in Northeast China. *Acta Geogr. Sin.* **2018**, *73*, 818–831.
35. Kong, X.; Jiang, X.; Liu, Y.; Jin, Z.F. Spatiotemporal Coupling Between Territorial Space Development Intensity and Resource Environmental Carrying Capacity and Its Planning Implications: A Case Study of Jiangsu Province. *China Land Sci.* **2020**, *34*, 10–17.
36. Gao, J.L.; Wei, Y.D.; Chen, W.; Yenneti, K. Urban Land Expansion and Structural Change in the Yangtze River Delta, China. *Sustainability* **2015**, *7*, 10281–10307. [CrossRef]
37. Zhao, K.; Chen, D.; Zhang, X.; Zhang, X.; Health, P. How Do Urban Land Expansion, Land Finance, and Economic Growth Interact? *Int. J. Environ. Res. Public Health* **2022**, *19*, 5039. [CrossRef]
38. Shu, C.; Xie, H.L.; Jiang, J.F.; Chen, Q.R. Is Urban Land Development Driven by Economic Development or Fiscal Revenue Stimuli in China? *Land Use Policy* **2018**, *77*, 107–115. [CrossRef]
39. Chen, D.; Lu, X.; Hu, W.; Zhang, C.; Lin, Y. How urban sprawl influences eco-environmental quality: Empirical research in China by using the Spatial Durbin model. *Ecol. Indic.* **2021**, *131*, 108113. [CrossRef]
40. Long, H.L.; Liu, Y.Q.; Hou, X.G.; Li, T.T.; Li, Y.R. Effects of land use transitions due to rapid urbanization on ecosystem services: Implications for urban planning in the new developing area of China. *Habitat. Int.* **2014**, *44*, 536–544. [CrossRef]
41. De Boeck, F. Urban expansion, the politics of land, and occupation as infrastructure in Kinshasa. *Land Use Policy* **2020**, *93*, 103880. [CrossRef]
42. Hasse, J.E.; Lathrop, R.G. Land resource impact indicators of urban sprawl. *Appl. Geogr.* **2003**, *23*, 159–175. [CrossRef]
43. Li, C.; Ji, J. Spatial-temporal characteristics and driving factors of green economic efficiency in China. *Ann. Oper. Res.* **2021**. [CrossRef]
44. Jacobs, J. *The Economy of Cities*; Vintage: New York, NY, USA, 2016.
45. Fischer, G.; Sun, L.J.A. Model based analysis of future land-use development in China. *Agric. Ecosyst. Environ.* **2001**, *85*, 163–176. [CrossRef]
46. Holcombe, R.G. South Korea's economic future: Industrial policy, or economic democracy? *J. Econ. Behav. Organ.* **2013**, *88*, 3–13. [CrossRef]
47. Yang, J.; Yang, Y.; Tang, W. Development of evaluation model for intensive land use in urban centers. *Front. Arch. Res.* **2012**, *1*, 405–410. [CrossRef]
48. Shuai, S.; Fan, Z. Modeling the role of environmental regulations in regional green economy efficiency of China: Empirical evidence from super efficiency DEA-Tobit model. *J. Environ. Manag.* **2020**, *261*, 110227. [CrossRef] [PubMed]
49. Peuckert, J.; Transitions, S. What shapes the impact of environmental regulation on competitiveness? Evidence from Executive Opinion Surveys. *Environ. Innov. Soc. Transit.* **2014**, *10*, 77–94. [CrossRef]
50. Yuan, Y.; Xie, R. Research on industrial structure adjustment effect of environmental regulation—Empirical test based on panel data of Chinese provinces. *China Ind. Econ.* **2014**, *8*, 57–69.
51. Charnes, A.; Cooper, W.W.; Huang, Z.M.; Sun, D. Polyhedral cone-ratio DEA models with an illustrative application to large commercial banks. *J. Econ.* **1990**, *46*, 73–91. [CrossRef]

52. Du, J.; Liang, L.; Zhu, J. A slacks-based measure of super-efficiency in data envelopment analysis: A comment. *Eur. J. Oper. Res.* **2010**, *204*, 694–697. [CrossRef]
53. Li, H.; Shi, J.F. Energy efficiency analysis on Chinese industrial sectors: An improved Super-SBM model with undesirable outputs. *J. Clean. Prod.* **2014**, *65*, 97–107. [CrossRef]
54. Wang, H.R.; Cui, H.R.; Zhao, Q.Z. Effect of green technology innovation on green total factor productivity in China: Evidence from spatial durbin model analysis. *J. Clean. Prod.* **2021**, *288*, 125624. [CrossRef]
55. De Marchi, V. Environmental innovation and R&D cooperation: Empirical evidence from Spanish manufacturing firms. *Res. Policy* **2012**, *41*, 614–623. [CrossRef]
56. Nagaoka, S.; Motohashi, K.; Goto, A. Patent statistics as an innovation indicator. In *Handbook of the Economics of Innovation*; Elsevier: Amsterdam, The Netherlands, 2010; Volume 2, pp. 1083–1127.
57. Wang, X.; Yeung, G.; Li, X.; Wang, L. Does inter-regional investment by publicly listed companies promote local green total factor productivity? A study of the mediation effects of green patents in China. *J. Clean. Prod.* **2022**, *339*, 130582. [CrossRef]
58. Fabrizi, A.; Guarini, G.; Meliciani, V. Green patents, regulatory policies and research network policies. *Res. Policy* **2018**, *47*, 1018–1031. [CrossRef]
59. Zhi-Hong, Z.; Yi, Y.; Jing-Nan, S. Entropy method for determination of weight of evaluating indicators in fuzzy synthetic evaluation for water quality assessment. *J. Environ. Sci.* **2006**, *18*, 1020–1023. [CrossRef]
60. Jawadi, F.; Mallick, S.K.; Sousa, R.M. Fiscal and monetary policies in the BRICS: A panel VAR approach. *Econ. Model.* **2016**, *58*, 535–542. [CrossRef]
61. Li, T.; Lahr, M. Urbanization, Land Revenue and Market Equilibrium in China. *Urban Plan. Des. Res.* **2014**, *2*, 54–58.
62. Jun, C.; Qi, Y.; Li, D. Land finance of Chinese local governments: Formation and distortionary effects on urbanization. *China Financ. Econ. Rev.* **2014**, *3*, 38–55.
63. Huang, Z.; Du, X. Strategic interaction in local governments' industrial land supply: Evidence from China. *Urban Stud.* **2017**, *54*, 1328–1346. [CrossRef]
64. Fan, X.; Qiu, S.; Sun, Y. Land finance dependence and urban land marketization in China: The perspective of strategic choice of local governments on land transfer. *Land Use Policy* **2020**, *99*, 105023. [CrossRef]
65. Chen, Y. Financialising urban redevelopment: Transforming Shanghai's waterfront. *Land Use Polic* **2022**, *112*, 105126. [CrossRef]
66. Sun, J.; Chen, T.; Cheng, Z.; Wang, C.C.; Ning, X. A financing mode of Urban Rail transit based on land value capture: A case study in Wuhan City. *Transp. Policy* **2017**, *57*, 59–67. [CrossRef]
67. Li, X.; Hong, G. Land finance and urban economy development. *China Land Sci.* **2013**, *27*, 41–47.
68. Ruzi, L.; Yaobin, L.; Wengang, W.; Dejin, X. China's urban land finance expansion and the transmission routes to economic efficiency. *Acta Geogr. Sin.* **2020**, *75*, 10002126.
69. Wei, Y.-M.; Chen, K.; Kang, J.-N.; Chen, W.; Wang, X.-Y.; Zhang, X.J.E. Policy and management of carbon peaking and carbon neutrality: A literature review. *Engineering* **2022**. [CrossRef]
70. Solow, R.M. A contribution to the theory of economic growth. *Q. J. Econ.* **1956**, *70*, 65–94. [CrossRef]

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Spatio-Temporal Evolution and Obstacle Factors Analysis of Tourism Ecological Security in Huanggang Dabieshan UNESCO Global Geopark

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Abstract: The United Nations Educational, Scientific and Cultural Organization (UNESCO) Global Geoparks (UGGp) and geotourism activities not only improve people's scientific quality by popularizing geoscience knowledge, but also play important roles in protecting precious geoheritages and promoting the development of regional economies. However, tourism activities also have a negative impact on the local ecological environment, placing the regional ecological system under great pressure. Therefore, this paper constructed a tourism ecological security evaluation indicator system suitable for geoparks by using the "Driving-Pressure-State-Impact-Response" (DPSIR) model. The spatial autocorrelation and obstacle degree model are used to analyze the spatio-temporal characteristics and influencing factors of the tourism ecological security index (TESI) of Huanggang Dabieshan UGGp in 2000, 2005, 2010, 2015 and 2018, respectively. The results indicate that the TESI of the study area has gradually improved from 2000 to 2018. Spatially, the level of TESI presents a gradient distribution from the townships where the main scenic spots are located to the surrounding townships. The main obstacle factors affecting TESI include: per capita tourism income, proportion of comprehensive tourism revenue in GDP, per capita net income of rural residents, proportion of tertiary industry in GDP, coverage of nature reserves, planning integrity of geopark, informatization of geopark, growth rate of tourists, comprehensive utilization rate of solid waste, etc. The influencing factors of TESI varied from time to time. Balancing the conflict between local tourism activities and environmental protection, encouraging the participation of local communities, and strengthening science popularization for the local public will effectively improve the tourism ecological security of geoparks.

Keywords: tourism ecological security; Driving-Pressure-State-Impact-Response (DPSIR) model; spatial autocorrelation; obstacle analysis; Huanggang Dabieshan UNESCO Global Geopark (UGGp)

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1. Introduction

In recent decades, the vigorous development of the tourism industry has brought a lot of environmental pressure and influence, which seriously threaten ecological security and has received great attention. The development of tourism destinations, tourism resources and tourism markets has promoted the rapid development of the regional economy, increased foreign exchange income; promoted the development of the service industry, provided a large number of jobs, improved infrastructure, and increased the visibility of tourism destinations [1]. However, tourism has brought enormous pressures and risks on the local ecological environment mainly caused by the development of tourism resources, the construction of scenic spots, the passenger flow of tourists, and so on [1,2].

According to statistics, tourism has contributed much to global greenhouse gas emissions, accounting for 12.5% of total global emissions [3]. Research shows that emissions caused by tourism are projected to double from 2005 to 2035 [4]. Tourism activities such as transportation and accommodation involve higher energy consumption and carbon intensity, which have a big impact on the climate [5,6]. Moreover, some tourism activities have directly interfered with the local flora and fauna communities and the associated ecosystems, and disturbed the habitats of birds [7–9]. The consumption of resources and the destruction of ecological environments not only affect the diversity and functionality of the ecosystems of tourism destinations, but also seriously threaten the ecological security of these places.

Ecological security is an emerging research field in recent years, which has received extensive attention from academics [10–14]. It refers to the state in which an ecosystem provides material resources and services for the survival of human society and promotes economic development on the basis of ensuring its own integrity and health [15]. Ecological security assessment research has been carried out from national and regional perspectives [16–20]. The research objects include cities, land, river basins, ecologically fragile areas, ecological protection areas and so on [21–28]. Tourism ecological security is the concrete practice of ecological security in the tourism discipline. The concept of ecological security has been integrated into research on ecotourism and sustainable tourism for a long time [29–32]. Many studies have shown that tourism development can balance conflicts between socio-economic development and environmental protection in these regions to a certain extent [33]. Therefore, the ecological security of tourism destinations has always been a subject of widespread concern [34–36]. At the same time, it is also one of the important fields in the study of tourism destination sustainable development [35]. Consequently, tourism ecological security can be roughly summarized as a state that, through the rational development of tourism resources and the governance of ecological environment, the ecosystem of tourism destination keeps structural stability and functional diversity, provides a rich material foundation and environmental space for tourism development, and maintains the coordinated and sustainable development of the nature-society-economy complex ecosystem.

The study of tourism ecological security involves the fields of ecology, tourism science, geography, environmental science, energy science, etc. [37–41]. Early studies on tourism ecological security mainly focused on the impact of tourism activities on the environment, including tourism environmental capacity, tourism environmental protection, tourism carrying capacity and sustainable tourism [30,42–47]. Subsequently, more research has been done on the evaluation and measurement, spatial and temporal pattern, driving mechanism, prediction and early warning of tourism ecological security [48–53].

The evaluation of tourism ecological security mainly focuses on evaluation indicators and methods. The "Pressure-State-Response" (PSR) model, "Driving-Pressure-State-Impact-Response" (DPSIR) model, "Pressure-State-Response-Environment-Economy-Society" (PSR-EES) model, and other quantitative models are usually used to establish the evaluation indicator system of tourism ecological security [25,49,54,55]. Quantitative research methods mainly include tourism environmental carrying capacity, ecological footprint (EF) method, comprehensive index method, analytic hierarchy process (AHP) method, improved Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, grey relation projection method, and so on [27,56–60]. The grey correlation degree and obstacle degree model are usually used to analyze influencing factors [53,61,62]. Compared with other evaluation models, the DPSIR model is more comprehensive, logical and systematic. It has high applicability for tourism ecological security evaluation [50], which can effectively identify the operating status of the tourism ecosystem. It can not only fully reflect the interactive relationship among human activities, the ecological environment and socioeconomic development, but also indicate the cyclic characteristics of system development [51]. The obstacle degree model can quantify the obstruction degree of influencing factors [63], which is conducive to accurately identifying the main obstacle indicators for further evaluation. Therefore, they are selected as the research methods for this paper.

From the existing literature, the evaluation and methods of tourism ecological security usually depend on the research object. Therefore, it is necessary to establish an appropriate evaluation indicator system [27]. Many kinds of tourism destinations have been studied, e.g., forest, lake, mountain areas, island and other different types of tourism destinations [48,58,64–66]. However, little research has been focused on geoparks, which aim to achieve geoheritage conservation and regional sustainable development. The United Nations World Tourism Organization (UNWTO) recommended five central pillars for sustainable development through tourism in 2017, including inclusive and sustainable economic growth, employment and poverty alleviation, environmental protection and climate change, heritage and cultural values, mutual understanding, peace, and security [47]. The United Nations Educational, Scientific and Cultural Organization (UNESCO) proposed the establishment of the Global Geoparks Network (GGN) in 1999 to manage and protect geoheritages and landscapes of international geological significance, and advocate the sustainable utilization of natural resources and sustainable tourism [67]. The "International Geoscience and Geoparks Programme (IGGP)" was officially approved in 2015, updating GGN to UNESCO Global Geoparks (UGGp). The Geoparks Initiative highlights the potential for interaction between the development of social economy and culture and the conservation of eco-environment [68]. At present, the research on geoparks is mainly focused on the classification and evaluation of geoheritage resources, geoheritage characteristics and geomorphological formation processes, tourist behavior characteristics and perception, geotourism projects design and geoproducts innovation, local community participation, etc. [69–75]. In fact, with the development of geopark construction and the increase in tourism activities, the local ecosystem faces great pressure. Thus, this paper aims to establish a tourism ecological security evaluation indicator system for geoparks, to enrich the theory of tourism ecology and ecological security. It can provide feasible paths and improvement measures for the sustainable development of geoparks through the tourism ecological security evaluation.

In this paper, Huanggang Dabieshan UGGp is selected as a typical case for the following reasons. Firstly, the widely distributed geoheritages and landscapes in Huanggang Dabieshan UGGp are of great international significance in terms of geological and ecological aesthetics. The study area is an important part of the "geological-geographical-climatic-ecological" dividing line in eastern China. It is also rich in biodiversity, which is a relatively well-preserved storehouse of species resources in Central China. Secondly, in the past decade, with the rapid development of tourism, both the landscape and the ecosystem of Huanggang Dabieshan UGGp have been under pressure from the consumption of tourism resources and human activities. It has posed a great threat to the geoheritages and ecosystems. Thirdly, compared with other tourism destinations, geoparks have their unique features, mainly in the unique geotourism resources and geological science popularization and education functions. Finally, few studies on tourism ecological security take geoparks as the object so that this paper tries to fill the gap and puts forward some suggestions for reference.

Therefore, the purpose and significance of this paper are as follows: (1) establish a tourism ecological security evaluation model for Huanggang Dabieshan UGGp. A comprehensive multi-factors evaluation indicator system based on the DPSIR model is constructed and some evaluation indicators are selected that are different from other tourism destinations, which can enrich the theoretical research of geopark and ecological security. (2) explore the tourism ecological security index (TESI) of Huanggang Dabieshan UGGp and its spatio-temporal distribution characteristics. The spatial and temporal distribution trend is obtained through spatial autocorrelation analysis. The changes of the TESI level throughout the study area are analyzed in different dimensions. (3) diagnose the main influencing factors affecting tourism ecological security. The core factors affecting the TESI of Huanggang Dabieshan UGGp in different periods are identified through an obstacle degree model. (4) discuss the countermeasures and suggestions for ecotourism and sustainable development of geoparks, so as to provide theoretical guidance for Huanggang Dabieshan UGGp and other geoparks to coordinate the relationship between conservation and tourism development. It is conducive to promote the formulation and implementation of relevant policies.

The research framework is shown in Figure 1.

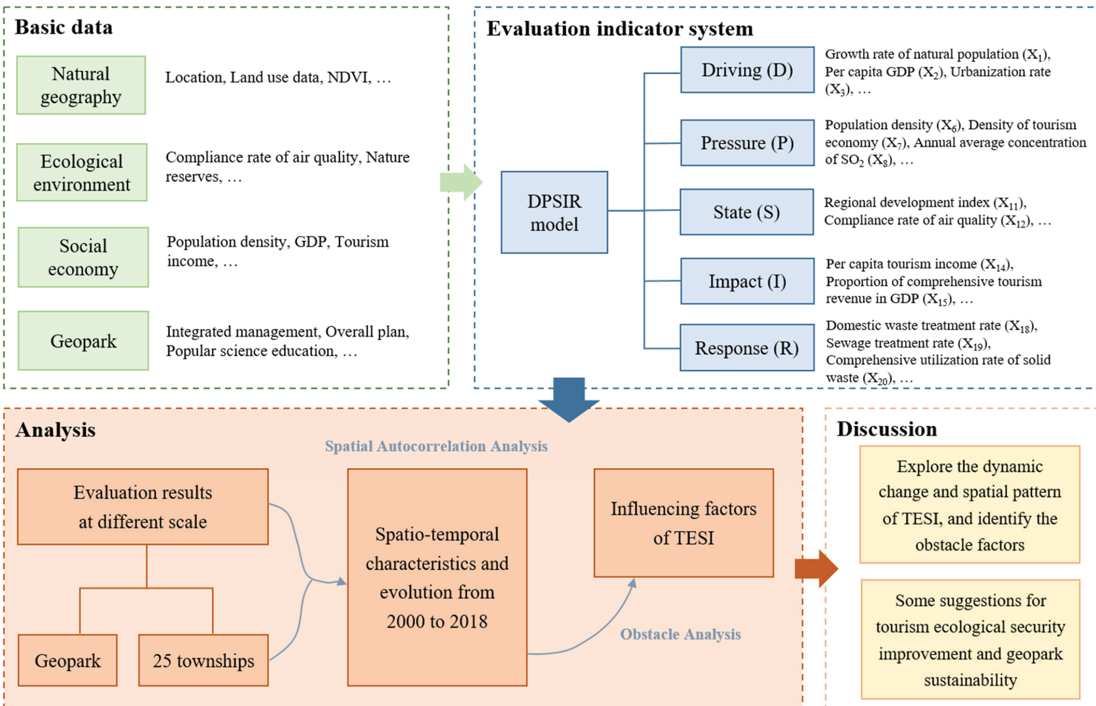

Figure 1. The framework of tourism ecological security evaluation of Huanggang Dabieshan UGGp.

2. Materials and Methods

2.1. Study Area

Huanggang Dabieshan UGGp is situated in Eastern Asia, Huanggang City, Hubei Province of the People's Republic of China, with a total area of 2625.54 square kilometers (Figure 2). The administrative division of the study area involves Macheng City, Luotian County and Yingshan County, including 25 townships.

Huanggang Dabieshan UGGp is characterized by a continental orogenic belt, a tectonic deformation metamorphic belt and granite mountain landforms. The terrain of the geopark gradually tilts from north to south. Among them, there are 96 peaks with an altitude of more than 1000 m in the north. The highest peak, at 1729.13 m above sea level, is located at the junction of Luotian County and Yingshan County in the northeast.

During the ongoing geological evolution, various typical geological landscapes have been formed in this area, which mainly includes 4 global-level, 5 national-level, 21 provincial-level and 23 local-level geoheritages. The unique location belonging to the subtropical monsoon climate zone produces excellent natural conditions, which have created a region with dazzling biodiversity. Huanggang Dabieshan UGGp boasts valuable geoheritages, unique ecological landscapes and beautiful cultural sights, which has made it a rare and significant geopark and geoheritages reserve in the world.

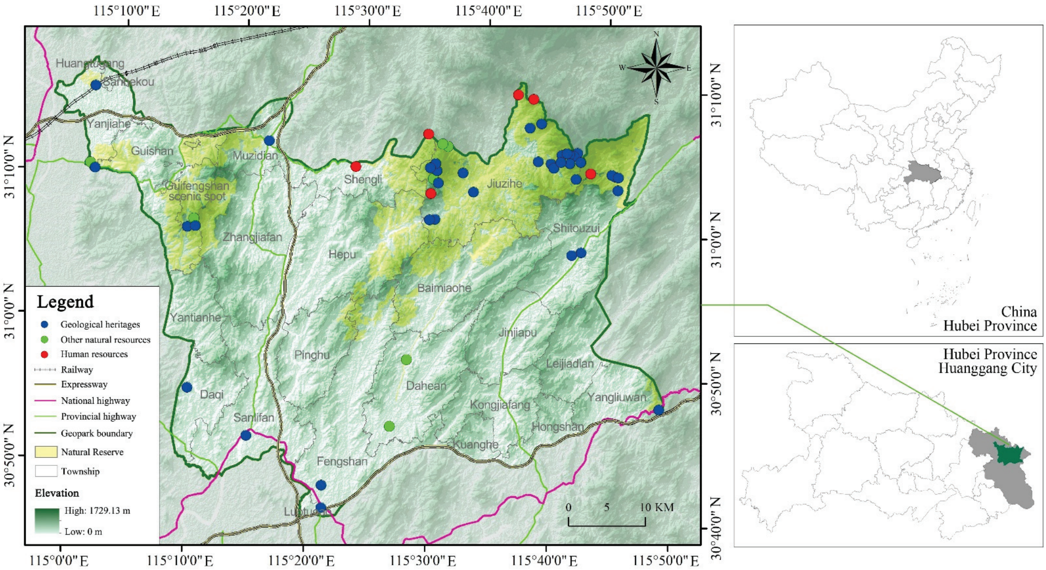

Figure 2. Geographical location of Huanggang Dabieshan UGGp.

The study area was approved as a national geopark in 2009 and became a member of UGGps in 2018. As the main tourism destination in the east of Hubei Province and Huanggang City, Huanggang Dabieshan UGGp has attracted a large number of tourists from local and surrounding cities, and promoted the development of the local tourism economy and related service industries. The tourism economy in Huanggang City has grown at an annual rate of more than 20%, with Huanggang Dabieshan UGGp as the leading tourism industry [76]. In 2018, the number of tourists in Huanggang City increased to 36.45 million and total tourism revenue reached 3.85 billion dollars.

The main tourist areas of Huanggang Dabieshan UGGp include Tiantangzhai, Bodaofeng, Wujiashan, Guifengshan, Jiulongshan, etc. The typical geological tourist attractions are granite pictographic stone landscapes, including Philosopher Peak, Guifeng Peak (Stone Tortoise), Longtan Gorge, etc. Every spring and summer, Huanggang Dabieshan UGGp is crowded with tourists enjoying flowering rhododendrons and their summer vacation. According to incomplete statistics, the geopark's ticket revenue alone reached 101 million dollars in 2018. The comprehensive tourism revenue reached 957million dollars, accounting for 31% of the regional Gross Domestic Product (GDP).

After more than a decade of tourism development, the huge tourist flow and the development of resources and tourism projects inevitably brought a series of negative impacts on the ecological environment. The evaluation of tourism ecological security in Huanggang Dabieshan UGGp can not only obtain the influencing factors affecting the environment in this area, but also explore the appropriate development direction of the geopark, and provide a scientific basis for the sustainable and healthy development of Huanggang Dabieshan UGGp, which has important research value and practical significance.

2.2. Data Sources

The land use data, spatial distributions of population density, GDP, Normalized Difference Vegetation Index (NDVI) and other data of the study area were obtained from the Resource and Environment Science and Data Center of Chinese Academy of Sciences (http://www.resdc.cn/, accessed on 5 April 2022). The administrative boundaries, nature reserves, and tourism resources came from field investigation and project statistics provided by Huanggang Dabieshan National Geopark Administrative Office.

Other socio-economic data were collected from *Hubei Statistical Yearbook*, *Huanggang Statistical Yearbook*, *China County Statistical Yearbook*, the environmental quality report of Huanggang City, etc. Some missing data were filled by the moving average method.

Due to the large sample size, this paper only selected five periods of data in 2000, 2005, 2010, 2015 and 2018 for analysis. The spatial and temporal distribution characteristics of TESI in the study area will be presented in 25 townships.

2.3. Methods

2.3.1. Evaluation Indicator System for Tourism Ecological Security

Academics have established many indicator systems for evaluating research [25,55,60]. Among them, the "Driving-Pressure-State-Impact-Response" (DPSIR) model was established by the European Environment Agency (EEA) in 1993. It has integrated the "Pressure-State-Response" (PSR) model and the "Driving Force-State-Response" (DSR) model, and added "Impact" indicators in its framework [77]. The DPSIR model can effectively reflect the interaction between elements in a system. It has been widely applied to quantitative research, such as environmental assessment, water resources ecological security assessment, sustainable development capacity assessment, etc. [78–80].

In the tourism ecosystem, the DPSIR model can effectively measure the relationship between tourism activities and the ecological environment, and reflect the positive feedback of human society [51]. The operational mechanism of the DPSIR model can be summarized as follows [81–84]: as the long-term driving force (D) affecting the tourism ecological security, social and economic factors have imperceptibly caused various pressures (P) on the natural environment, ecology and social resources. These pressures (P) are directly reflected in the changes of the regional social economy and environmental state (S). Furthermore, it has a series of impacts (I) on the regional ecosystem, prompting human to take a series of positive response (R) measures to achieve the goal of sustainable development. At the same time, these response (R) measures not only act on the system composed of human economy and society (D), but also directly have a positive impact (I) on pressure (P) and state (S), so as to form a circular, closed loop (Figure 3).

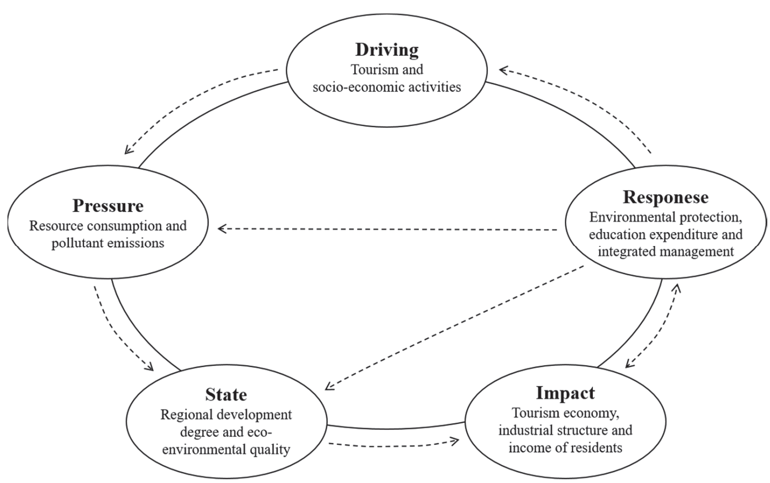

Figure 3. The operational mechanism of the DPSIR model.

Considering the impact of natural conditions, human activities, economic growth, social development and other factors on the tourism ecosystem of geopark, the DPSIR model is chosen as the evaluation model of the tourism ecological security of Huanggang Dabieshan UGGp. Combined with the previous literature, field investigation and interviews and acquired data [25,27,49–53,85], 25 indicators are selected.

Driving indicators represent human socio-economic activities. The growth of population, urbanization, national economy, and tourism demand are the most basic driving forces.

Pressure indicators describe the load of the exploitation on the ecological environment. The reasons for the change are given from the perspectives of population density, tourism economic density, and annual average concentration of pollutants.

State indicators reflect the ecological environment and socio-economic development of the study area. The regional development index is the ratio of the total area of regional cultivated land and construction land to the total area of regional land, reflecting the development state of human activities and urbanization process in a period. The compliance rate of air quality and NDVI indicate air quality status and vegetation coverage status, respectively.

Impact indicators refer to the indicators that bring changes to the maintenance of tourism ecological security and industrial development when the ecological environment or socio-economic system changes. Tourism revenue, rural residents' income, and proportion of tertiary industry in GDP reflect that the higher the scale of tourism and tertiary industry is, the more investment will be made in improving tourism ecological security, and the greater the positive impact will be produced on TESI.

Response indicators reflect the positive measures taken by the government and the geopark to improve the regional tourism ecological security. Domestic waste treatment rate, sewage treatment rate, and comprehensive utilization rate of solid waste represent the situation of cleaner production, environmental treatment and the degree of resources recycling and reuse. The coverage of nature reserves reflects the degree of local government's protection and attention to the ecological environment. The proportion of education expenditure in GDP indicates the importance of education development in the region, which indirectly reflects the education level of the local residents. Planning integrity, interpretive coverage and informatization of geopark refer to the management response of Huanggang Dabieshan UGGp. The better the management, the greater the role of promotion for the TESI. Since the study area is a geopark, the selection of indicators should be distinguished from other tourism destinations. The *UNESCO Global Geopark Applicant's Evaluation Document A—Self Evaluation* is an assessment document officially released by UNESCO, which is referential [86]. The contents relate to overall planning, a science popularization interpretation system, and informatization construction are extracted and summarized into the last three indicators. The value is assigned by calculating the ratio of the total self-assessment score of planning, interpretation and informatization to the total standard score. As an official document that UGGps need to be evaluated every four years, it is applicable to all the geoparks.

The complete evaluation indicator system is shown in Table 1.

Table 1. Evaluation indicator system for tourism ecological security.

First-Level Indicator	Second-Level Indicator	Number	Unit	Attribute	Weight
Driving	Growth rate of natural population	X_1	‰	–	0.0256
	Per capita GDP	X_2	dollar	–	0.0211
	Urbanization rate	X_3	%	–	0.0034
	Growth rate of tourists	X_4	%	–	0.0237
	Growth rate of comprehensive tourism revenue	X_5	%	–	0.0108
Pressure	Population density	X_6	per/km^2	–	0.0048
	Density of tourism economy	X_7	ten thousand yuan/km^2	–	0.0098
	Annual average concentration of SO_2	X_8	μg/m$_3$	–	0.0312
	Annual average concentration of NO_2	X_9	μg/m$_3$	–	0.0126
	Annual average concentration of inhalable particulate matter (PM_{10})	X_{10}	μg/m$_3$	–	0.0316

Table 1. *Cont.*

First-Level Indicator	Second-Level Indicator	Number	Unit	Attribute	Weight
State	Regional development index	X_{11}	%	−	0.0144
	Compliance rate of air quality	X_{12}	%	+	0.0301
	NDVI	X_{13}		+	0.0141
Impact	Per capita tourism income	X_{14}	dollar	+	0.1038
	Proportion of comprehensive tourism revenue in GDP	X_{15}	%	+	0.0654
	Per capita net income of rural residents	X_{16}	dollar	+	0.0639
	Proportion of tertiary industry in GDP	X_{17}	%	+	0.0337
Response	Domestic waste treatment rate	X_{18}	%	+	0.0654
	Sewage treatment rate	X_{19}	%	+	0.0316
	Comprehensive utilization rate of solid waste	X_{20}	%	+	0.0418
	Coverage of nature reserves	X_{21}	%	+	0.1684
	Proportion of education expenditure in GDP	X_{22}	%	+	0.0234
	Planning integrity of geopark	X_{23}	%	+	0.0541
	Interpretive coverage of geopark	X_{24}	%	+	0.0599
	Informatization of geopark	X_{25}	%	+	0.0555

Note: "+" indicates positive indicator and "−" indicates negative indicator.

2.3.2. Comprehensive Index Method

Because of the difference in dimension and order of magnitude, the original data need to be standardized. For the positive indicator,

$$x'_{ij} = (x_{ij} - x_{jmin}) / (x_{jmax} - x_{jmin}) \tag{1}$$

and for the negative indicator,

$$x'_{ij} = (x_{jmax} - x_{ij}) / (x_{jmax} - x_{jmin}) \tag{2}$$

In the above formulas, x'_{ij} stands for the standardized value of the original data; x_{ij} stands for the original value of indicator j in year i; x_{imax} and x_{jmin} stands for the maximum and minimum values of indicator j among all years, respectively.

The entropy weight method is used to calculate the weight of each indicator in the evaluation system. It can analyze the degree of correlation between indicators based on objective information, and reduce the impact of subjective factors to a certain extent [19,53,58]. The formulas are as follows:

$$p_{ij} = x'_{ij} / \sum_{j=1}^{n} x'_{ij} + 0.000001 \tag{3}$$

$$E_j = -k \sum_{j=1}^{n} p_{ij} \ln p_{ij} \tag{4}$$

$$w_j = (1 - E_j) / \sum_{j=1}^{n} (1 - E_j) \tag{5}$$

In the above formulas, p_{ij} represents the proportion of the standardized value of indicator j in year i to the sum of all the standardized values of indicator j. Since $\ln p_{ij}$ is meaningless when p_{ij} = 0, the formula is revised to (3).

E_j represents the entropy of indicator j; k represents the Boltzmann constant, $k = 1/\ln(n)$; w_j represents the information entropy weight of indicator j. The weights of all indicators are shown in Table 1.

The TESI can be calculated by the comprehensive index method. The formula is as follows:

$$TESI_i = \sum_{j=1}^{n} w_j x'_{ij} \quad (6)$$

where $TESI_i$ is the TESI in year i; w_j and x'_{ij} are the weight and standardized value of indicator j; and n is the number of indicators in the evaluation system. The TESI level can be classified into 5 types [35,53,58]: unsafe, less unsafe, critical safe, relatively safe, and safe (Table 2).

Table 2. Classification of TESI level.

Level	I	II	III	IV	V
Category	Unsafe	Less unsafe	Critical safe	Relatively safe	Safe
Range	(0, 0.2]	(0.2, 0.4]	(0.4, 0.6]	(0.6, 0.8]	(0.8, 1]

2.3.3. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis is a method of exploratory spatial data analysis, which reveals the similarity and spatial correlation of attribute values of adjacent regions [50,51,87–89]. This method is usually measured by Moran's I, including the Global Moran Index and the Local Moran Index. The interval of Moran's I value ranges from −1 to 1. If Moran's I value is greater than 0 and passes the autocorrelation significance test, it illustrates that the change trend of a spatial unit is the same as that of adjacent units. That is, the spatial autocorrelation is positive and there is aggregation. If Moran's I value is less than 0, the spatial autocorrelation is negative. The larger the absolute value of Moran's I is, the stronger the spatial autocorrelation will be. When the value is equal to 0, the spatial autocorrelation is random. The formulas are as follows:

$$I_G = \sum_{i=1}^{n} \sum_{j \neq i}^{n} w_j (y_i - \overline{y})(y_j - \overline{y}) / S^2 \sum_{i=1}^{n} \sum_{j \neq i}^{n} w_{ij} \quad (7)$$

$$I_L = \frac{y_i - \overline{y}}{S^2} \sum_{j \neq i}^{n} w_{ij} (y_i - \overline{y}) \quad (8)$$

where I_G is the Global Moran Index; I_L is the Local Moran Index; n is the number of spatial units; y_i and y_j are the observed values of spatial units; $\overline{y}$ is the average of the observed values; S^2 is the variance of the observed values; w_{ij} is a weight matrix based on the spatial adjacency relationship.

2.3.4. Obstacle Analysis

Obstacle factors refer to the barriers that restrict and hinder the tourism ecological security of geoparks. It is helpful to improve the level of TESI by evaluating the barrier effect of each indicator and finding out the main obstacle factors [58,62,90]. The obstacle degree model consists of three indexes: deviation degree (I_{ij}), factor contribution degree (w_{ij}) and obstacle degree (O_{ij}). The formula is as follows:

$$I_{ij} = 1 - x'_{ij} \quad (9)$$

$$O_{ij} = I_{ij} w_{ij} / \sum_{j=1}^{n} I_{ij} w_{ij} \times 100\% \quad (10)$$

where I_{ij} indicates the gap degree between the indicator j and the target of tourism ecological security; w_{ij} is expressed by the weight of each indicator, which represents the contribution degree of a single factor to the overall objective of tourism ecological security; O_{ij} is the obstacle degree of indicator j on tourism ecological security in year i.

3. Results

3.1. Spatio-Temporal Characteristics of TESI

3.1.1. TESI of Huanggang Dabieshan UGGp

It is shown from Table 3 that the TESI of Huanggang Dabieshan UGGp has gradually increased from 2000 to 2018, and that the security level has improved from less unsafe to relatively safe.

Table 3. TESI of Huanggang Dabieshan UGGp from 2000 to 2018.

Year	2000	2005	2010	2015	2018
TESI	0.176	0.227	0.440	0.551	0.657
Level	I	II	III	III	IV

According to the overall change of TESI in the study area, it can be divided into three stages. In the unsafe stage (2000-2005), the TESI increased very slowly from 0.176 to 0.227, which were all in the status of unsafe. Various social, economic and environmental problems have serious constraints on the tourism ecological security. In the critical safe stage (2010-2015), the TESI continued to grow from 0.44 to 0.551. The tourism ecological security of Huanggang Dabieshan UGGp has reached the status of critical safe from unsafe. In the relatively safe stage (2018), the TESI rose to 0.657. The study area is basically in a relatively safe status.

3.1.2. Evolution of TESI Level in Different Townships

Taking 25 townships as evaluation units, the TESI of each township is calculated and shown in Figure 4. It can be seen that, in terms of time, the TESI of each township has shown a steady upward trend. The TESI of all the townships was at a low level in 2000 and 2005, and then presented a multi-level development state since 2010. ArcGIS software is used for visualization, as shown in Figure 5.

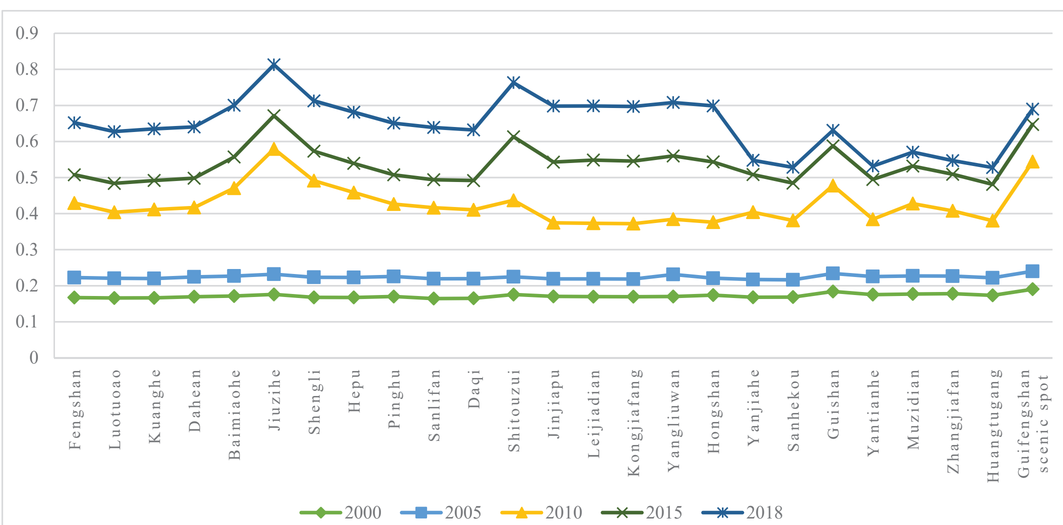

Figure 4. TESI of each township in Huanggang Dabieshan UGGp from 2000 to 2018.

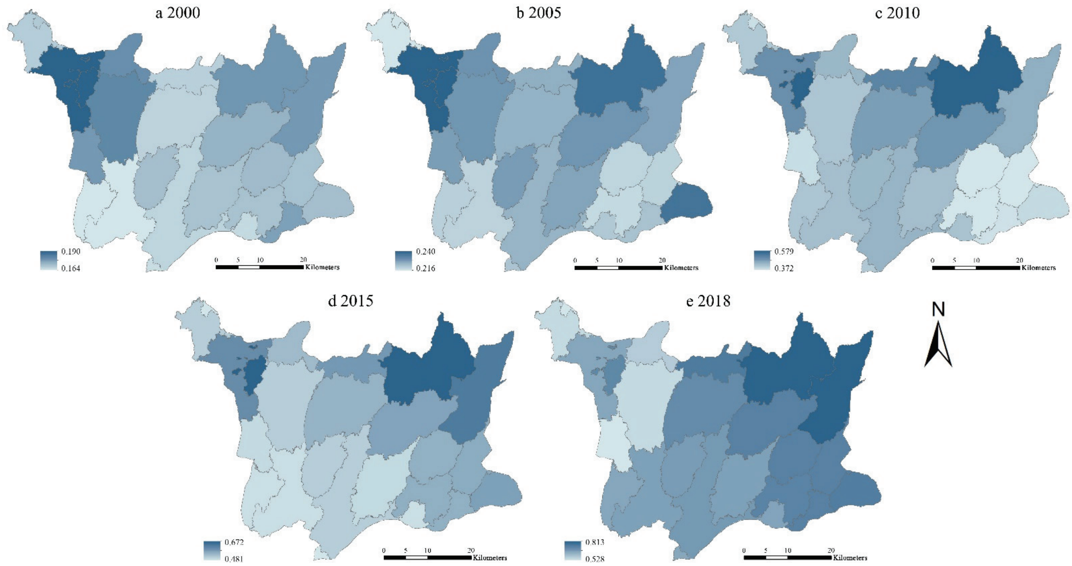

Figure 5. Distribution of TESI in Huanggang Dabieshan UGGp from 2000 to 2018.

3.2. Spatial Pattern Analysis

The Moran's *I* value of TESI from 2000 to 2018 was calculated by GeoDa software. The Global Moran's *I* values of these 5 phases were greater than 0, and passed the significance test of 5%. It revealed that the TESI in Huanggang Dabieshan UGGp from 2000 to 2018 had a significant positive correlation, which means it had obvious spatial distribution characteristics of aggregation. The townships with higher TESI tended to be adjacent, as did the townships with lower TESI.

From the perspective of time series, Moran's *I* value showed a "W" trend of increasing fluctuation, and reached its highest level in 2018. The decrease in Moran's *I* value showed that the uniformity of TESI distribution in Huanggang Dabieshan UGGp had reduced, as townships with changes in TESI had increased. The increase in Moran's *I* value indicated that the level of TESI had been increased and the uniformity of TESI distribution had been improved. The spatial correlation of TESI had been gradually strengthened, as the distribution of TESI tended to be stable.

As illustrated in Figure 6, the TESI showed an obvious spatial disparity. The TESI of most townships were in "High-High (HH)" and "Low-Low (LL)" quadrants, indicating that it had strong local autocorrelation and the overall pattern was relatively stable. Most townships were surrounded by townships with similar security level; that is, it had a strong spatial dependence.

According to Figure 7, the TESI generally presented dynamic spatial agglomeration with "HH" type and "LL" type, which showed positive local spatial autocorrelation. From 2000 to 2018, "HH" agglomeration was successively concentrated in the Guifengshan scenic spot, Guishan, Shengli, Jiuzihe, and Shitouzui, which were little different to the neighboring townships and belonged to local homogeneous distribution. "LL" agglomeration was successively distributed in Fengshan, Kongjiafang, Leijiadian, Sanlifan, and Yanjiahe. "Low-High (LH)" agglomeration indicated the low level of TESI in "LH" township and high level of TESI in neighboring townships, which only existed in Zhangjiafan in 2010. "High-Low (HL)" agglomeration showed the high level of TESI in "HL" township and low level of TESI in neighboring townships, presenting an obvious polarization effect and negative correlation. It did not exist in the study area throughout the study period.

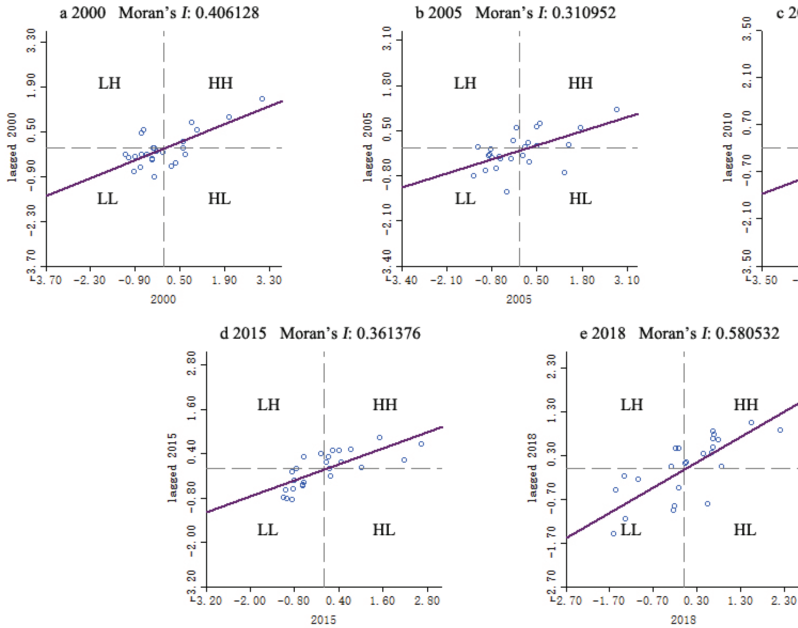

Figure 6. Moran scatter plot of TESI in Huanggang Dabieshan UGGp from 2000 to 2018. HH, High-High agglomeration; HL, High-Low agglomeration; LL, Low-Low agglomeration; LH, Low-High agglomeration.

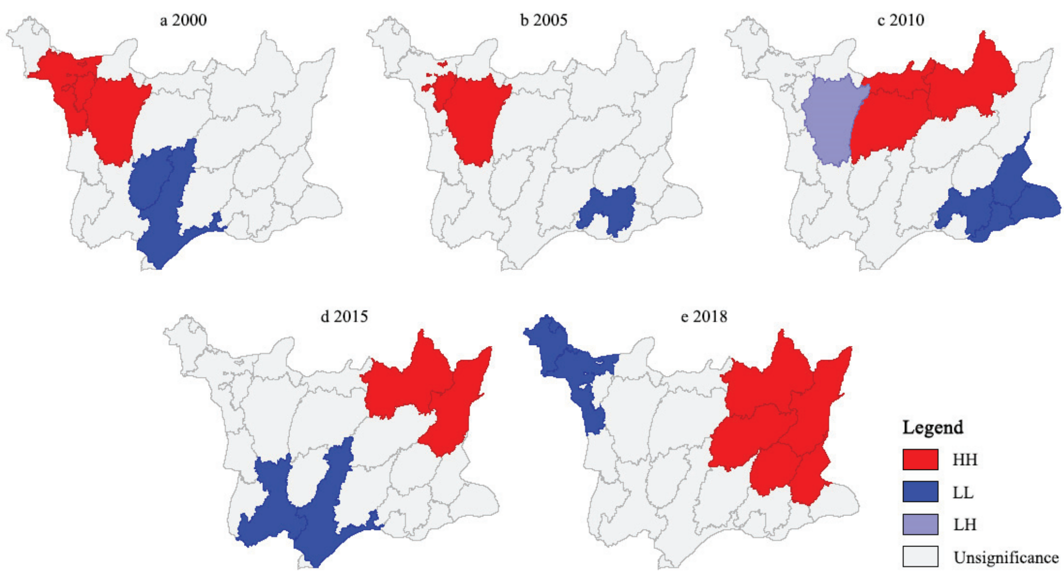

Figure 7. Local indicators of spatial autocorrelation (LISA) cluster maps of TESI in Huanggang Dabieshan UGGp from 2000 to 2018. HH, High-High agglomeration; LL, Low-Low agglomeration; LH, Low-High agglomeration.

3.3. Obstacle Factors of TESI

This paper only lists the top 8 obstacle factors of obstruction degree each year due to lack of space. As shown in Table 4, the main obstacles to the tourism ecological security of Huanggang Dabieshan UGGp included: per capita tourism income (X_{14}), proportion of comprehensive tourism revenue in GDP (X_{15}), per capita net income of rural residents (X_{16}), proportion of tertiary industry in GDP (X_{17}), coverage of nature reserves (X_{21}), planning integrity of geopark (X_{23}), informatization of geopark (X_{25}), growth rate of tourists (X_4), comprehensive utilization rate of solid waste (X_{20}), etc.

Table 4. Ranking of Obstacle factors of TESI.

Year	Item	Ranking							
		1	2	3	4	5	6	7	8
2000	Obstacle factor	X_{21}	X_{14}	X_{15}	X_{18}	X_{16}	X_{24}	X_{25}	X_{23}
	Degree of obstruction (%)	20.563	12.673	7.987	7.987	7.802	7.316	6.782	6.602
2005	Obstacle factor	X_{21}	X_{14}	X_{18}	X_{15}	X_{16}	X_{24}	X_{25}	X_{23}
	Degree of obstruction (%)	21.944	13.511	8.591	8.046	7.920	7.682	6.734	6.596
2010	Obstacle factor	X_{14}	X_{16}	X_{15}	X_{20}	X_{17}	X_{25}	X_4	X_{23}
	Degree of obstruction (%)	23.379	11.691	10.808	10.015	8.093	5.977	4.054	3.853
2015	Obstacle factor	X_{14}	X_8	X_4	X_{15}	X_1	X_{20}	X_{16}	X_{17}
	Degree of obstruction (%)	18.334	10.816	8.198	8.017	7.363	7.306	6.118	6.052
2018	Obstacle factor	X_{20}	X_1	X_2	X_{11}	X_{22}	X_7	X_8	X_{12}
	Degree of obstruction (%)	18.445	17.702	14.550	9.928	7.779	6.768	5.756	5.486

Among these influencing factors, per capita tourism income (X_{14}), proportion of comprehensive tourism revenue in GDP (X_{15}), and per capita net income of rural residents (X_{16}) were the main obstacles to the tourism ecological security of the geopark from 2000 to 2015. The impact of per capita tourism income (X_{14}) was strong and remained a major barrier until 2015.

Coverage of nature reserves (X_{21}), planning integrity of geopark (X_{23}) and informatization of geopark (X_{25}) were the main obstacles to tourism ecological security from 2000 to 2010.

From 2000 to 2005, domestic waste treatment rate (X_{18}) and interpretive coverage of geopark (X_{24}) showed that poor ecological environment quality and weak management also had a certain impact on tourism ecological security.

The common obstacles in 2010-2015 were: growth rate of tourists (X_4), proportion of tertiary industry in GDP (X_{17}), and comprehensive utilization rate of solid waste (X_{20}). The common barriers in 2015-2018 were natural population growth rate (X_1) and annual average concentration of SO_2 (X_8).

The greatest barriers in 2015 and 2018 were per capita tourism income (X_{14}) and comprehensive utilization rate of solid waste (X_{20}), respectively. In 2018, per capita GDP (X_2), density of tourism economy (X_7), regional development index (X_{11}), compliance rate of air quality (X_{12}), comprehensive utilization rate of solid waste (X_{20}) and proportion of education expenditure in GDP (X_{22}) also became important obstacle factors to tourism ecological security.

4. Discussion

4.1. Selection of Evaluation Indicators

In order to explore the reasons and trends of tourism ecological security, the material basis and ecological environmental conditions, which were provided by the tourism destination ecosystem for tourism and socio-economic development, should be comprehensively evaluated. A multi-dimensional evaluation is carried out by taking into account the pressure of resource consumption and emission brought about by tourism development and human social activities, as well as the response and maintenance measures taken by socio-economic systems and geoparks. By summarizing the existing literature and field investigations, and considering the availability of data, the indicators selected in this paper included the development of geopark tourism, population, economy, current situation of ecological environment, environmental protection and governance, etc. Most of the indicators had a high occurrence rate in the existing literature.

The driving indicators were selected from the aspects of geopark tourism and socio-economic development [84]. The growth rate of tourists and the growth rate of comprehensive tourism revenue represented the development of the tourism industry, reflecting that the more popular and attractive the geopark is to tourists, the higher the indirect threats to the ecosystem would be. The growth rate of natural population, per capita GDP and urbanization rate indicate the regional social and economic development, which can indirectly reflect the negative impacts of socio-economic development on regional resources consumption and ecological environment.

The pressure indicators are selected from the damage caused by tourism and human activities to the ecosystem. Population density indicates that resources consumption will increase ecological and environmental problems. Some scholars take tourism economic density as an impact indicator [50,51], but this paper holds that the density of tourism economy is the tourism economic income carried on the unit land, which indirectly reflects the consumption of regional resources and the threat faced by ecological environment, so it is used as a pressure indicator. The emission of pollutants also shows the negative damage of economic development on regional ecological environment. Similar indicators such as industrial wastewater discharge, industrial SO_2 emission, industrial smoke dust emission and total exhaust emission should be selected based on the availability of data [22,49,50,52].

The state indicators were selected from the urbanization process and the health degree of ecological environment. The regional development index reflects human activities and the process of urbanization. The existing literature also used indicators such as the number of star hotels and the number of tourism practitioners [27,49]. This study did not conduct a complete survey of all the townships in the study area, so the data cannot be supported. Future research can consider these indicators that reflect the current situation of tourism development. The compliance rate of air quality and NDVI reflect the degree of air pollution and vegetation coverage in the region. Indicators such as per capita green area and green coverage rate of built-up areas are mostly used for urban and other research areas [27,50,52]. The study area in this paper is located in mountainous areas, with good overall vegetation coverage and relatively less construction land, so only NDVI was used. Forest coverage index, biodiversity index and ecological vulnerability index can be used to reflect the status of ecological resources in the future work.

The impact indicators reflect the impacts and changes of natural ecology and social resources under pressure, which are usually expressed in terms of per capita tourism income, per capita net income of rural residents, proportion of comprehensive tourism revenue in GDP and proportion of tertiary industry in GDP [50–53]. These indicators usually reflect positive impacts. Geoparks that benefit from tourism activities will pay more attention to the capital investment in tourism development and ecological environmental protection. Residents who benefit from tourism activities will cherish and participate in the tourism industry, and form a mutually beneficial and win-win situation with the geopark. The tertiary industry reflects the regional industrial structure. It is dominated by the service industry, with less resource consumption and light environmental pollution. The larger the proportion of the tertiary industry, the less damage and threat the ecological environment will suffer from.

The response indicators are selected from the positive measures taken by the government and managers to improve the regional tourism ecological security. The treatment of domestic waste, sewage and solid waste is the key factor for the sustainability of the ecological environment, so that the related indicators are used frequently. The coverage of nature reserves indicates the degree of local government's attention to the ecological environmental protection. The number of college students has been used to reflect the education level of local residents [51,52]; this paper replaced it by the proportion of education expenditure in GDP due to the difficulty of data acquisition. The problems they reflect are basically the same, which mean the long-term measures of talent education. Some studies have used the proportion of investment in environmental protection [52,58], which is not used in this paper due to incomplete statistical data, but is necessary to be considered in the future. The indicators of management response of the geopark are selected according to the characteristics of the study area, so that other study areas should choose the corresponding indicators on the basis of their own actual situation.

In summary, the indicators of tourism ecological security evaluation should be scientific and reasonable, and have been widely accepted and used. Indicators that are relatively important, frequently used and proved useful in the existing literature should be adopted. The characteristics of the study area need to be reflected. The availability of data needs to be sufficiently considered.

4.2. Dynamic Change of TESI Level

Consistent with previous research, with the development of tourism economy, the TESI of Huanggang Dabieshan UGGp generally shows an upward trend [27,51,53]. When the geopark had not been established, the study area was dominated by traditional extensive agriculture. The awareness of ecological and environmental protection was weak, and the TESI level of the region was low. Since completion of the national geopark in 2009, in order to support the tourism development, build the tourism brand of Huanggang City and Eastern Hubei Province, the government of Huanggang City paid enough attention to the construction of the geopark and invested enough funds to comprehensively improve the ecological environment and ecotourism development. The tourism ecological security level of the study area has improved since 2010. In order to apply for UGGp and make tourism more ecological, the management agency formulated a reasonable development plan since 2013, such as the strengthening of management, the construction of a tourism talent team, the improvement of supporting infrastructure and the formulation of regulations on the protection of geoheritages and other resources.

At the same time, with the implementation of the 11th five-year plan, the construction of ecological civilization, the strategy of "two circles and one belt", and the construction of "Ecological Hubei", resource-saving and environment-friendly society became the main objective of current development [22], which contributed to the gradual improvement of the ecological environment in Huanggang City and the study area.

Moreover, with the popularization of basic education in China, the scientific and cultural quality of the resident population is constantly improving. It has been verified that a high level of educational attainment can promote pro-environmental behavior [91,92]. Accordingly, it has enhanced the tourism ecological awareness of the majority of local residents and tourists, and promoted the tourism ecological security of the study area to a certain extent.

From the development level of each township, the townships with a high level of TESI are the main scenic spots of Huanggang Dabieshan UGGp. With the development of geopark construction and tourism activities, more and more attention has been paid to these townships, and supporting measures such as investment, management and protection have also gradually been followed up. Furthermore, Huanggang Dabieshan UGGp has carried out a lot of work in the fields of geoscience popularization and education, ecological environmental protection, and township renovation in order to apply for UGGp. Therefore, the improvement of tourism ecological security is more obvious than in other townships. In addition, in townships with high security levels, there are various kinds of nature reserves, such as Dabieshan National Nature Reserve, Wujiashan National Forest Park, Zhangjiazui National Wetland Park, Tiantanghu National Wetland Park, etc. The natural conditions also have an important effect on the TESI of each township in Huanggang Dabieshan UGGp.

Townships with low TESI have also been positively affected by the development of the tourism economy and the comprehensive tourism income has increased continuously, but at the same time, it has also put pressure on tourist flow and the ecological environment. Due to the distribution of more cultivated land and construction land, higher population density, more resource consumption, and lower or no coverage of nature reserves, these townships have a relatively low level of TESI compared with other townships in the same period.

4.3. Spatial Pattern of TESI

Previous research has found that tourism ecological security has spatial dependence and spatial correlation, and the spatial spillover effect is obvious [50,93]. In this paper, the fluctuation of Moran's I value of TESI indicates that the spatial correlation and agglomeration of tourism ecological security are increasing, which is consistent with the previous research results. The TESI level of a township is not independent in geographical space. It is often affected by neighboring townships and has a spatial interaction effect. Most townships are surrounded by townships with a similar security level, which also shows that tourism ecological security has spatial dependence and spillover effect.

"HH" agglomeration areas are mainly distributed in the Guifengshan scenic spot, Shengli, Jiuzihe, and Shitouzui. With the passage of time, the agglomeration area has transferred from northwest to northeast, which has played an active role in promoting the security level of surrounding townships, with radiation and spatial diffusion effect. The "LL" agglomeration area is mainly concentrated in Fengshan, Kongjiafang, Leijiadian, Sanlifan, and Yanjiahe. It has undergone several changes with the trend of "southwest-southeast-southwest-northwest", which were jointly affected by macro policies and natural resource conditions. Only Zhangjiafan is "LH" type in 2010 because of the lack of outstanding tourism resources, excellent natural conditions and regional cooperation. Although it was adjacent to a township with a high level of TESI, it had not been driven by spatial dependence and spillover.

The great differences in the TESI of townships indicate that the regional tourism ecological security has obvious spatial differentiation characteristics, which accords with the conclusion of Ruan et al. [51]. In addition, in accordance with the previous research, economic advantages have an important impact on tourism ecological security [51,94]. There are more tourism activities in the townships where the tourist attractions are located. The development level of tourism economy here is higher, so there is more capital investment and maintenance. Therefore, the TESI level of these townships is relatively higher than that of other townships.

4.4. Identification of Obstacle Factors

It is profitable to penetrate into the restrictive factors and driving mechanisms of the tourism ecological security level in a region by obstacle analysis. A decision-making basis for tourism industry development, ecological environment protection, and industrial structure adjustment in geopark and surrounding areas can be provided in the future, too.

During the study period, tourism economic factors and ecological factors have played an important role in TESI, which is consistent with Tang's conclusion [27]. Through the sorting and comparison, it can be seen that before the establishment of the geopark, the level of socio-economic development of the study area was relatively low, and the tourism industry had not yet started. The contribution of tourism economy was particularly small, accounting for only 1% of regional GDP. The overall planning of regional development was insufficient. Little attention was paid to ecological environmental protection. In addition, the low living standard of local residents led to their lack of awareness of environmental and ecological protection. A series of reasons had restricted the TESI of the research area during 2000 to 2005. Accordingly, per capita tourism income, proportion of comprehensive tourism revenue in GDP, per capita net income of rural residents, proportion of tertiary industry in GDP, domestic waste treatment rate, coverage of nature reserves, planning integrity of geopark, interpretive coverage of geopark, and informatization of geopark were important influencing factors.

With the construction of Huanggang Dabieshan UGGp in 2013 and the development of the tourism industry, the economic benefits brought by tourism were increasing gradually, and the investment indirectly used for development and protection was increasing. The growth of the proportion of tertiary industry in GDP reflected the optimization of industrial structures. Services and business-oriented industries consumed fewer resources and produced less environmental pollution, thus causing less damage and fewer threats to the ecological environment. All of these made the obstruction degree of indicators which are related to tourism and economy showed a downward trend in 2015. However, at the initial stage of geopark construction, the number of tourists showed an explosive growth, reflecting the lack of tourists' density control, making the growth rate of tourists the most important obstacle factor in 2015.

With the rapid growth of tourism income, the resource consumption caused by the investment in tourism development and urbanization had been increasing, which had led to the aggravation of environmental pollution and the deterioration of ecological quality to a certain extent. These changes indicated that resource utilization and ecological environmental management were facing increasing pressure. This had been confirmed by the research of York, Tang and Wang et al. [2,95,96]. Therefore, density of tourism economy, annual average concentration of SO_2, regional development index, compliance rate of air quality, and comprehensive utilization rate of solid waste were important factors hindering tourism ecological security in 2018. Overall, the obstruction degree of these socio-economic factors, although the main hindrances, were decreasing relative to the earlier period because TESI was generally developing in a good direction.

In addition, the proportion of education expenditure in GDP became a more significant barrier in 2018, suggesting that local education spending had remained at the same level for a long time. Although the general public was constantly becoming better educated, the disadvantage of the proportion of education expenditure in GDP was obvious when the economic and ecological indicators had noticeably improved. Consequently, the government needed to pay more attention to public education. The high scientific and cultural quality levels of residents will encourage their behavior to be more civilized, which will be more beneficial to the promotion of TESI of Huanggang Dabieshan UGGp.

4.5. Policy Implications

Over the past 20 years, China has made unremitting efforts to promote the construction of geoparks. By the end of 2021, 41 geoparks in China have become members of UGGps, and 281 geoparks have been officially named National Geoparks in China. The establishment of geoparks effectively protect precious and non-renewable geoheritage resources, as well as other natural, ecological and cultural landscape resources in an area. In addition, the construction of a nature reserve system with national parks as the main body has become one of the key tasks of China's ecological civilization construction [97]. These measures have engendered a vital impact on the development of national and local tourism and the protection of the ecological environment. Huanggang Dabieshan UGGp should not only respond to national policy, but also explore a way suitable for its own development.

Firstly, balancing the conflict between human activities and ecosystem protection is the key to achieving the natural and socioeconomic sustainability of geoparks [76]. On the one hand, based on the existing overall plan, the administration should strictly implement the regulation of "no development in core protection areas and appropriate construction of tourism supporting facilities in non-core areas", in order to abate negative effects on the ecological environment caused by human activities. On the other hand, the government needs to fully consider the coordination of local tourism policies and environmental protection policies, and gradually eliminate the weaknesses of tourism development and management. The government should also innovate environmental governance mechanisms, strengthen the construction of environmental treatment infrastructures, reduce the emission of various pollutants, and establish an early warning system for tourism ecological security.

Secondly, tourism enterprises need to be supported, and the investment of environmental protection funds should be increased. An ecological compensation mechanism should be set up with the support of regional public environmental protection finance.

Thirdly, promoting sustainable tourism, creating jobs and advertising local culture and products are some of the goals of UGGp [98]. Encouraging the participation of local communities in geotourism activities is instrumental in creating new employment opportunities and generating economic income for people living in rural areas [99]. When the geopark obtains economic benefits, it is bound to better increase the protection and economic strength, and thus local residents will pay more attention to protection because of the benefit from development.

Finally, it is essential to strengthen science popularization for the local public. Geoheritages, other natural resources, and cultural heritages are inheritances. Education in the form of teaching and entertainment can enhance the residents' awareness of geoheritages and ecological environmental protection, which is conducive to enabling them to spontaneously maintain and improve the ecological environment of Huanggang Dabieshan UGGp.

4.6. Limitations

Some limitations need to be explained here. Due to the limitation of the data, this study only analyzed the data from 2000, 2005, 2010, 2015 and 2018. It is difficult to obtain the township-level data corresponding to some indicators, so that other data with similar meanings are used instead, which may cause deviation in the results. The variety and typicality of the data need to be further improved. The assessment of the greatest threats to the values of geopark may also affect TESI to some extent. It might be helpful to take the assessment into consideration. In addition, only one geopark is selected for evaluation, and the research scale is small. Consequently, further studies are essential to compare and analyze tourism ecological security in different geoparks in order to explore the overall spatio-temporal pattern of tourism ecological security of geoparks in China. It will be effective to master the driving mechanism of tourism ecological security of geoparks, and provide a theoretical reference for management strategies and sustainable development of geoparks.

5. Conclusions

On the basis of the DPSIR model, this paper constructs the tourism ecological security evaluation indicator system for the geopark. In this paper, the entropy weight method, comprehensive index method, spatial autocorrelation and obstacle degree model are used to examine the tourism ecological security of Huanggang Dabieshan UGGp. It analyzes the spatial and temporal evolution pattern and the influencing factors of TESI in the study area from 2000 to 2018. The conclusions are as follows:

1. The TESI of Huanggang Dabieshan UGGp shows a steady growth trend. During 2000 to 2005, the TESI was generally low in all the townships. In 2010, the TESI entered a critical safety level, and by 2018, the TESI had reached a relatively safe level. Especially, the TESI is higher in the townships where tourism resources are concentrated, tourism infrastructure is perfect, and tourism economy is highly developed.
2. The results of spatial autocorrelation analysis illustrated that the spatial agglomeration degree in Huanggang Dabieshan UGGp had shown a trend of first slowing down and then strengthening from 2000 to 2018. It indicated significant global and local spatial aggregation characteristics, and the overall pattern tended to be stable. The townships with different TESI levels represented obvious zone effects in spatial distribution, which showed the law of spatial decline. The TESI of townships where the main tourist attractions were located were at a high level, and the TESI of surrounding townships were at a low level.

3. Through obstacle analysis, it can be seen that the main obstacle factors included per capita tourism income, proportion of comprehensive tourism revenue in GDP, per capita net income of rural residents, proportion of tertiary industry in GDP, coverage of nature reserves, planning integrity of geopark, informatization of geopark, growth rate of tourists, comprehensive utilization rate of solid waste, etc. National policies, environmental governance, tourism load level, tourism development level, and geopark management have different impacts on the tourism ecological security in different periods.

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References

1. Drius, M.; Bongiorni, L.; Depellegrin, D.; Menegon, S.; Pugnetti, A.; Stifter, S. Tackling challenges for Mediterranean sustainable coastal tourism: An ecosystem service perspective. *Sci. Total Environ.* **2019**, *652*, 1302–1317. [CrossRef] [PubMed]
2. Wang, S.; Mu, Y.; Zhang, X.; Xie, J. Polar tourism and environment change: Opportunity, impact and adaptation. *Polar Sci.* **2020**, *25*, 100544.
3. Scott, D.; Peeters, P.; Gössling, S. Can tourism deliver its "aspirational" greenhouse gas emission reduction targets? *J. Sustain. Tour.* **2010**, *18*, 393–408. [CrossRef]
4. Li, L.; Li, J.; Tang, L.; Wang, S. Balancing Tourism's Economic Benefit and CO_2 Emissions: An Insight from Input–Output and Tourism Satellite Account Analysis. *Sustainability* **2019**, *11*, 1052. [CrossRef]
5. Zhang, L.; Gao, J. Exploring the effects of international tourism on China's economic growth, energy consumption and environmental pollution: Evidence from a regional panel analysis. *Renew. Sustain. Energy Rev.* **2016**, *53*, 225–234. [CrossRef]
6. Rico, A.; Martínez-Blanco, J.; Montlleó, M.; Rodríguez, G.; Tavares, N.; Arias, A.; Oliver-Solà, J. Carbon footprint of tourism in Barcelona. *Tour. Manag.* **2019**, *70*, 491–504. [CrossRef]
7. Tejedo, P.; Justel, A.; Benayas, J.; Rico, E.; Convey, P.; Quesada, A. Soil trampling in an Antarctic Specially Protected Area: Tools to assess levels of human impact. *Antarct. Sci.* **2009**, *21*, 229–236. [CrossRef]
8. Liggett, D. Destination Icy Wilderness. In *Exploring the Last Continent: An Introduction to Antarctica*; Liggett, D., Storey, B., Cook, Y., Meduna, V., Eds.; Springer International Publishing: Cham, Switzerland, 2015; pp. 379–398.
9. Stephen, K. Societal Impacts of a Rapidly Changing Arctic. *Curr. Clim. Chang. Rep.* **2018**, *4*, 223–237. [CrossRef]
10. Whitford, W.G.; Rapport, D.J.; DeSoyza, A.G. Using resistance and resilience measurements for 'fitness' tests in ecosystem health. *J. Environ. Manag.* **1999**, *57*, 21–29. [CrossRef]
11. Jiang, X.F. Challenge of entering WTO to china's ecological security and strategic countermeasures. *Environ. Prot.* **2000**, *10*, 23–25.
12. Moran, E.F. News on the land project. *Glob. Change Newsl.* **2003**, 18–20.
13. Wang, G.; Cheng, G.; Qian, J. Several problems in ecological security assessment research. *Chin. J. Appl. Ecol.* **2003**, *14*, 1551–1556.
14. Liu, D.; Chang, Q. Ecological security research progress in China. *Acta Ecol. Sin.* **2015**, *5*, 111–121. [CrossRef]
15. Pan, N.; Du, Q.; Guan, Q.; Tan, Z.; Sun, Y.; Wang, Q. Ecological security assessment and pattern construction in arid and semi-arid areas: A case study of the Hexi Region, NW China. *Ecol. Indic.* **2022**, *138*, 108797. [CrossRef]
16. Brown, L.R. *Building a Sustainable Society*; WW Norton & Company, Inc.: New York, NY, USA, 1981; pp. 75–85.
17. Liu, Y.; Kong, F.; Gonzalez, E.D.R.S. Dumping, waste management and ecological security: Evidence from England. *J. Clean. Prod.* **2017**, *167*, 1425–1437. [CrossRef]
18. Gao, J.; Zou, C.; Zhang, K.; Xu, M.; Wang, Y. The establishment of Chinese ecological conservation redline and insights into improving international protected areas. *J. Environ. Manag.* **2020**, *264*, 110505. [CrossRef]
19. Han, B.L.; Liu, H.X.; Wang, R.S. Urban ecological security assessment for cities in the Beijing–Tianjin–Hebei metropolitan region based on fuzzy and entropy methods. *Ecol. Model.* **2015**, *318*, 217–225. [CrossRef]

20. Yan, Y.; Ju, H.; Zhang, S.; Chen, G. The Construction of Ecological Security Patterns in Coastal Areas Based on Landscape Ecological Risk Assessment-A Case Study of Jiaodong Peninsula, China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 12249. [CrossRef]
21. Chai, J.; Wang, Z.; Zhang, H. Integrated Evaluation of Coupling Coordination for Land Use Change and Ecological Security: A Case Study in Wuhan City of Hubei Province, China. *Int. J. Environ. Res. Public Health* **2017**, *14*, 1435. [CrossRef]
22. Ke, X.; Wang, X.; Guo, H.; Yang, C.; Zhou, Q.; Mougharbel, A. Urban ecological security evaluation and spatial correlation research—based on data analysis of 16 cities in Hubei Province of China. *J. Clean. Prod.* **2021**, *311*, 127613. [CrossRef]
23. Zhang, W.; Zhang, Z.; Tian, N.; Wu, S.; Yang, C. Land Ecological Security Evaluation and Trend Forecast of Hunan Province Based on P-S-R Model. *Sustain. Dev.* **2012**, *2*, 117–123.
24. Guo, S.; Wang, Y. Ecological Security Assessment Based on Ecological Footprint Approach in Hulunbeir Grassland, China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4805. [CrossRef] [PubMed]
25. Yao, Y. Study on Index System of the Environmental Change and Ecological Security for a River Basin Based on DPSIR Model. *Meteorol. Environ. Res.* **2012**, *3*, 50–54.
26. Li, J.; Chen, Y.; Xu, C.; Li, Z. Evaluation and analysis of ecological security in arid areas of Central Asia based on the emergy ecological footprint (EEF) model. *J. Clean. Prod.* **2019**, *235*, 664–677. [CrossRef]
27. Tang, C.; Wu, X.; Zheng, Q.; Lyu, N. Ecological security evaluations of the tourism industry in Ecological Conservation Development Areas: A case study of Beijing's ECDA. *J. Clean. Prod.* **2018**, *197*, 999–1010. [CrossRef]
28. Xu, J.; Fan, F.; Liu, Y.; Dong, J.; Chen, J. Construction of Ecological Security Patterns in Nature Reserves Based on Ecosystem Services and Circuit Theory: A Case Study in Wenchuan, China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3220. [CrossRef]
29. Yu, K. Landscape ecological security patterns in biological conservation. *Acta Ecol. Sin.* **1999**, *19*, 8–15.
30. Sun, Y.; Wang, R. Environment capacity of eco-tourism resort. *Chin. J. Appl. Ecol.* **2000**, *11*, 564–566.
31. Simón, F.J.G.; Narangajavana, Y.; Marqués, D.P. Carrying capacity in the tourism industry: A case study of Hengistbury Head. *Tour. Manag.* **2004**, *25*, 275–283. [CrossRef]
32. Hunter, C.; Shaw, J. The ecological footprint as a key indicator of sustainable tourism. *Tour. Manag.* **2007**, *28*, 46–57. [CrossRef]
33. Tang, C.; Zhong, L.; Chen, T. Characteristics of Spatial Differentiation and Development Modes for Ecotourism Resources in the Sanjiangyuan Region. *Resour. Sci.* **2009**, *31*, 1825–1831.
34. Ross, S.; Wall, G. Ecotourism: Towards congruence between theory and practice. *Tour. Manag.* **1999**, *20*, 123–132. [CrossRef]
35. Liu, X.; Yang, Z.; Di, F.; Chen, X. Evaluation on tourism ecological security in nature heritage sites -Case of Kanas nature reserve of Xinjiang, China. *Chin. Geogr. Sci.* **2009**, *19*, 265–273. [CrossRef]
36. Liu, S.D.; Wang, R.J.; Gao, J. Ecological Security Research of Shanghai Hangzhou Bay North Shore under the Impact of Tourism Activities. *Adv. Mater. Res.* **2012**, *573*, 313–318. [CrossRef]
37. Dong, R.; Zhang, X.; Li, H. Constructing the Ecological Security Pattern for Sponge City: A Case Study in Zhengzhou, China. *Water* **2019**, *11*, 284. [CrossRef]
38. Jurado, E.N.; Tejada, M.T.; García, F.A.; González, J.C.; Macías, R.C.; Peña, J.D.; Gutiérrez, F.F.; Fernández, G.G.; Gallego, M.L.; García, G.M.; et al. Carrying capacity assessment for tourist destinations: Methodology for the creation of synthetic indicators applied in a coastal area. *Tour. Manag.* **2012**, *33*, 1337–1346. [CrossRef]
39. Tang, C.; Zhong, L.; Cheng, S. A review on sustainable development for tourist destination. *Prog. Geogr.* **2013**, *32*, 984–992.
40. Ben Jebli, M.; Hadhri, W. The dynamic causal links between CO2 emissions from transport, real GDP, energy use and international tourism. *Int. J. Sustain. Dev. World Ecol.* **2018**, *25*, 568–577. [CrossRef]
41. Ben Jebli, M.; Ben Youssef, S.; Apergis, N. The dynamic linkage between renewable energy, tourism, CO2 emissions, economic growth, foreign direct investment, and trade. *Lat. Am. Econ. Rev.* **2019**, *28*, 2. [CrossRef]
42. O'Reilly, A.M. Tourism carrying capacity: Concept and issues. *Tour. Manag.* **1986**, *7*, 254–258. [CrossRef]
43. McCool, S.F.; Lime, D.W. Tourism Carrying Capacity: Tempting Fantasy or Useful Reality? *J. Sustain. Tour.* **2001**, *9*, 372–388. [CrossRef]
44. Li, H.Q.; Hou, L.C. Evaluation on Sustainable Development of Scenic Zone Based on Tourism Ecological Footprint: Case Study of Yellow Crane Tower in Hubei Province, China. *Energy Procedia* **2011**, *5*, 145–151.
45. Bera, S.; Majumdar, D.D.; Paul, A.K. Estimation of Tourism Carrying Capacity for Neil Island, South Andaman, India. *J. Costal Sci.* **2015**, *2*, 46–53.
46. Canteiro, M.; Córdova-Tapia, F.; Brazeiro, A. Tourism impact assessment: A tool to evaluate the environmental impacts of touristic activities in Natural Protected Areas. *Tour. Manag. Perspect.* **2018**, *28*, 220–227. [CrossRef]
47. Pan, S.; Gao, M.; Kim, H.; Shah, K.J.; Pei, S.; Chiang, P. Advances and challenges in sustainable tourism toward a green economy. *Sci. Total Environ.* **2018**, *635*, 452–469. [CrossRef]
48. Nie, N.; Wang, H.; Xiong, J. Research on Tourism Ecological Security of Lake in Dongting Lake. *Appl. Mech. Mater.* **2011**, *1366*, 2657–2660. [CrossRef]
49. Zhou, B.; Zhong, L.; Chen, T.; Zhang, A. Spatio-temporal Pattern and Obstacle Factors of Ecological Security of Tourism Destination: A Case of Zhejiang Province. *Sci. Geogr. Sin.* **2015**, *35*, 599–607.
50. Ma, X.; Sun, B.; Hou, G.; Zhong, X.; Li, L. Evaluation and spatial effects of tourism ecological security in the Yangtze River Delta. *Ecol. Indic.* **2021**, *131*, 108190.

51. Ruan, W.; Li, Y.; Zhang, S.; Liu, C. Evaluation and drive mechanism of tourism ecological security based on the DPSIR-DEA model. *Tour. Manag.* **2019**, *75*, 609–625. [CrossRef]
52. Liu, D.; Yin, Z. Spatial-temporal pattern evolution and mechanism model of tourism ecological security in China. *Ecol. Indic.* **2022**, *139*, 108933. [CrossRef]
53. Yang, L.; Cao, K. Tourism Ecological Security Early Warning of Ili River Valley Based on DPSIR Model. *Ecol. Econ.* **2020**, *36*, 111–117.
54. Pei, L.; Du, L.; Yue, G. Ecological Security Assessment of Beijing Based on PSR Model. *Procedia Environ. Sci.* **2010**, *2*, 832–841.
55. Zhao, C.; Zhou, B.; Su, X. Evaluation of Urban Eco-Security—A Case Study of Mianyang City, China. *Sustainability* **2014**, *6*, 2281–2299. [CrossRef]
56. Corbau, C.; Benedetto, G.; Congiatu, P.P.; Simeoni, U.; Carboni, D. Tourism analysis at Asinara Island (Italy): Carrying capacity and web evaluations in two pocket beaches. *Ocean. Coast. Manag.* **2019**, *169*, 27–36. [CrossRef]
57. Liu, X.M.; Jiang, D.; Wang, Q.; Liu, H.M.; Li, J.; Fu, Z. Evaluating the sustainability of nature reserves using an ecological footprint method: A case study in China. *Sustainability* **2016**, *8*, 1272. [CrossRef]
58. Wang, Y.; Wu, C.; Wang, F.; Sun, Q.; Wang, X.; Guo, S. Comprehensive evaluation and prediction of tourism ecological security in droughty area national parks—A case study of Qilian Mountain of Zhangye section, China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 16816–16829. [CrossRef]
59. Dong, S.; Wu, Y.; Liu, S.; Su, X.; Zhao, H.; Zhang, Y. Evaluation on grassland eco-security of the Altun Mountain National Nature Reserve. *Acta Agrestia Sin.* **2016**, *24*, 906–909.
60. He, G.; Yu, B.; Li, S.; Zhu, Y. Comprehensive evaluation of ecological security in mining area based on PSR–ANP–GRAY. *Environ. Technol.* **2018**, *39*, 3013–3019. [CrossRef]
61. Wang, Y.; Feng, Y.; Zuo, J.; Rameezdeen, R. From "Traditional" to "Low carbon" Urban Land Use: Evaluation and Obstacle Analysis. *Sustain. Cities Soc.* **2019**, *51*, 101722. [CrossRef]
62. Chen, Y.; Zhu, M.; Lu, J.; Zhou, Q.; Ma, W. Evaluation of ecological city and analysis of obstacle factors under the background of high-quality development: Taking cities in the Yellow River Basin as examples. *Ecol. Indic.* **2020**, *118*, 106771. [CrossRef]
63. Ou, Z.; Zhu, Q.; Sun, Y. Regional ecological security and diagnosis of obstacle factors in underdeveloped regions: A case study in Yunnan Province, China. *J. Mt. Sci.* **2017**, *14*, 870–884. [CrossRef]
64. Lu, S.; Li, J.; Guan, X.; Gao, X.; Gu, Y.; Zhang, D.; Mi, F.; Li, D. The evaluation of forestry ecological security in China: Developing a decision support system. *Ecol. Indic.* **2018**, *91*, 664–678. [CrossRef]
65. Liu, S.D.; Gao, J.; Pan, W.T. Ecological Security Research of the Northern Slope of Qinling Mountains under the Impact of Tourism Activities. *Adv. Mater. Res.* **2014**, *955*, 1634–1639. [CrossRef]
66. Xiao, J.; Yu, Q.; Liu, K.; Chen, D.; Chen, J.; Xiao, J. Evaluation of the ecological security of island tourist destination and island tourist sustainable development: A case study of Zhoushan Islands. *Acta Geogr. Sin.* **2011**, *66*, 842–852.
67. Henriques, M.H.; Canales, M.L.; García-Frank, A.; Gomez-Heras, M. Accessible Geoparks in Iberia: A Challenge to Promote Geotourism and Education for Sustainable Development. *Geoheritage* **2019**, *11*, 471–484. [CrossRef]
68. AbdelMaksoud, K.M.; Emam, M.; Al Metwaly, W.; Sayed, F.; Berry, J. Can innovative tourism benefit the local community: The analysis about establishing a geopark in Abu Roash area, Cairo, Egypt. *Int. J. Geoherit. Parks* **2021**, *9*, 509–525. [CrossRef]
69. Ansori, C.; Setiawan, N.I.; Warmada, I.W.; Yogaswara, H. Identification of geodiversity and evaluation of geosites to determine geopark themes of the Karangsambung-Karangbolong National Geopark, Kebumen, Indonesia. *Int. J. Geoherit. Parks* **2022**, *10*, 1–15. [CrossRef]
70. Wang, L.; Tian, M.; Wang, L. Geodiversity, geoconservation and geotourism in Hong Kong Global Geopark of China. *Proc. Geol. Assoc.* **2015**, *126*, 426–437. [CrossRef]
71. Fung, C.K.W.; Jim, C.Y. Segmentation by motivation of Hong Kong Global Geopark visitors in relation to sustainable nature-based tourism. *Int. J. Sustain. Dev. World Ecol.* **2015**, *22*, 76–88.
72. Fung, C.K.W.; Jim, C.Y. Unraveling Hong Kong Geopark experience with visitor-employed photography method. *Appl. Geogr.* **2015**, *62*, 301–313. [CrossRef]
73. Neto de Carvalho, C. Tourism in the Naturtejo Geopark, under the Auspices of UNESCO, as Sustainable Alternative to the Mining of Uranium at Nisa (Portugal). *Procedia Earth Planet. Sci.* **2014**, *8*, 86–92. [CrossRef]
74. Rodrigues, J.; Neto de Carvalho, C.; Ramos, M.; Ramos, R.; Vinagre, A.; Vinagre, H. Geoproducts—Innovative development strategies in UNESCO Geoparks: Concept, implementation methodology, and case studies from Naturtejo Global Geopark, Portugal. *Int. J. Geoherit. Parks* **2021**, *9*, 108–128. [CrossRef]
75. Lee, Y.; Jayakumar, R. Economic impact of UNESCO Global Geoparks on local communities: Comparative analysis of three UNESCO Global Geoparks in Asia. *Int. J. Geoherit. Parks* **2021**, *9*, 189–198. [CrossRef]
76. Zheng, L.; Wang, Y.; Li, J. How to achieve the ecological sustainability goal of UNESCO Global Geoparks? A multi-scenario simulation and ecological assessment approach using Dabieshan UGGp, China as a case study. *J. Clean. Prod.* **2021**, *329*, 129779. [CrossRef]
77. Waheed, B.; Khan, F.; Veitch, B. Linkage-Based Frameworks for Sustainability Assessment: Making a Case for Driving Force-Pressure-State-Exposure-Effect-Action (DPSEEA) Frameworks. *Sustainability* **2009**, *1*, 441–463. [CrossRef]
78. Kazuva, E.; Zhang, J.; Tong, Z.; Si, A.; Na, L. The DPSIR Model for Environmental Risk Assessment of Municipal Solid Waste in Dar es Salaam City, Tanzania. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1692. [CrossRef]

79. Borji, M.; Moghaddam Nia, A.; Malekian, A.; Salajegheh, A.; Khalighi, S. Comprehensive evaluation of groundwater resources based on DPSIR conceptual framework. *Arab. J. Geosci.* **2018**, *11*, 158. [CrossRef]
80. Asmelash, A.G.; Kumar, S. Assessing progress of tourism sustainability: Developing and validating sustainability indicators. *Tour. Manag.* **2019**, *71*, 67–83. [CrossRef]
81. Benitez-Capistros, F.; Hugé, J.; Koedam, N. Environmental impacts on the Galapagos Islands: Identification of interactions, perceptions and steps ahead. *Ecol. Indic.* **2014**, *38*, 113–123. [CrossRef]
82. Li, W. Environmental management indicators for ecotourism in China's nature reserves: A case study in Tianmushan Nature Reserve. *Tour. Manag.* **2004**, *25*, 559–564. [CrossRef]
83. Cooper, P. Socio-ecological accounting: DPSWR, a modified DPSIR framework, and its application to marine ecosystems. *Ecol. Econ.* **2013**, *94*, 106–115. [CrossRef]
84. Wang, S.; Sun, C.; Li, X.; Zou, W. Sustainable Development in China's Coastal Area: Based on the Driver-Pressure-State-Welfare-Response Framework and the Data Envelopment Analysis Model. *Sustainability* **2016**, *8*, 958. [CrossRef]
85. Rasoolimanesh, S.M.; Ramakrishna, S.; Hall, C.M.; Esfandiar, K.; Seyfi, S. A systematic scoping review of sustainable tourism indicators in relation to the sustainable development goals. *J. Sustain. Tour.* **2020**, 1–21. [CrossRef]
86. How to Become a Geopark. Available online: http://en.unesco.org/global-geoparks/how-to-become-geopark (accessed on 5 April 2022).
87. Anselin, L. *Spatial Econometrics: Methods and Models*; Kluwer Academic: Dordrecht, The Netherlands, 1988.
88. Anselin, L. Local Indicators of Spatial Association-LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
89. Ord, J.K.; Getis, A. Testing for local spatial autocorrelation in the presence of global autocorrelation. *J. Reg. Sci.* **2001**, *41*, 411–432. [CrossRef]
90. He, R.; Tang, Z.; Dong, Z.; Wang, S. Performance Evaluation of Regional Water Environment Integrated Governance: Case Study from Henan Province, China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 2501. [CrossRef]
91. Kotchen, M.J.; Boyle, K.J.; Leiserowitz, A.A. Willingness-to-pay and policy-instrument choice for climate-change policy in the United States. *Energy Policy* **2013**, *55*, 617–625. [CrossRef]
92. Jin, T.; Li, M. Does education increase pro-environmental willingness to pay? Evidence from Chinese household survey. *J. Clean. Prod.* **2020**, *275*, 122713.
93. Li, X.; Wu, L.; Wu, Q.; Zhou, Y. A study on the measurement and diagnosis of obstacle factors of tourism ecological security in China. *Ecol. Econ.* **2017**, *33*, 90–95.
94. Yin, K.; Wang, R.; An, Q.; Yao, L.; Liang, J. Using eco-efficiency as an indicator for sustainable urban development: A case study of Chinese provincial capital cities. *Ecol. Indic.* **2014**, *36*, 665–671. [CrossRef]
95. York, R.; Rosa, E.A.; Dietz, T. STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecol. Econ.* **2003**, *46*, 351–365. [CrossRef]
96. Tang, M.; Ge, S. Accounting for carbon emissions associated with tourism-related consumption. *Tour. Econ.* **2018**, *24*, 510–525. [CrossRef]
97. Wang, Q.; Yu, G.; He, H.; He, N.; Sheng, W. Thinking of construction of the nature reserve system and integrated management system in China. *Resour. Sci.* **2015**, *37*, 1357–1366.
98. McKeever, P.J. UNESCO Global Geoparks and Agenda 2030. In Proceedings of the 8th International Conference on UNESCO Global Geoparks, Madonna di Campiglio, Italy, 8–14 September 2018.
99. Farsani, N.T.; Coelho, C.; Costa, C. Geotourism and Geoparks as Novel Strategies for Socio-economic Development in Rural Areas. *Int. J. Tour. Res.* **2011**, *13*, 68–81. [CrossRef]

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Identification of Priority Implementation Areas and Configuration Types for Green Infrastructure Based on Ecosystem Service Demands in Metropolitan City

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Abstract: During urbanization in developing countries, fragmentation of green infrastructure due to increasing populations and the expansion of construction land leads to an extremely serious imbalance between the supply and demand for urban ecosystem services. In this study, the central city of Zhengzhou, a central city in central China, was selected as the study area and the excessive demand for six ecosystem services, namely, air purification, flood regulation, heat regulation, hydrological regulation, CO_2 sequestration and recreational services, was quantitatively evaluated. The entropy method was used to calculate the weights of various ecosystem services, and spatial overlay analysis was performed to obtain the comprehensive ecosystem service excessive demand. Finally, bivariate spatial autocorrelation analysis was used to explore the response of population density to comprehensive excessive demand for ESs. The results of this study indicate that: (1) The most prevalent need is for more CO_2 regulation service throughout the study area. (2) Except for hydrological regulation service, the spatial distribution of the remaining highly excessive ecosystem service demands are mostly concentrated in old neighborhoods. (3) Of the six excessively demanded economic services, rainwater regulation obtained the greatest weight, reflecting the poor urban infrastructure configuration for countering the rapidly increasing threat of flooding caused by climate change in the city. (4) The comprehensive ecosystem service excessive demand results show that there are eight priority green infrastructure implementation blocks in the central city of Zhengzhou. (5) There were three agglomeration types between population density and comprehensive excessive demand for ESs: high-high type, low-high type and low-low type. The spatial distribution characteristics of population density and comprehensive ES demand are positively correlated. The results of this study could help to provide information for decision making when delineating the priority areas and types of green infrastructure implementation in developing cities.

Keywords: urban ecosystem services; green infrastructure; excessive demand; spatial priority evaluation; urban block

1. Introduction

Ecosystem services (ESs) that directly and indirectly benefit people are partitioned into four different types: provisioning, regulating, cultural and support services [1]. ESs and the natural capital stock that produces them are critical for the functioning and sustainable development of human society. Urban ecosystem services (UESs) can increase urban resilience [2], whereas green infrastructure (GI) is the "natural life support system" that includes all green open spaces around and within the city and constitutes the supply system of UESs [3,4]. UESs depend directly on the quantity, quality and diversity of the GI that produces them, whereas urban ES demand reflects the number of ESs that society expects to receive [2,5].

In the context of rapid urbanization, the continuous expansion of urban construction land has led to a decrease in the size and type of GI and an increase in fragmentation, resulting in a continual decrease in the supply capacity of UESs [4]. Human beings overconsume ecological resources, which causes cities to exhibit a serious imbalance between the supply and demand for ESs in terms of quantity and space. The existing supply and demand configuration of GI does not meet the real ES needs of cities, which is a challenge for current research to determine the capacity of an ecosystem to supply services and the social demand for those services [6]. When the supply of ESs cannot meet the demand, there is an excessive demand for them [7]. Identifying the areas of ecosystem service excessive demand within a city can be used as a priority evaluation method for GI planning to provide a basis for GI construction within a city.

Concerning the research scale, current research related to assessing the supply and demand for ESs is mainly focused on macroregions [7–14]. Although many researchers have made innovative explorations on street-scale GI design [15–18], the complex dynamic supply and demand mechanism still needs to be combined with urban functional zoning and specific demand groups for more systematic studies. In terms of research methods, the basic idea behind existing ecosystem service supply and demand assessment methods is mainly to calculate and superimpose aggregate supply and aggregate demand separately to identify excessive supply or excessive demand. The quantitative assessment of aggregate supply is usually based on the land use/land cover (LULC) supply or expert scoring calculations [7,19,20]. Quantitative methods and indicators of aggregate demand include unit demand values based on LULC [2], unit demand based on socioeconomic spatial characteristics, the proportion of affected groups or infrastructure [21], and public willingness statistics [22]. When evaluating the spatial allocation of ecosystem service supply and demand, these aforementioned indicators or methods are usually mixed and a single technique is used to identify excessive demand or supply values by directly subtracting the supply and demand values or by normalizing both and then superimposing them. However, the above methods are not applicable to small-scale spatial studies. Since it is usually difficult to balance ecosystem service supply and demand, assessing the spatial allocation by direct superposition and normalization tends to obscure and ignore the absolute ranges of supply and demand, and thus, cannot yield accurate and valuable assessment results.

The main objective of the present study is to explore a quantitative assessment method for direct ecosystem service excessive demand on the urban neighborhood scale in Zhengzhou, and use the assessment results as the basis for the optimization of urban GI construction. At the same time, the research methods can also provide a reference for microscale GI planning of other similar cities. In this study, we take the central area of Zhengzhou City, Henan Province, China as the research area and select the appropriate urban ecosystem service types, as well as the corresponding quantitative indicators and critical thresholds of excessive demand, and conduct a comprehensive quantitative assessment and spatial mapping of its excess demand to obtain the types and spatial distribution of ecosystem service excessive demand in this city. Finally, GIS spatial statistics and bivariate spatial correlation were used to analyze the correspondence between ES excessive demand and population density.

2. Materials and Methods

2.1. The Study Area

Zhengzhou, the capital of the central province of Henan in China, is located at longitude 112°42′–114°14′ E and latitude 34°16′–34°58′ N. The specific area of study is the center of the city (Figure 1). The study area contains 106 streets (townships) with a total area of 628 km^2, a total population of 5.726 million, and an average population density of 0.9118 million/km^2.

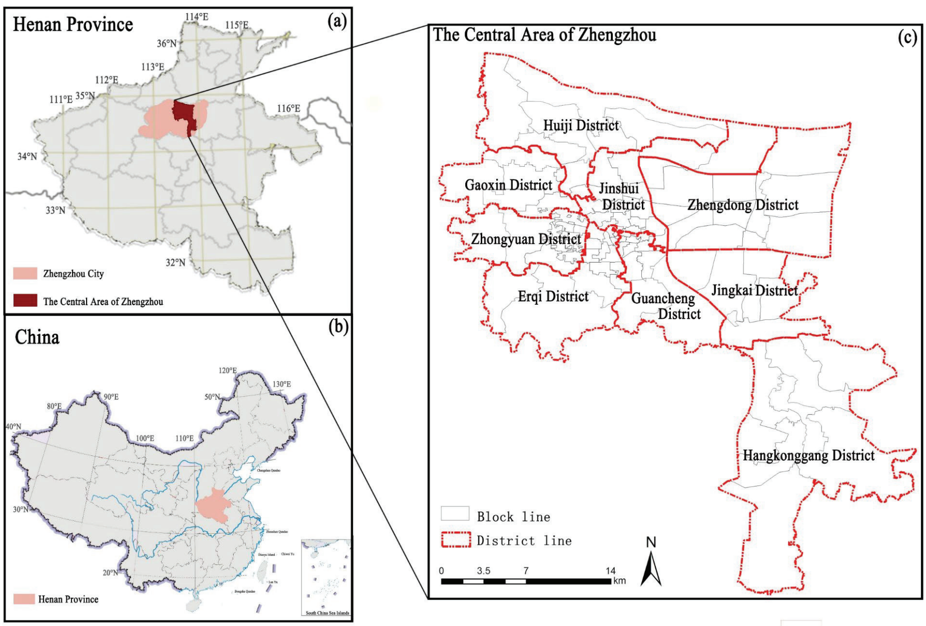

Figure 1. Administrative boundaries (**a**), geographic location (**b**) and topography (**c**) of Zhengzhou city.

The climate type of the study area is temperate continental with four distinct seasons, where it has high temperature and rain in the summer and is cold and dry in the winter. The average annual rainfall in the last 10 years was 796.93 mm, with the highest continuous rainfall reaching 624.1 mm in 10 h; the annual maximum temperature is 39 °C, the minimum temperature is −4.2 °C and the maximum urban heat island temperature difference reaches 43.2 °C. In addition, as a developing city since 2000, Zhengzhou has entered a phase of rapid urban expansion and the ecological space within the city has been severely eroded and destroyed. Moreover, natural disasters such as floods, high temperatures and air pollution occur frequently. Due to heavy industrial complexes in the provinces and cities to the north of the city and the influence of the northwest monsoon in the winter, air pollution is significant in the autumn and winter seasons. Based on the ecological and environmental problems occurring in the study area mentioned above, improving the living space within the city, meeting the urban demand for ESs, and increasing the city's ability to withstand natural disasters are matters that need to be urgently addressed during its current stage of development. Although Zhengzhou has been aware of ecological problems and put forward some improvement measures in recent years, there is no qualitative basis for uneven GI utilization benefits in different regions, especially in the old city, and the problem of too many people and too little green space is very serious. Our study is dedicated to quantitatively assessing the actual demand for ecosystem services on the neighborhood scale and providing a relevant planning and construction basis for the rational allocation of GI.

2.2. City Ecosystem Service Types and Threshold Selection

Urban ecosystem service demand assessment from a GI perspective should take the spatial mobility characteristics of urban ecosystem services, the service supply capacity of GI [3,12] and the demand of the city into account to determine which of the ecosystem services need to be assessed. Our selection of ecosystem service types is based on the following criteria:

(1) GI elements within the city and the demand for urban ecosystem services. For some regulatory services (rainfall, temperature, hydrological regulation, etc.) and cultural services (recreation, spiritual services, aesthetic enjoyment, etc.), the area of GI implementation will determine whether such services can be used effectively.
(2) Concern for stakeholders. For example, persistent haze, the summer heat island effect, and water pollution in Zhengzhou over the past 10 years, especially due to climate change, summer rainstorms and floods, have become predominant problems faced by the city in the past two years that have largely affected its sustainable development.
(3) Policy requirements for carbon emissions. To ensure the implementation of the United Nations 2030 Agenda for Sustainable Development, the country has set the goal of "striving to peak CO_2 emissions by 2030 and achieving carbon neutrality by 2060".
(4) Data accessibility. Given the above, we finally selected five ESs (air purification, flood regulation, heat regulation, hydrological regulation and CO_2 sequestration) and one cultural service (recreational) for excessive demand assessment.

Combined with previous studies [20,23–26], urban ESs have helped to improve and maintain environmental quality under a certain degree of ecological pressure. However, when the latter exceeds a specified limit, the ecosystem service supply fails to maintain good environmental quality; i.e., ecosystem service demand is not fully satisfied. Therefore, we can use environmental quality standards for the expectation threshold associated with regulating the demand for ESs, and similarly, we can use the corresponding industry normative standards for cultural services, thereby establishing the same critical thresholds for excessive demand.

2.3. Data Preparation

Data for the study area included PM2.5 concentrations from the 2020 daily air quality reports from the monitoring stations of the Zhengzhou Ecological Environment Bureau (http://sthjj.zhengzhou.gov.cn, accessed on 9 April 2021), population levels from the 2020 Zhengzhou Statistical Yearbook (https://navi.cnki.net/knavi/yearbooks, accessed on 15 March 2021), days of urban flooding from Landsat 8 OLI remote-sensing data of Zhengzhou in 2020 (http://www.gscloud.cn, accessed on 22 May 2020), surface temperatures from the 2020 Zhengzhou Meteorological Observatory statistics (https://earthexplorer.usgs.gov/, accessed on 11 June 2020), accessibility of regional parks in towns from the park green space of Zhengzhou in 2020 (https://google-earth.gosur.com/cn/, accessed on 20 May 2020), water quality from the report of the Zhengzhou Ecological Environment Bureau on the water quality ranking of the rivers within the city in 2020 (slt.henan.gov.cn/bmzl/szygl/szygb/, accessed on 28 March 2021) and CO_2 emissions from motor vehicle carbon emission data and 2020 neighborhood green-space carbon absorption data (https://navi.cnki.net/knavi/yearbooks, accessed on 15 May 2021), with excessive data from on-site research (Table 1).

In addition, it should be noted that we used precipitation data from 2021 because Zhengzhou experienced historically rare, heavy rainfall in July 2021, during which the maximum depth of the water reached 3 m and covered more than 95% of the city. The disaster paralyzed the entire city and affected 9 counties and cities downstream. This is a situation that had not occurred in this partially arid inland city in the past century, and thus it is necessary to highlight and add weight to the excessive demand for rainfall regulation in the city in this study.

Table 1. ES excessive demand evaluation indicators and demand thresholds.

ES	Indicators	Secondary Indicators	Excess Demand Threshold	Data
Air purification	$PM_{2.5}$ pollution risk index	$PM_{2.5}$ concentration	35 μg/m^3	Daily average $PM_{2.5}$ concentration data at monitoring stations in Zhengzhou in 2020
		Population density	-	Population statistics by neighborhood in Zhengzhou in 2020
		Social vulnerability	-	Share of elderly and child population
Flood regulation	Flood risk index	Simulated water damage depth	15 cm	Modeled waterlogging depth data for 2020; rainfall statistics for 2021
		Number of affected infrastructure and population	-	Remote-sensing data on urban buildings and roads; 2019 population statistics by neighborhood in Zhengzhou
		Social vulnerability	-	Share of elderly and child population
Heat regulation	High-temperature risk index	Surface temperature	35 °C	Remote-sensing image data for Zhengzhou City in 2020
		Population density	-	Population statistics by neighborhood in Zhengzhou in 2020
		Social vulnerability	-	Share of elderly and child population
Hydrological regulation	Water quality safety index	Average annual water quality	Excellent	Zhengzhou Ecological Environment Bureau Report on Water Quality of Rivers in Zhengzhou City in 2019
		Population density	-	Population statistics by neighborhood in Zhengzhou in 2020
		Social vulnerability	-	Share of elderly and child population
CO_2 sequestration	CO_2 emission risk index	CO_2 emission	-	Neighborhood population carbon emissions data in 2020; neighborhood green-space carbon sequestration data in 2020
		Population density	-	Population statistics by neighborhood in Zhengzhou in 2020
		Social vulnerability	-	Share of elderly and child population
Recreational services	Low recreational opportunity population	Park accessibility	15 min	Park land and road vector data for Zhengzhou in 2020
		Population density	-	Population statistics by neighborhood in Zhengzhou in 2020

2.4. *Quantification Index Selection and Calculation*

The frequency and severity of events usually do not fully reflect the magnitude and damage of a disaster, and the exposure and vulnerability of the city to a disaster need to be considered simultaneously. Therefore, to quantify the risk of disaster (risk, R), we selected the disaster risk assessment framework proposed by the Intergovernmental Panel on Climate Change (IPCC) based on "Hazard-Exposure-Vulnerability" [27], as expressed in the following equation:

$$R = H \times E \times V \quad (1)$$

where R is the corresponding disaster risk when hazard H exceeds the critical threshold, exposure E is the direct exposure carrier of the disaster and vulnerability V is the ability of the affected object to withstand or cope with the disaster. We calculated the selected indicators based on the disaster assessment framework in the evaluation of the following six ESs.

2.4.1. Air Purification

Due to the influence of the geographical location and seasonal climate, air pollution in the study area is the highest in winter and alternates in the winter, spring and autumn–winter seasons. Haze is the predominant problem affecting urban air quality in the area, with the primary pollutant being $PM_{2.5}$. Therefore, we used the $PM_{2.5}$ pollution risk index as an excessive demand evaluation indicator for air purification. The risk index should be used to measure vulnerability in socioeconomic terms more comprehensively than by simply using indicators such as concentration or the number of occasions that the pollution limit is exceeded, because the lower the vulnerability the stronger the demand for the ecosystem service. Therefore, we used $PM_{2.5}$ concentration, population density and social vulnerability as secondary indicators (Table 1). Firstly, we used the annual average $PM_{2.5}$ concentration limit (35 $\mu g/m^3$) specified in the Ambient Air Quality Standards (GB 3095-2012) as the excessive demand threshold. The selection of the annual average indicator for evaluation can reflect the ecosystem service demand levels for different neighborhoods, and the selection of extreme values can affect the actual objectivity of the assessment results. By using a reclassification tool, areas with annual average $PM_{2.5}$ concentrations of less than 35 $\mu g/m^3$ were classified as 0, whereas other areas were classified into five levels from 1 to 5 using the natural breakpoint method (with "1" indicating the lowest level of stress and "5" indicating the highest level of stress) as the stress index. The population density and the proportions of the elderly and children in the population on the street scale within an urban area were similarly reclassified and assigned values from 1 to 5, which were used as the exposure evaluation index and the social vulnerability evaluation index, respectively.

Subsequently, we normalized the indicators as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

where x is the original value, x' is the normalized value, $x_{\min}$ is the minimum value and $x_{\max}$ is the maximum value.

Finally, according to the risk assessment framework in Equation (1), the $PM_{2.5}$ risk index for the study area was obtained and reclassified using six levels from 0 (no excessive demand) to 5 (the most excessive demand).

2.4.2. Flood Regulation

As a relatively arid inland city, Zhengzhou has rarely experienced heavy rainfall or flooding in the past 50 years. However, since 2000, the rapid expansion of the city size and the inability of infrastructure development to meet the demands of urban development has resulted in frequent and multi-scale flooding within the city during rainfall events. Coupled with global climate change and environmental deterioration, the city has been highlighted by heavy rainfall and flooding in the past two years. Therefore, we selected the flood risk index as a quantitative indicator to assess the excessive demand for a rainfall and flood regulation service in urban neighborhoods within the study area and selected the simulated waterlogging depth, the quantity of affected infrastructure and population, and social vulnerability as secondary indicators (Table 1). Satellite remote-sensing monitoring technology was used to obtain the inundation extent, and the ArcGIS spatial analysis and data management functions were applied to obtain the inundation depth in combination with the ground elevation data of the study area to obtain the flood risk index. According to the evaluation criteria of the inundation level in the Planning Standards for Urban Inundation Prevention and Control issued by the Ministry of Housing and Urban-Rural Development, a water depth of 15 cm on a road was taken as the excessive demand threshold for the rainfall regulation service. The disaster-bearing bodies for an internal flooding disaster, including road network density, building area density and population density, were selected for the exposure index evaluation.

2.4.3. Heat Regulation

The prominent environmental problem in the study area in summer is urban high temperature with a significant heat island phenomenon. The maximum daily temperature in urban areas reached 39 °C in 2020, and the temperature in many places is 6–8 °C higher than in suburban areas. We selected surface temperature, population density and social vulnerability as secondary indicators to construct an urban high-temperature risk assessment index system to assess excessive demand for heat regulation services (Table 1). According to the group standard for climate recreational site evaluation issued by the National Weather Service Association and the three levels of high-temperature warning signals established by the meteorological department for hot weather (yellow, orange and red warnings mean that the maximum temperature will be above 35 °C for 3 consecutive days, rise to 37 °C within 24 h and rise to 40 °C within 24 h, respectively), we selected 35 °C as the threshold value for the temperature regulation service demand in this evaluation.

We selected the Landsat 8 thermal infrared remote-sensing band for a day in summer 2020 and used the ENVI remote-sensing processing software to perform remote-sensing inversion of the surface temperature in the study area by employing the atmospheric correction method. The surface temperature obtained from the inversion was then reclassified to obtain the corresponding high-temperature risk disaster-stress index. The exposure and vulnerability indices were calculated in the same way as for the air purification service.

2.4.4. Hydrological Regulation

We selected the water quality security index as a quantitative index to assess the excessive demand for the urban water hydrological regulation service. We graded the water bodies in the urban districts in the study area that did not reach the excellent standard from 1–5 according to the report of the Zhengzhou Ecological Environment Bureau on the water quality ranking of the rivers within Zhengzhou in 2019, whereas neighborhoods without water bodies were graded as 0. The index was calculated by using the China surface water environmental quality class 3 standard (GB3838-2002) and urban sewage treatment plant pollutant discharge class 1 A standard (GB18918-2002). For local water bodies where the water quality was not being monitored (e.g., rivers and local water runoff areas with intermittent flow during particular months), we conducted on-site research and supplemented the missing data.

2.4.5. CO_2 Sequestration

We selected the CO_2 emission risk index as the quantitative indicator of excessive demand for the CO_2 regulation service, and CO_2 emission, population density and social vulnerability as secondary indicators (Table 1), indicating the degree of stress hazard , exposure index and the proportion of the elderly and children in the population, respectively. Because the scope of this study involves the inner city on the neighborhood scale, we added together the carbon emissions from people and motor vehicles and carbon sequestration from green spaces as the total carbon emissions (Equations (3)–(6)). By combining the data from the IPCC Technical Report and Methodological Guidelines [28] and previous studies [29,30], the carbon emissions per vehicle per year for motor vehicles were assumed to be 2.7 t, the CO_2 exhalation per person per year was assumed to be 0.079 t, and the carbon emission factor for urban green spaces was assumed to be -5.77 t/(hm^2·a).

Carbon emissions from motor vehicles can be calculated by using:

$$C_e = \sum (P_n \times \theta_n) \tag{3}$$

where C_e denotes the CO_2 emissions from P_n motor vehicles in the region and θ_n denotes the CO_2 emissions per motor vehicle per year.

Carbon emissions from human respiration can be calculated using the following formula:

$$C_p = \sum(P_i \times \theta_i) \tag{4}$$

where C_p denotes the CO_2 emissions per person in the region, P_i denotes the number of people in the region and θ_i denotes the CO_2 emissions per person per year.

The equation for calculating carbon emission in urban green spaces is as follows:

$$C_l = \sum(S_i \times \delta_i) \tag{5}$$

where C_l indicates the CO_2 uptake in the green space, S_i indicates its area and δ_i indicates the rate of carbon sequestration per unit area of the green space.

Thus, total carbon emissions can be calculated as:

$$C = C_e + C_p + C_l \tag{6}$$

Due to limited available data, the population and motor vehicle carbon emissions used are not representative of all carbon emissions in the study area; thus, we used the natural breakpoint method to directly classify the processed data into levels from 0–5.

2.4.6. Recreational Services

Accessibility is an important indicator affecting the degree of urban green-space use that reflects the ease with which residents can overcome spatial resistance to approach and use park land and the relationship between urban green space and potential use demand within a regional unit [31,32]. We used open space opportunities as a primary quantitative indicator of excessive demand and the number of people with low open space opportunities as a secondary indicator. We applied use of the point-of-interest (POI) method to obtain the base data for urban neighborhood discrimination and location data for green spaces by cleaning and classifying the POI data and using ArcGIS to obtain the park service capacity for the total green-space area in the neighborhood. To take the "boundary effect into consideration", we included neighboring parks outside the study area in the analysis process. According to the "Service Radius Classification Requirements for Urban Parks", an excessive demand threshold of 15 min was used as the criterion for good accessibility. The number of people in the low accessibility range in each neighborhood was obtained by superimposing the population density. Finally, the excessive demand for recreational services was reclassified from 0–5.

2.5. Weighting Calculation

We determined the weights for each excessive demand from the perspective of overall fairness based on measuring the discrete degree of each excessive demand index using MATLAB software and the entropy method in the objective assignment method. The specific calculation steps are as follows.

Normalize the indicators:

$$x_{ij} = \frac{D_{ij} - D_{j\min}}{D_{j\max} - D_{j\min}} \tag{7}$$

Calculate the share of excessive demand for the ecosystem service item j in block i:

$$X_{ij} = \frac{x_{ij}}{\sum_{i=1}^{x} x_{ij}} \tag{8}$$

Calculate the information entropy of each requirement:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} X_{ij} \ln X_{ij}, e_j \in [0,1] \tag{9}$$

Calculate the information entropy redundancy:

$$d_j = 1 - e_j \tag{10}$$

Calculate the weight of each excessive demand:

$$W_j = \frac{d_j}{\sum_{i=1}^{n} d_j} \tag{11}$$

Based on the weights, the comprehensive ecosystem service excessive demand value for each neighborhood can be calculated as:

$$S_i = \sum_{j=1}^{n} W_j x_{ij} \tag{12}$$

In Equations (7)–(12), D_{ij} is the value of the jth ecosystem service demand in the ith block; $D_{j\max}$ and $D_{j\min}$ are the maximum and minimum values of the matrix column in which the jth ecosystem service excessive demand is located, respectively; m is the number of blocks and n is the total number of ecosystem service excessive demands evaluated.

2.6. Bivariate Moran's I Calculation

After preliminary analysis, we found that the spatial numerical distribution of comprehensive ES excessive demand and population had a certain degree of spatial autocorrelation. Bivariate spatial autocorrelation has high applicability and effectiveness in describing the spatial correlation and dependence characteristics of two geographic elements [33]. At present, this method has not been found to be used to explore the spatial relationship between ES demands and population distribution. Therefore, we innovatively attempted to adopt this method.

Bivariate Moran's I is an extension and expansion based on Moran's I index, which measures the correlation between the attribute values of spatial units and other attribute values in adjacent spaces [34,35]. It can be used as an effective method to analyze the correlation characteristics between comprehensive UES demand and population density. Bivariate Moran's I is divided into two levels: global Moran's I and local Moran's I. The calculation formula is as follows:

$$I_{ab} = \left(\frac{x_{ma} - \overline{x}_a}{\delta_a}\right)\left(\frac{x_{ab} - \overline{x}_b}{\delta_b}\right) \sum_{j=1}^{n} w_{mo} \tag{13}$$

In Equation (13), x_{ma} is the value of the variable a of the spatial unit m, x_{ab} is the value of the variable b of the spatial unit o, $\overline{x}_a$ and $\overline{x}_b$ are the mean values of a and b, respectively, δ_a and δ_b are the variances of a and b, w_{mo} is the spatial weight matrix between unit m and o, and I_{ab} is the Moran's I statistic and its value is between $(-1, 1)$: less than 0 means negative correlation, equal to 0 means no correlation and greater than 0 means positive correlation. Data processing was conducted in GeoDa 1.6.7.

3. Results

3.1. Excessive Demand Evaluation for Each UES

Figure 2 shows the evaluation results for each ecosystem service excessive demand. The numbers of blocks with the air purification service excessive demand from 5 to 0 were 3, 2, 7, 21, 58 and 1; there are obvious differences in the spatial distribution, with the areas having high excessive demand being concentrated in the old blocks with high populations and building densities in Guancheng District, including Beixia, Nanguan and East Hanghai blocks. Guancheng District is the old city of Zhengzhou, with dense buildings and population, and a lack of green space, including the Beixia block with an area of 1.2 km^2, a population of 89,886, and a green area of 0.017 km^2; the Nanguan block with an area of 1.7 km^2, a population of 43,884, and a green area of 0.078 km^2; and the

East Hanghai block with an area of 8.6 km^2, a population of 39,043, and a green area of 0.7 km^2. The above three blocks are mostly covered by small roads, and there is almost no three-dimensional greening and rooftop greening, thus it is difficult to improve the air quality effectively.

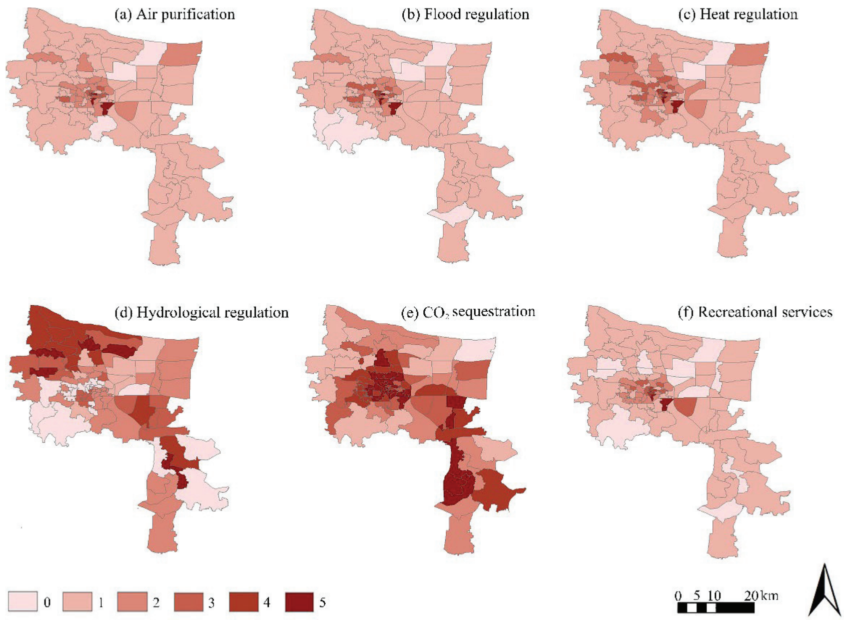

Figure 2. The results of excessive demand evaluation for each urban ecosystem service.

The numbers of blocks with excessive demand for flood regulation from 5 to 0 were 3, 4, 9, 12, 59 and 1; the numbers of blocks with excessive demand for heat regulation from 5 to 0 were 3, 5, 12, 52 and 1. The results for the high-demand neighborhoods are the same as for air purification, indicating that not only are the dense building population and the extreme lack of green-space resources a problem, but also the various infrastructures for drainage and the construction of pavements and buildings in such old neighborhoods are relatively outdated and unable to meet the requirements of energy efficiency and environmental protection, so much so that they cannot meet the needs of current urban development.

The numbers of blocks with excessive demand for hydrological regulation from 5 to 0 were 5, 9, 16, 31, 10 and 1. Wutong and Shuangqiao blocks in Gaoxin District, Yingbin and Yangjin blocks in Huiji District, and the Binhe block in Hangkonggang District have high demand. Among these areas, Wutong, Shuangqiao and Yingbin blocks have black smelly water bodies, and the rest of the blocks are located in the middle and lower reaches of urban rivers where some of their river water quality classes are monitored as V. That is the main reason for the high overall demand value of hydrological regulation of the blocks.

The numbers of blocks with excessive demand for CO_2 sequestration from 5 to 0 were 30, 21,14, 13, 15 and 1. The results in Figure 2 show that CO_2 regulation is the indicator with the highest number of high-demand neighborhoods among all single ES demand services, and the demand for CO_2 regulation has the widest spatial distribution, which reflects the serious inequality between carbon emissions and carbon sequestration within the city. The high-demand neighborhoods are mainly located in Jinshui District (Fengqing, Nanyangxincun, Nanyang, Dashiqiao, Wenhua, Jingba, Fengchan and Fenghuangtai blocks), Zhongyuan District (Mianfang, Jianshe and Linshanzhai blocks), Eerqi District (Wulibao, Minggong, Mifengzhang, Jiefang, Dehua, Yima, Jianzhong and

Huaihe blocks), Guancheng District (Xidajie, Nanguan, Dongdajie, Longhai, Erligang and East Hanghai blocks), Jingkai District (Jinghang block), which is located in the southern part of the new city near the surrounding industrial land, and Hangkonggang District (Zhenggang, Xingang and Yinhe blocks). The high demand for CO_2 regulation in the old city is directly related to the high density of human life and motor vehicle emissions, as well as the small and sporadic distribution of the GI area, which makes it difficult to neutralize the continuously increasing CO_2 emissions. The main reason for the high demand for CO_2 regulation is the proximity of these neighborhoods to industrial areas and expanding construction areas on the outskirts of the city, (although we did not count the CO_2 emissions from the industry here) the high motor vehicle emissions from industrial and construction transportation, and the lack of GI land for CO_2 absorption in these neighborhoods. The GI land area of the Jinghang block is 0.0001 km^2, and the GI land areas of Zhenggang, Xingang and Yinhe blocks are 7.06 km^2, 9.59 km^2 and 14.52 km^2, respectively, thus the final calculation shows that the excessive demand is high.

The numbers of blocks with excessive demand for recreational services from 5 to 0 were 3, 5, 8, 15, 51 and 1. As can be seen from Figure 2, the excessive demand for recreation services is more concentrated in the south of Jinshui District, the east of Zhongyuan District, and the north of Erqi and Guancheng Districts, which are among the earliest developed central urban areas of Zhengzhou City where the green infrastructure and recreation space allocated at the beginning of development were not serious considerations of the government at the time of planning and construction; therefore, there is woefully inadequate public open green space. In particular, the Dehua block in Erqi District and Nanguan and East Hanghai blocks in Guancheng District have the highest demand for recreation services in terms of walking arrival time.

3.2. Evaluation of the Comprehensive Excessive Demand for UESs

According to the weighted calculation results, excessive demand for flood regulation had the largest weight of 0.406, followed by air purification (0.305), heat regulation (0.119), recreational services (0.074), CO_2 regulation (0.073) and hydrological regulation (0.021). ArcGIS software was used to comprehensively stack the obtained weight values and obtain the comprehensive ecosystem service excessive demand after recalculating the classification (Figure 3). The results show that the numbers of blocks with comprehensive ecosystem service excessive demand values from 5 to 0 were 8, 21, 31, 25, 9 and 0, among which there were eight with particularly high excessive demands: Minggong, Jiefang and Dehua blocks in Erqi District; Duling block in Jinshui District; and Beixia, Xidajie, Nanguan and East Hanghai blocks in Guancheng District. (Table 2). From the spatial structure perspective, the areas with high excessive demands are mainly distributed in the old blocks in the city, whereas the blocks with low excessive demands are mainly distributed in the areas near the urban edge or new urban areas.

Improving the GI unit efficiency supply regulation should be based on comprehensive demand rather than on a single benefit or purpose. The above eight blocks with the highest excessive demands for comprehensive ESs should be prioritized for GI construction in the central city of Zhengzhou in the future. It should be emphasized that using the comprehensive ES excessive demand identifies high-priority areas for GI implementation, whereas the specific implementation type of GI is obtained by analyzing each excessively demanded ES. First of all, according to the comprehensive ES excessive demand results obtained by weighted superposition, the eight blocks with high comprehensive ES excessive demand can be set as priority implementation areas for GI, after which the corresponding single excessively demanded ES for each area can be analyzed. For instance, the ecosystem service excessive demands for the Xidaijie block follow this pattern: CO_2 regulation (5) > recreational services (4) and heat regulation (4) > air purification (3) = flood regulation (3) > hydrological regulation. Therefore, CO_2 regulation should be the primary goal for the future GI planning of this street. Overall, among the eight blocks with high, comprehensive ecosystem service excessive demand, CO_2 regulation ranks first, which also indicates that for the GI construction for the central city of Zhengzhou, priority should be given to reducing CO_2 emissions in the future. In addition, the improvement of urban air quality, prevention of flooding and dealing with urban high temperatures are second only to the reduction of CO_2 emissions for the implementation of GI.

Table 2. High, comprehensive ES excessive demand blocks.

ES High-Value Neighborhood	District	Air Purification	Rainfall Regulation	Temperature Regulation	Hydrological Regulation	CO_2 Regulation	Recreational Services
Jiefang	Erqi District	4	4	4	1	5	4
Nanguan	Guancheng District	5	5	5	2	5	5
East Hanghai	Guancheng District	5	5	5	2	5	5
Beixia	Guancheng District	5	5	5	2	4	4
Dehua	Erqi District	4	4	4	2	5	5
Xidajie	Guancheng District	3	3	4	2	5	4
Minggong	Erqi District	4	4	4	0	5	3
Duling	Guancheng District	4	4	4	0	5	4

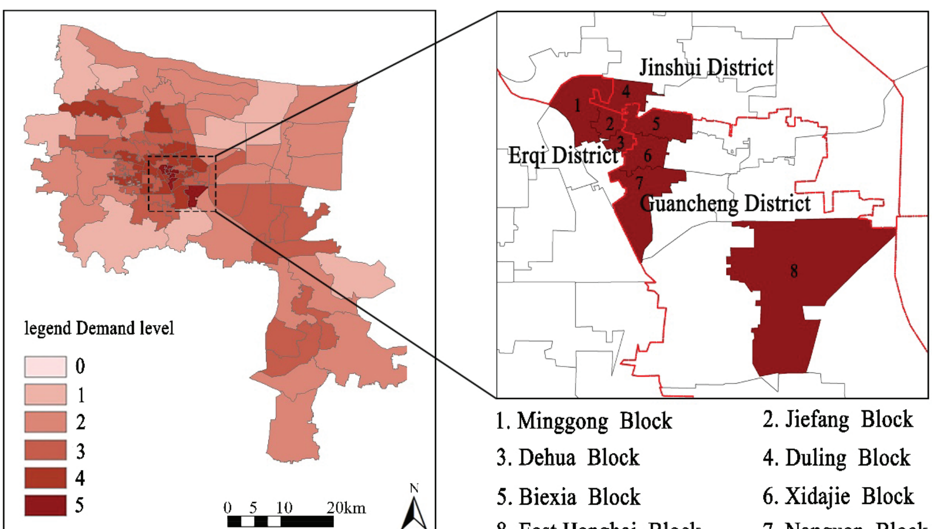

Figure 3. Evaluation of the comprehensive excessive demand for UESs.

3.3. Bivariate Spatial Autocorrelation Analysis

Using GeoDa software, the bivariate spatial autocorrelation analysis was carried out with population density (PD) as the first variable (X) and comprehensive excessive demands for ESs (CEDES) as the second variable (Y). The global Moran's I was 0.259 (Figure 4). Randomization 999 was selected in GeoDa for the significance test. The results showed that the p values were all 0.001, indicating a significant spatial positive correlation between LST and habitat quality under the confidence of 99.9%; that is, with the increase in population density, the comprehensive excessive demand for ESs in the center of Zhengzhou also increases.

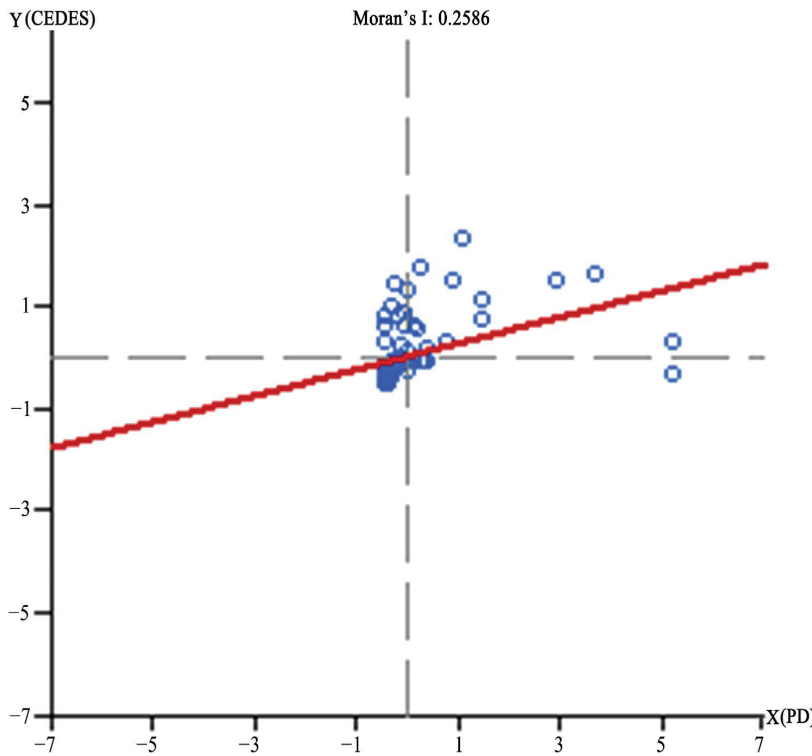

Figure 4. The Moran's I scatter diagram of population density and comprehensive excessive demands for ESs.

The global Moran's I only represents the overall correlation trend of the two variables and cannot reflect the agglomeration differences in specific spatial locations. Therefore, the local Moran's I was further calculated, and the results (LST-habitat quality) were divided into three aggregation types: high-high (H-H), low-high (L-H) and low-low (L-L). The LISA (local indicators of spatial association) cluster map of population density and comprehensive excessive demand for ESs clearly shows the spatial agglomeration characteristics of regions that passed the significance test (Figure 5).

The H-H type is scattered in Erqi District and Guancheng District. Erqi District includes Duling, Jiefang, Yimalu and Dehua blocks; Guancheng District includes Beixia, Xidajie, Dongdajie and Longhai blocks. The above areas are located in the center of the old blocks in Zhengzhou, with typical characteristics of high population density, high building density and very little GI distribution. Among these blocks, the highest population density is found in the Dehua block, which is 162,325 persons/km^2, and the lowest is in the Longhai Road block, with 18,711 people/km^2. Their high demand for ESs is reflected in all aspects of GI configuration, including improving air quality, reducing waterlogging, lowering summer temperatures, increasing recreational space, etc.

The L-H type is distributed in Guancheng District and Jinshui District. Guancheng District includes South Zijingshan and Erligang blocks; Jinshui District includes Renmin and Fenghuangtai blocks. The population density is 9274 people/km^2 in the South Zijingshan block, 7244 people/km^2 in the Erligang block, 16,381 people/km^2 in the Renmin block and 11,137 people/km^2 in the Fenghuangtai block. The reasons for the relatively low population density and high additional demand are the high traffic flow in the South Zijingshan block and the excessive building density in the residential area; the Erligang block, Renmin block and Fenghuangtai block's inclusion is mainly caused by the high demand for CO_2 regulation.

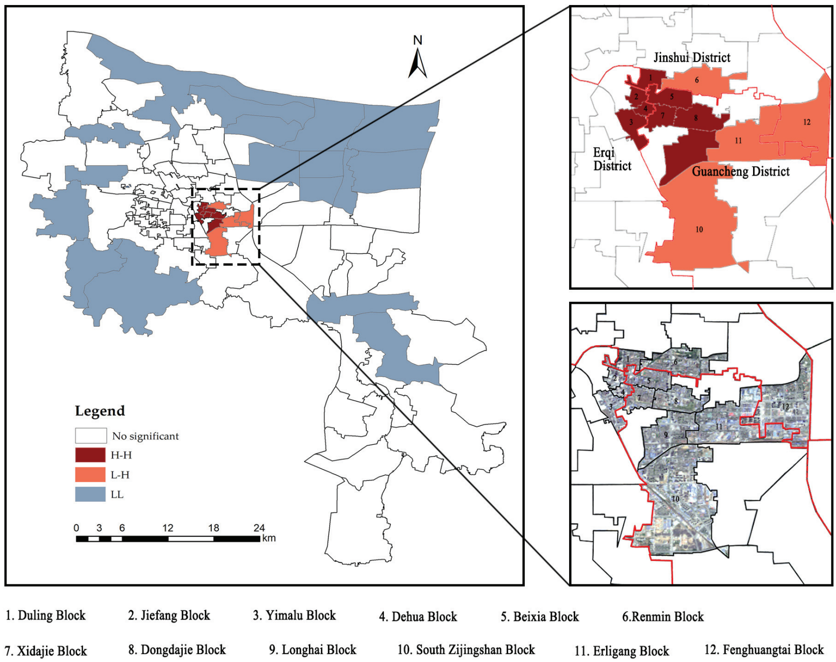

Figure 5. Local indicators of spatial association cluster map of population density and comprehensive excessive demand for ESs.

The L-L type is mainly distributed in the fringes of the central urban area. These blocks were developed late, with low population density and relatively complete infrastructure. The layout of buildings and roads in the blocks is more reasonable. In addition to the surrounding suburbs, there are large areas of green space to reduce the risk of disasters in these areas.

4. Discussion

4.1. Excessive Demand Evaluation for Each UES

At present, the versatility of GI has been widely accepted and recognized, but research into and implementing it are often carried out to bestow a single benefit [36]. This ignores the overall benefits of GI to some extent and is not conducive to the efficient use of social capital. In addition, most of the benefits generated by GI are highly localized and located in or near supply areas, making decisions on their allocation important for local environmental and social equity. This is why we assessed several ES needs, including regulation services and cultural services, separately.

Taking the central area of Zhengzhou as an example, we conducted a single quantitative evaluation and spatial mapping on six excessively demanded ESs (air purification, flood regulation, heat regulation, hydrological regulation, CO_2 regulation and recreational services) based on environmental quality standards with the block as the basic unit. The results show that:

(1) Comparing the evaluation results of the six indicators, except for hydrological regulation and CO_2 regulation, the other four indicators show that the high-demand areas are located in the old urban areas, which were the first to be developed but now have poor environmental conditions. Therefore, in terms of supply, old urban areas need to be equipped with GI facilities that can solve air pollution, waterlogging, high temperature and lack of open space, and the corresponding solution strategy needs to be based on the construction characteristics of each neighborhood, such as adding three-dimensional greening and green roofs for buildings that meet the implementation goals. For example, the rational design of road space and pavement, with rainwater gutters and permeable paving materials that can both increase the road space and pavement can be reasonably designed, and the rain gutters and permeable paving materials can not only increase the water permeability and water storage but also increase the planting space; furthermore, small, abandoned spaces around the streets can be used to create recreational places and so on.

(2) The evaluation of hydrological regulation in this study focuses on the water quality of rivers and public-space landscape lakes in urban areas; there are neighborhoods without river or lake distribution and these areas cannot be evaluated, thus their demand value is 0. As a result, in the calculation process of evaluating the comprehensive ES demand, this indicator has the lowest weight value, which has no influence on the final results. From the final evaluation results, the water environment quality in the areas located in the northwest and southeast of the central city is poor, mainly because: firstly, there are more rivers in the northwest of the city, but the construction along the rivers is lagging behind, there is a lack of coherent green space, and there is more unused land distribution, which makes it easy to have garbage accumulation or sewage discharge; secondly, the southeast of the city is located downstream of the city rivers, plus the area is in the expansion and construction stage and there is a certain industrial distribution in the periphery, which makes the water body more vulnerable to pollution. The implementation of GI in the river area should focus on increasing the spatial coherence and the purification effect of plants on water bodies, as to form an urban greenway combining blue and green spaces.

(3) Combined with the evaluation results of CO_2 regulation, the central old city and the new city in the southeast, as the high-value areas of CO_2 emissions, are influenced by the daily activities of residents and construction and industrial development, respectively. Based on the above factors, firstly, in the neighborhoods with high CO_2 emissions in the old city, the implementation of GI should focus on increasing the planting space that can collect CO_2 as much as possible while focusing on the use of relevant energy-saving facilities; secondly, for the economic development zone and aviation port area in the southeast, there is a larger area of space for GI construction, and thus it is necessary to reserve enough land for GI and build energy-saving and emission-reducing green buildings at the early stage of planning and construction.

4.2. Comprehensive Excessive Demand for UESs

Based on the results of the individual ES demand evaluation, we then assessed the additional demand for comprehensive ESs in each neighborhood within the central city of Zhengzhou. The purpose of the comprehensive ES demand evaluation was to identify priority areas for GI implementation, which helps decision-making authorities to make decisions with limited financial and resource support that are more equitable to the local environment and society. Compared with previous studies on ecosystem services [37,38], we paid more attention to the practicality of comprehensive demand of ES supply and demand in urban GI planning and construction. For example, Morse Wayde C et al. explored the relationship between outdoor recreation and ecosystem services, and Ruchira Gangahagedara et al. proposed research trends and research priors for ESs related to multidirectional biodiversity and climate change. Based on the results of this study, the following optimization measures about the implementation of GI are proposed for the future:

(1) In terms of spatial priority, the results of excessive ES demand after comprehensive superposition indicate that there are eight high-demand blocks in total, and all of them are clustered at the junction of Guancheng District and Erqi District. These blocks belong to the earliest developed areas in Zhengzhou. Therefore, the implementation of GI should give priority to old neighborhoods and old city renewal. Here, we propose two preliminary strategies: hard GI and soft GI. First, hard GI includes the use of permeable and water-storage materials in the road pavement and energy-saving facilities in buildings, etc. Hard GI is an effective supplement to the original, backward infrastructure in the neighborhood that enhances the drainage function inside the streets and reduces CO_2 emissions and excessive use of energy. Secondly, soft GI includes green space mainly for planting. On the one hand, in the old neighborhoods with extremely limited land space there are small spaces with poor or unreasonable utilization, such as street corners and street edges, in which GI layout can be utilized in the form of pocket parks and where miniature dotted and strip planting can be used for renewal and renovation; on the other hand, three-dimensional greening and rooftop greening can be added to buildings and structures with feasibility. In short, the scattered layout of soft GI in the form of "stitching" can improve the neighborhood air quality, reduce the heat island effect of small-scale space, absorb waterlogging and meet the residents' recreational needs with maximum efficiency. In addition, enhancing and maintaining the development and the quality of the green infrastructure in the blocks should not be ignored, and improving the development level of green infrastructures such as rivers, parks and road green belts can enhance the function of ESs such as hydrology and climate in the blocks.
(2) In terms of the excessively demanded ESs for the center of Zhengzhou, the decision-makers should first consider the supply of GI to improve the CO_2 regulation service. There is a close relationship between carbon emissions and air quality. The reason for this result is directly related to the backward energy-saving facilities, excessive population and building density in old blocks. Therefore, in addition to the above measures, a more in-depth study of tree species selection and enhanced connectivity for non-motorized mobility within the GI could increase CO_2 uptake by plants and improve the convenience of low-carbon travel for the population to some extent.

4.3. Bivariate Spatial Autocorrelation Analysis

We conducted a spatial autocorrelation analysis of population density and comprehensive ES demand. The calculation results of the Moran's I and LISA cluster map can help us to analyze the reasons for additional ES demand in different neighborhoods in the city more thoroughly and can scientifically verify the demand types of GI calculated by the established ES excessive demand evaluation system and the areas in urgent need of priority construction. For example, it can be seen from the analysis results that although population density and ES demand have the most direct correlation, high-demand and high-population density blocks do not equate. Therefore, we should focus on four areas of GI functionality configuration:

(1) For H-H type blocks, GI should be allocated based on low per capita resources and small available space, and environmental issues directly related to people's health should be primarily solved, such as improving air quality and alleviating high temperatures in summer.
(2) For L-H type blocks, due to the relatively low population density, GI configuration has a large role to play. Therefore, a GI supply strategy should be proposed for these blocks one by one, based on the single ES demand assessment results of each block.
(3) For L-L type blocks, which are mainly distributed in new areas around central urban areas, the population density and demand for ecosystem services are relatively low. However, our on-the-spot investigation found that a large amount of green infrastructure, such as street green spaces, greenways and comprehensive parks, in these blocks is inefficiently utilized. Therefore, GI configuration needs to pay

attention to individual blocks with high demand for a single ES and be based on functional supplement.

(4) For blocks with high ES demand not reflected in the above three types, such as Ming-gong, Nanguan and East Hanghai blocks, we need to further analyze the main reasons for high ES demand and propose corresponding GI supply strategies according to the results of individual ES evaluation.

5. Conclusions

The aim of the present study was to provide effective auxiliary information to aid decision-making on GI from two aspects: the implementation area and the type of GI. Based on the above research, the conclusions of this paper are as follows:

(1) We attempted to establish a new evaluation system in the context of the mismatch of urban GI supply and demand and use environmental quality standards and industry code standards to establish excessive demand thresholds for ESs. We demonstrated the applicability of the evaluation system in regulation services and recreation services.

(2) Our evaluation method can effectively maximize the urban GI configuration by providing intuitive quantitative results to reflect the actual demand for ESs in urban areas and improve the ability of urban areas to resist natural disasters. The assessment method based on establishing excessive demands for ESs could be applied to other ecologically fragile ecological areas affected by urban development and climate change.

(3) In the implementation of GI, many researchers provide measures to enhance resilience and prevent natural disasters. For example, Daeyoung Jeong et al. proposed a GI planning strategy for disaster prevention and evacuation in coastal cities [39]. We recommend that more quantitative environmental assessments be incorporated into planning, particularly in GI planning.

(4) The present study has some limitations. Firstly, we did not consider subjective service needs outside of the ecological environment, such as aesthetics, historical and cultural heritage, etc. Secondly, our assessment method is for excessive demand for ESs on the urban scale. However, in practice, green-space planning on only one scale may not enable full realization of the effect of providing GI on a larger scale. In addition, In this study, we only analyzed the autocorrelation between population density and comprehensive ES demand. Due to the limitations of collectible data, etc., there was no one-by-one analysis between population density and ES individual indicators. In the future, we will continue to study the internal driving mechanism quantitatively and combine corresponding engineering techniques to help maximize the ecological benefits of GI. For example, in old, built-up urban areas, GI supplements should be carried out by planting landscapes such as roof gardens, vertical greening and street green spaces, and GI such as permeable roads and drainage facilities should be improved or increased in areas where conditions permit. In later expansion areas, the GI construction should mainly focus on increasing recreational places and green land, improving water-permeable facilities in large areas, and encouraging the large-scale implementation of roof greening and vertical greening in new buildings.

(5) In the follow-up study, we will improve the evaluation system from two aspects: on the one hand, we will further consider adding more evaluation indicators, such as biodiversity, travel efficiency, urban style, etc. On the other hand, we will further explore the internal mechanism of high and low imbalance, including how to regulate population from the planning scale, the developmental direction of built-up areas, the construction of the interconnected ecological network, etc. Therefore, our next task is to consider how to carry out large-scale and multi-level ecosystem service assessments and GI planning in the context of territorial space planning, with the focus on smaller-scale convergence and coordination, which is also an important challenge in this field of research.

The above research results can help the city stakeholders to prioritize green spaces and categories of GI implementation and provide more objective auxiliary information for decision-making in regard to the planning and implementation of GI. Our method augments GI allocation for green-space system planning by taking background socioeconomic factors into account and helps to maximize the comprehensive ecosystem service benefits provided by GI.

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References

1. Corvalan, C.; Hales, S.; McMichael, A.; Butler, C.; Campbell-Lendrum, D.; Confalonieri, U.; Leitner, K.; Lewis, N.; Patz, J.; Polson, K.; et al. *Ecosystems and Human Well-Being: Health Synthesis*; World Health Organization: Geneva, Switzerland, 2005; ISBN 978-92-4-156309-3.
2. Calderón-Contreras, R.; Quiroz-Rosas, L.E. Analysing Scale, Quality and Diversity of Green Infrastructure and the Provision of Urban Ecosystem Services: A Case from Mexico City. *Ecosyst. Serv.* **2017**, *23*, 127–137. [CrossRef]
3. Benedict, M.A.; McMahon, E.T. Green Infrastructure: Smart Conservation for the 21st Century. *Renew. Resour. J.* **2002**, *20*, 12–17.
4. Wang, Y.-C.; Shen, J.-K.; Xiang, W.-N. Ecosystem Service of Green Infrastructure for Adaptation to Urban Growth: Function and Configuration. *Ecosyst. Health Sustain.* **2018**, *4*, 132–143. [CrossRef]
5. Schröter, M.; Barton, D.N.; Remme, R.P.; Hein, L. Accounting for Capacity and Flow of Ecosystem Services: A Conceptual Model and a Case Study for Telemark, Norway. *Ecol. Indic.* **2014**, *36*, 539–551. [CrossRef]
6. Martín-López, B.; Iniesta-Arandia, I.; García-Llorente, M.; Palomo, I.; Casado-Arzuaga, I.; Amo, D.G.D.; Gómez-Baggethun, E.; Oteros-Rozas, E.; Palacios-Agundez, I.; Willaarts, B.; et al. Uncovering Ecosystem Service Bundles through Social Preferences. *PLoS ONE* **2012**, *7*, e38970. [CrossRef]
7. Goldenberg, R.; Kalantari, Z.; Cvetkovic, V.; Mörtberg, U.; Deal, B.; Destouni, G. Distinction, Quantification and Mapping of Potential and Realized Supply-Demand of Flow-Dependent Ecosystem Services. *Sci. Total Environ.* **2017**, *593–594*, 599–609. [CrossRef]
8. Wenke, R. Review of Heartland of Cities: Surveys of Ancient Settlement and Land Use on the Central Floodplain of the Euphrates. *Am. Anthropol.* **1982**, *84*, 174–176. [CrossRef]
9. Núñez, D.; Nahuelhual, L.; Oyarzún, C. Forests and Water: The Value of Native Temperate Forests in Supplying Water for Human Consumption. *Ecol. Econ.* **2006**, *58*, 606–616. [CrossRef]
10. Palacios-Agundez, I.; Onaindia, M.; Barraqueta, P.; Madariaga, I. Provisioning Ecosystem Services Supply and Demand: The Role of Landscape Management to Reinforce Supply and Promote Synergies with Other Ecosystem Services. *Land Use Policy* **2015**, *47*, 145–155. [CrossRef]
11. Uthes, S.; Matzdorf, B. Budgeting for Government-Financed PES: Does Ecosystem Service Demand Equal Ecosystem Service Supply? *Ecosyst. Serv.* **2016**, *17*, 255–264. [CrossRef]
12. Bukvareva, E.; Zamolodchikov, D.; Kraev, G.; Grunewald, K.; Narykov, A. Supplied, Demanded and Consumed Ecosystem Services: Prospects for National Assessment in Russia. *Ecol. Indic.* **2017**, *78*, 351–360. [CrossRef]

13. Wolff, S.; Schulp, C.J.E.; Kastner, T.; Verburg, P.H. Quantifying Spatial Variation in Ecosystem Services Demand: A Global Mapping Approach. *Ecol. Econ.* **2017**, *136*, 14–29. [CrossRef]
14. Bryan, B.A.; Ye, Y.; Zhang, J.; Connor, J.D. Land-Use Change Impacts on Ecosystem Services Value: Incorporating the Scarcity Effects of Supply and Demand Dynamics. *Ecosyst. Serv.* **2018**, *32*, 144–157. [CrossRef]
15. Wickham, J.D.; Riitters, K.H.; Wade, T.G.; Vogt, P. A National Assessment of Green Infrastructure and Change for the Conterminous United States Using Morphological Image Processing. *Landsc. Urban Plan.* **2010**, *94*, 186–195. [CrossRef]
16. Aparicio Uribe, C.H.; Bonilla Brenes, R.; Hack, J. Potential of Retrofitted Urban Green Infrastructure to Reduce Runoff—A Model Implementation with Site-Specific Constraints at Neighborhood Scale. *Urban For. Urban Green.* **2022**, *69*, 127499. [CrossRef]
17. Arthur, N.; Hack, J. A Multiple Scale, Function, and Type Approach to Determine and Improve Green Infrastructure of Urban Watersheds. *Urban For. Urban Green.* **2022**, *68*, 127459. [CrossRef]
18. Li, K.; Li, C.; Liu, M.; Hu, Y.; Wang, H.; Wu, W. Multiscale Analysis of the Effects of Urban Green Infrastructure Landscape Patterns on PM2.5 Concentrations in an Area of Rapid Urbanization. *J. Clean. Prod.* **2021**, *325*, 129324. [CrossRef]
19. Larondelle, N.; Lauf, S. Balancing Demand and Supply of Multiple Urban Ecosystem Services on Different Spatial Scales. *Ecosyst. Serv.* **2016**, *22*, 18–31. [CrossRef]
20. Burkhard, B.; Kroll, F.; Nedkov, S.; Müller, F. Mapping Ecosystem Service Supply, Demand and Budgets. *Ecol. Indic.* **2012**, *21*, 17–29. [CrossRef]
21. Gopalakrishnan, V.; Bakshi, B.R.; Ziv, G. Assessing the Capacity of Local Ecosystems to Meet Industrial Demand for Ecosystem Services. *AIChE J.* **2016**, *62*, 3319–3333. [CrossRef]
22. Syrbe, R.-U.; Grunewald, K. Ecosystem Service Supply and Demand—The Challenge to Balance Spatial Mismatches. *Int. J. Biodivers. Sci. Ecosyst. Serv. Manag.* **2017**, *13*, 148–161. [CrossRef]
23. van Oudenhoven, A.P.E.; Petz, K.; Alkemade, R.; Hein, L.; de Groot, R.S. Framework for Systematic Indicator Selection to Assess Effects of Land Management on Ecosystem Services. *Ecol. Indic.* **2012**, *21*, 110–122. [CrossRef]
24. Villamagna, A.M.; Angermeier, P.L.; Bennett, E.M. Capacity, Pressure, Demand, and Flow: A Conceptual Framework for Analyzing Ecosystem Service Provision and Delivery. *Ecol. Complex.* **2013**, *15*, 114–121. [CrossRef]
25. Baró, F.; Haase, D.; Gómez-Baggethun, E.; Frantzeskaki, N. Mismatches between Ecosystem Services Supply and Demand in Urban Areas: A Quantitative Assessment in Five European Cities. *Ecol. Indic.* **2015**, *55*, 146–158. [CrossRef]
26. Shi, Y.; Shi, D.; Zhou, L.; Fang, R. Identification of Ecosystem Services Supply and Demand Areas and Simulation of Ecosystem Service Flows in Shanghai. *Ecol. Indic.* **2020**, *115*, 106418. [CrossRef]
27. Field, C.B.; Barros, V.; Stocker, T.F.; Dahe, Q.; Jon Dokken, D.; Ebi, K.L.; Mastrandrea, M.D.; Mach, K.J.; Plattner, G.K.; Allen, S.K.; et al. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2012; Volume 9781107025066, ISBN 978-1-107-02506-6.
28. Field, C.B.; Barros, V.R.; Dokken, D.J.; Mach, K.J.; Mastrandrea, M.D.; Bilir, T.E.; Chatterjee, M.; Ebi, K.L.; Estrada, Y.O.; Genova, R.C.; et al. Climate Change 2014 Impacts, Adaptation and Vulnerability: Part A: Global and Sectoral Aspects: Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In *Climate Change 2014 Impacts, Adaptation and Vulnerability*; Cambridge University Press: Cambridge, UK, 2014; pp. 1–1131. ISBN 978-1-107-05807-1.
29. Chen, B.; Zhang, H.; Wang, T.; Zhang, X. An Atmospheric Perspective on the Carbon Budgets of Terrestrial Ecosystems in China: Progress and Challenges. *Sci. Bull.* **2021**, *66*, 1713–1718. [CrossRef]
30. Misra, A.; Roorda, M.J.; MacLean, H.L. An Integrated Modelling Approach to Estimate Urban Traffic Emissions. *Atmos. Environ.* **2013**, *73*, 81–91. [CrossRef]
31. Chiesura, A. The Role of Urban Parks for the Sustainable City. *Landsc. Urban Plan.* **2004**, *68*, 129–138. [CrossRef]
32. Kessel, A.; Green, J.; Pinder, R.; Wilkinson, P.; Grundy, C.; Lachowycz, K. Multidisciplinary Research in Public Health: A Case Study of Research on Access to Green Space. *Public Health* **2009**, *123*, 32–38. [CrossRef]
33. Zhang, Y.; Liu, Y.; Zhang, Y.; Liu, Y.; Zhang, G.; Chen, Y. On the Spatial Relationship between Ecosystem Services and Urbanization: A Case Study in Wuhan, China. *Sci. Total Environ.* **2018**, *637–638*, 780–790. [CrossRef]
34. Moran, P.A.P. Notes on Continuous Stochastic Phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef] [PubMed]
35. Anselin, L. Local Indicators of Spatial Association—LISA. *Geogr. Anal.* **2010**, *27*, 93–115. [CrossRef]
36. Meerow, S.; Newell, J.P. Spatial Planning for Multifunctional Green Infrastructure: Growing Resilience in Detroit. *Landsc. Urban Plan.* **2017**, *159*, 62–75. [CrossRef]
37. Morse, W.C.; Stern, M.; Blahna, D.; Stein, T. Recreation as a Transformative Experience: Synthesizing the Literature on Outdoor Recreation and Recreation Ecosystem Services into a Systems Framework. *J. Outdoor Recreat. Tour.* **2022**, *38*, 100492. [CrossRef]
38. Gangahagedara, R.; Subasinghe, S.; Lankathilake, M.; Athukorala, W.; Gamage, I. Ecosystem Services Research Trends: A Bibliometric Analysis from 2000–2020. *Ecologies* **2021**, *2*, 366–379. [CrossRef]
39. Jeong, D.; Kim, M.; Song, K.; Lee, J. Planning a Green Infrastructure Network to Integrate Potential Evacuation Routes and the Urban Green Space in a Coastal City: The Case Study of Haeundae District, Busan, South Korea. *Sci. Total Environ.* **2021**, *761*, 143179. [CrossRef]

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