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Special Issue Reprint

Spatial Optimization and Sustainable Development of Land Use

Edited by
Qingsong He, Linzi Zheng, Peng Zhou and Jiang Zhou

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Contents

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Editorial

Spatial Optimization and Sustainable Development of Land Use

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1. Introduction

As global urbanization accelerates and climate change intensifies, issues related to land use and management have increasingly garnered attention within the international academic community. In response to these pressing concerns, we organized a Special Issue on "Spatial Optimization and Sustainable Development of Land Use". The call for papers for this Special Issue began in March 2023, and as of 28 October 2024, we have received a total of 38 submissions from various countries and regions. Following a rigorous peer review process, 13 research papers were ultimately selected for publication. The papers included in the Special Issue exhibit several noteworthy characteristics. First, the research perspectives are diverse, encompassing both macro-scale studies of regional development and micro-level case analyses. Second, the employed research methods are advanced, achieving innovative breakthroughs while building upon traditional approaches. Third, the findings process significant practical implications, providing scientific evidence and policy recommendations that contribute to regional sustainable development. These studies collectively promote theoretical innovation and methodological renewal in land science, offering new ideas and solutions to current global land management challenges.

This Special Issue is particularly timely, as it not only aligns with the United Nations Sustainable Development Goals (SDGs) concerning sustainable land use but also offers important theoretical support and practical guidance for coordinated regional development in the post-pandemic era. The research findings presented herein will serve as a crucial reference for academics, policymakers, and practitioners, fostering further exploration in land science and enhancing sustainable development practices.

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2. Articles

This Special Issue encompasses four primary research domains: (1) the interactions between land policies and ecosystem services, (2) methodological innovations in the dynamic simulation and spatial analysis of land use, (3) the optimization of regional sustainable development and land management, and (4) studies on land use efficiency and the transfer of factors. The contributed papers demonstrate significant methodological innovations through the application of sophisticated analytical techniques, including nonlinear analysis, spatiotemporal modeling, and geographically weighted regression, while also highlighting the importance of cross-disciplinary integration.

2.1. Research on the Interaction Between Land Policies and Ecosystem Services

The interaction between land policies and ecosystem services is a pivotal research area addressed in this Special Issue. The article titled "The Gains and Losses of Cultivated Land Requisition–Compensation Balance: Analysis of the Spatiotemporal Trade-Offs and Synergies in Ecosystem Services Using Hubei Province as a Case Study" offers an in-depth examination of the spatiotemporal trade-offs and synergies in ecosystem services that arise from the cultivated land requisition-compensation balance policy, using Hubei Province, China, as a case study (Contributions 1). Another study conducted in Xinjiang, China, titled "Nonlinear Effects of Land Use Conflicts in Xinjiang: Critical Thresholds and Implications for Optimal Zoning" innovatively investigates the nonlinear characteristics of land use conflicts and proposes optimization methods for land use zoning based on ecological thresholds, identified through the delineation of critical threshold values (Contributions 2). Collectively, these studies underscore the significant impact of land policies on ecosystem services, providing essential scientific evidence for informed policy-making.

2.2. Innovations in Land Use Dynamic Simulation and Spatial Analysis Methods

In the realm of methodological innovation, several studies have concentrated on enhancing the simulation accuracy and analytical depth of land use changes. The article "Dynamics of the Oasis–Desert–Impervious Surface System and Its Mechanisms in the Northern Region of Egypt" employs innovative modeling techniques to analyze the interaction mechanisms within the oasis-desert-impervious surface system in northern Egypt (Contributions 3). Additionally, the study "Incorporation of Spatially Heterogeneous Area Partitioning into Vector-Based Cellular Automata for Simulating Urban Land Use Changes" introduces the concept of spatial heterogeneity zoning into vector-based cellular automata, significantly improving the accuracy of urban land use change simulations (Contributions 4). Furthermore, the article "Spatial–Temporal Characteristics and Influencing Factors of Land Use Carbon Emissions: An Empirical Analysis Based on the GTWR Model" conducts an in-depth analysis of the spatiotemporal characteristics and influencing factors of land use carbon emissions using the geographically and temporally weighted regression model (Contributions 5). These methodological innovations provide novel technical approaches and analytical frameworks that advance the field of land use research.

2.3. Regional Sustainable Development and Land Management Optimization

Researchers have proposed several innovative solutions to address land management challenges related to regional sustainable development. The article "Territorial Spatial Resilience Assessment and Its Optimization Path: A Case Study of the Yangtze River Economic Belt, China" pioneers a systematic assessment of regional territorial spatial resilience within the Yangtze River Economic Belt, establishing a comprehensive evaluation index system (Contributions 6). Another study, "Dynamic Matching and Spatial Optimization of Land Use and Resource-Environment Constraints in Typical Regions of the Yellow River Basin in China", introduces a dynamic matching framework that aligns land use with resource-environmental constraints in typical regions of the Yellow River Basin (Contributions 7). Additionally, the paper "The Impact of Urban Renewal on Spatial–Temporal Changes in the Human Settlement Environment in the Yangtze River Delta, China" systematically evaluates the multidimensional impacts of urban renewal on the human settlement environment in the Yangtze River Delta region (Contributions 8). The article "Research on the Manifestation and Formation Mechanism of New Characteristics of Land Disputes: Evidence from the Yangtze River Economic Belt, China" examined the emerging characteristics and formation mechanisms of land disputes in the Yangtze River Economic Belt (Contributions 9). Finally, the study "Temporal and Spatial Effects of Heavy Metal-Contaminated Cultivated Land Treatment on Agricultural Development Resilience" analyzes the spatiotemporal effects of remediation efforts on heavy metal-contaminated farmland and their impact on agricultural development resilience (Contributions 10). Collectively, these studies contribute to establishing a theoretical framework for regional sustainable development in land management, providing scientific guidance for practical applications.

2.4. Research on Land Use Efficiency and Factor Transfer

This Special Issue also emphasizes issues on land use efficiency and factor transfer. The article "Impacts of Rural–Urban Labor Transfer and Land Transfer on Land Efficiency in China: An Analysis of Mediating Effects" innovatively explores the mechanisms by which rural labor migration and land transfer influence land use efficiency (Contributions 11). Another study, "A Multi-Attribute Approach for Low-Carbon and Intensive Land Use of Jinan, China", employs a gray fuzzy integral multi-attribute evaluation model to systematically assess the efficiency and factor transfer of low-carbon intensive land use in Jinan from 2010 to 2017, revealing a dynamic transition in land use patterns from high consumption and emissions to low consumption, low emissions, and high efficiency (Contributions 12). The paper "Expanded Residential Lands and Reduced Populations in China, 2000–2020: Patch-Scale Observations of Rural Settlements" highlights the contradiction between the expansion of rural residential land and the decline in population in China from 2000 to 2020, exposing issues of low land use efficiency and resource waste (Contributions 13). These studies examine the relationship between factor mobility and land use efficiency from different perspectives, providing important references for policy-making.

3. Conclusions and Perspectives

The thirteen studies included in this Special Issue provide substantial theoretical contributions and practical insights into sustainable land management and regional coordinated development. They have advanced understandings in several key areas: the interaction between land policies and ecosystem services, innovations in spatial analysis methods, optimization of regional sustainable development, and improvements in land use efficiency. Methodologically, the research has evolved from traditional linear analysis to nonlinear approaches, transitioning from single-perspective evaluations to multi-dimensional, comprehensive assessments, thereby showcasing significant methodological innovations within land science.

These studies also highlight critical issues in regional development, providing scientific evidence that can inform policy-making. However, as global climate change intensifies, digital technologies rapidly evolve, and profound adjustments patterns undergo profound adjustments, land science research faces new challenges and opportunities. Future research needs to focus on several key areas:

1. Digital Technology Integration: There is a pressing need to enhance research on the application of digital technologies in land monitoring and management, particularly the integration of advanced technologies such as artificial intelligence and big data with traditional land science methodologies.
2. Vulnerability and Adaptability: Increased emphasis should be placed on studying land system vulnerability and adaptability in the context of climate change.
3. Cross-Regional Coordination Mechanisms: Research on the mechanisms for cross-regional coordination in land management should be strengthened, especially concerning the balance between key ecological function areas and economic development zones.
4. Policy Evaluation Methods: There is a need for further exploration of methods to evaluate the effectiveness of land policy implementation, aimed at providing more precise scientific support for policy optimization.

In light of these considerations, we are pleased to announce the launch of the second volume of this Special Issue available at https://www.mdpi.com/journal/land/special_issues/FN3NW08B0A (accessed on 10 November 2024). We warmly invite scholars from around the world to engage in further research on related topics. We look forward to collaborating with the global academic community to advance knowledge in land science and provide more theoretical guidance and practical references for promoting regional sustainable development. This new Special Issue will continue to uphold rigorous academic standards, offering a high-quality platform for scholarly exchange that fosters the deepening of land science research.

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List of Contributions:

1. He, Q.; Jiang, X.; Zhang, Y. The Gains and Losses of Cultivated Land Requisition–Compensation Balance: Analysis of the Spatiotemporal Trade-Offs and Synergies in Ecosystem Services Using Hubei Province as a Case Study. *Land* **2024**, *13*, 1641. https://doi.org/10.3390/land13101641.
2. Wu, J.; Wang, C.; He, X.; Zhou, C.; Wang, H. Nonlinear Effects of Land-Use Conflicts in Xinjiang: Critical Thresholds and Implications for Optimal Zoning. *Land* **2024**, *13*, 612. https://doi.org/10.3390/land13050612.
3. Liu, Y.; Ma, C.; Ma, L. Dynamics of the Oasis–Desert–Impervious Surface System and Its Mechanisms in the Northern Region of Egypt. *Land* **2024**, *13*, 1480. https://doi.org/10.3390/land13091480.
4. Zhu, J.; Zhu, M.; Na, J.; Lang, Z.; Lu, Y.; Yang, J. Incorporation of Spatially Heterogeneous Area Partitioning into Vector-Based Cellular Automata for Simulating Urban Land-Use Changes. *Land* **2023**, *12*, 1893. https://doi.org/10.3390/land12101893.
5. He, J.; Yang, J. Spatial–temporal characteristics and influencing factors of land-use carbon emissions: An empirical analysis based on the GTWR model. *Land* **2023**, *12*, 1506. https://doi.org/10.3390/land12081506.
6. Cui, J.; Jin, H.; Kong, X.; Sun, J.; Peng, Y.; Zhu, Y. Territorial Spatial Resilience Assessment and Its Optimisation Path: A Case Study of the Yangtze River Economic Belt, China. *Land* **2024**, *13*, 1395. https://doi.org/10.3390/land13091395.
7. Yu, Z.; Su, D.; Wang, S.; Wei, C.; Li, N.; Qu, Y.; Wang, M. Dynamic Matching and Spatial Optimization of Land Use and Resource-Environment Constraints in Typical Regions of the Yellow River Basin in China. *Land* **2023**, *12*, 1420. https://doi.org/10.3390/land12071420.
8. Zheng, L.; Zheng, Y.; Fu, Z. The Impact of Urban Renewal on Spatial–Temporal Changes in the Human Settlement Environment in the Yangtze River Delta, China. *Land* **2024**, *13*, 841. https://doi.org/10.3390/land13060841.
9. Tan, S.; Zou, S.; Zhao, Y.; He, Q.; Zhang, M. Research on the Manifestation and Formation Mechanism of New Characteristics of Land Disputes: Evidence from the Yangtze River Economic Belt, China. *Land* **2024**, *13*, 1002. https://doi.org/10.3390/land13071002.
10. Chen, D.; Hu, W. Temporal and spatial effects of heavy metal-contaminated cultivated land treatment on agricultural development resilience. *Land* **2023**, *12*, 945. https://doi.org/10.3390/land12050945.
11. Pei, S.; Zhao, S.; Li, X.; Li, J. Impacts of Rural–Urban Labour Transfer and Land Transfer on Land Efficiency in China: A Analysis of Mediating Effects. *Land* **2024**, *13*, 702. https://doi.org/10.3390/land13050702.
12. Yu, Q.; Li, J.; Lu, X.; Wang, L. A Multi-Attribute Approach for Low-Carbon and Intensive Land Use of Jinan, China. *Land* **2023**, *12*, 1197. https://doi.org/10.3390/land12061197.
13. Yang, F.; Sun, J.; Yang, J.; Liang, X. Expanded Residential Lands and Reduced Populations in China, 2000–2020: Patch-Scale Observations of Rural Settlements. *Land* **2023**, *12*, 1368. https://doi.org/10.3390/land12071368.

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Article

The Gains and Losses of Cultivated Land Requisition–Compensation Balance: Analysis of the Spatiotemporal Trade-Offs and Synergies in Ecosystem Services Using Hubei Province as a Case Study

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Abstract: The cultivated land requisition–compensation balance (CLRCB) policy is an important policy implemented by China to address the reduction in cultivated land and ensure food security. Although this policy has alleviated the loss of cultivated land quantity, it has had complex and diverse impacts on ecosystem services. Taking Hubei Province as the study area, this research explores the impact of the implementation of the CLRCB on ecosystem services and simulates the changes in ecosystem services in the study area in 2030 and the impact of CLRCB on the interactions among various services. The results show the following: (1) from 2000 to 2020, Hubei Province achieved a balance in the quantity of cultivated land through excessive compensation but failed to reach the goals of balancing cultivated land yield and productivity. (2) During the requisition–compensation process, habitat quality decreased by 501,862, and carbon storage lost 1.3×10^7 t, indicating negative ecological impacts; soil conservation services increased by 184.2×10^6 t, and water production increased by 21.29×10^8 m^3. Within the cultivated land requisition–compensation area, habitat quality and carbon storage, as well as soil conservation and water production, exhibited synergistic relationships, while the remaining pairs of ecosystem services showed trade-off relationships. (3) The simulation of ecosystem services in 2030 indicates that soil conservation and water production are highest under the natural development scenario, while habitat quality and carbon storage are highest under the ecological protection scenario, both of which are superior to the urban development scenario. Under the natural development scenario, the trade-off and synergistic relationships among various ecosystem services in the cultivated land requisition–compensation area remain unchanged, while these relationships change significantly under the other two scenarios. This study emphasizes that future CLRCB should not only focus on maintaining the quantity of cultivated land but also consider the comprehensive benefits of ecosystem services, in order to achieve sustainable land-use management and ecological conservation.

Keywords: cultivated land requisition–compensation balance; ecosystem services; trade-offs and synergies; InVEST model; future scenario simulation

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1. Introduction

China has experienced rapid urbanization and industrialization over the past few decades, leading to the occupation of a large amount of cultivated land [1,2]. According to statistics, from 1957 to 1996, China's net annual reduction in cultivated land exceeded 6 million mu (1 mu = 666.66 m^2); from 1996 to 2008, the net annual reduction exceeded 10 million mu; from 2009 to 2019, the net annual reduction exceeded 11 million mu. About 80% of the lost cultivated land was occupied by construction land, driven by population growth and the expansion of built-up areas [3]. Cultivated land is the foundation of grain production and a cornerstone for ensuring national food security as well as economic and social stability. China is the world's largest producer and consumer of grain, and food security has long been a critical issue of high concern for both the government and society. The reduction in arable land leads to a decline in food production potential and increases dependence on external supplies, posing a long-term threat to national food security. In recent decades, climate disasters such as droughts and floods have resulted in decreased food production, causing uncertainty and price volatility in global food markets. In the context of globalization and climate change, the protection of cultivated land is of significant practical importance for enhancing agricultural sustainability, mitigating the impacts of extreme weather on crops, and ensuring the stability of the food supply. To address the conflict between urban expansion and cultivated land protection, and to ensure national food security, the Chinese government began implementing the cultivated land requisition–compensation balance policy in 1997 [4]. This policy requires that when cultivated land is occupied by construction projects, an equivalent area and quality of cultivated land must be added through reclamation, rehabilitation, or improvement to maintain the dynamic balance of the total amount of cultivated land [5,6]. The core concept of the CLRCB policy is "occupy one, supplement one", meaning that for every mu of cultivated land occupied, one mu of cultivated land must be supplemented [7]. In the early stages of policy implementation, the balance was mainly achieved by increasing the area of cultivated land in agriculturally suitable regions. As the policy advanced, more places began to supplement cultivated land through land consolidation and reclamation projects. Despite the CLRCB achieving some success in maintaining the total amount of cultivated land, it has also gradually revealed some shortcomings. For instance, both the government and farmers show limited enthusiasm for enhancing the productivity of newly compensated land; newly added cultivated land often suffers from severe soil pollution and a relative decline in biodiversity; the use of ecological land to compensate for cultivated land has led to the degradation of ecosystem services.

Ecosystem services refer to the various direct or indirect benefits provided to humans by ecosystems and their components, including food provision, water regulation, soil conservation, and biodiversity maintenance [8]. Westman published a paper in Science entitled 'How Much Are Nature's Services Worth?', marking the modern historical origin of the concept of ESs [9]. In 1997, Daily proposed that ecosystem services refer to the conditions and processes provided by natural ecosystems and their species to supply and maintain human existence, as well as the products or services directly or indirectly obtained by the functions of ecosystems, and classified ecosystem services into 13 categories, including food production, biodiversity, and climate regulation [10]. In 2005, the Millennium Ecosystem Assessment reported that 15 out of 24 ecosystem services, or about 60 percent, were in decline [11]. Research shows that changes in land-use patterns have caused the degradation or disappearance of ecosystem services worldwide [12,13]. In Austria, the intensification of agricultural land use and urban sprawl have primarily led to declining ecosystem services in the lowlands [14]. In the Upper Blue Nile Basin, the transformation of bare land, cropland, and grassland to forest and shrubland improved habitat quality, carbon storage, and soil conservation, but decreased water yield [15]. Land-use change is considered one of the major drivers of changes in ecosystem services [16,17]. The conversion between different land-use types can significantly alter ecosystem structure and processes, thereby affecting the supply of ecosystem services [18]. Cultivated land, as an important component of land use, significantly impacts regional ecosystem services through its quantity and spatial distribution changes [19].

Since the implementation of the CLRCB, China has maintained a dynamic balance in its cultivated land reserves. However, while compensatory cultivated land improves the reserve of cultivated land resources, it also has a series of impacts on the ecological environment [20,21]. During the policy implementation, because the supplementary cultivated land is often located in marginal or ecologically fragile areas, it may lead to the weakening or loss of ecosystem service functions [22]. According to previous studies, the CLRCB may lead to a weakening of water regulation functions. The occupied cultivated land is usually located in plains and lowlands rich in water resources, while the supplementary cultivated land is often in marginal or arid and semi-arid regions, which have poorer water supply capacity. This regional disparity leads to uneven water resource utilization, further exacerbating water shortage problems [23,24]. Secondly, soil conservation functions may also be affected [25]. Extensive land consolidation activities, such as leveling land and constructing terraces, often destroy the original soil structure, increasing the risk of soil erosion. Especially in sloped and mountainous areas, excessive development and consolidation can easily trigger soil and water loss, leading to soil degradation and reduced productivity [26]. During the reclamation and occupation of cultivated land, a large amount of vegetation is cleared, and soil organic matter is destroyed, leading to a reduction in carbon storage and increased greenhouse gas emissions, which is detrimental to climate change mitigation [27]. Studies have shown that under the scenario of cultivated land requisition-compensation balance, the carbon storage loss caused by cultivated land expansion is almost equal to that caused by urban expansion. The main reason for carbon storage loss due to cultivated land expansion is the massive loss of forests and wetlands [28]. Furthermore, the CLRCB also significantly impacts biodiversity [29–31]. Many occupied cultivated lands are located in ecologically sensitive areas with high biodiversity, while newly reclaimed or rehabilitated cultivated lands often lack diverse vegetation cover. This loss of biodiversity not only affects the stability of ecosystems but also has long-term negative impacts on local agricultural production and the ecological environment [22].

A significant amount of research has explored the impact of the cultivated land requisition–compensation balance policy on ecosystem services [5,32,33]. The coordination and conflict between cultivated land protection and ecosystem services have been a focal point of study, revealing complex trade-offs and synergies among ecosystem services. This means that enhancing one type of service function may come at the expense of another, or multiple service functions may improve simultaneously [34,35]. For instance, there is often a trade-off between food production and carbon sequestration services, as farmland expansion leads to a reduction in natural vegetation, thereby decreasing regional carbon sequestration capacity [36]. Conversely, there is a synergy between water source conservation and biodiversity protection; increasing forest cover promotes soil and water conservation and maintains biodiversity [37]. However, most studies have focused on the assessment of single ecosystem services, lacking an in-depth analysis of the comprehensive trade-offs and synergies among multiple ecosystem services [38,39]. Additionally, existing research often employs static analysis methods, lacking systematic evaluation of the dynamic changes and long-term effects during the implementation of the CLRCB. The impact of this policy on ecosystem services is complex and multidimensional. As China is currently in a critical period of ecological civilization construction, scientifically evaluating the impact of the CLRCB on ecosystem services is crucial for guiding policy adjustments, reforms, and innovations.

Given the aforementioned issues, this study aims to systematically evaluate the impact of the CLRCB on ecosystem services in Hubei Province. Located in central China, Hubei is an important agricultural production and ecological function area, making the implementation of its cultivated land requisition–compensation balance policy both representative and typical. This study will employ remote sensing image analysis and ecosystem service assessment models to investigate the changes in the area and quality of cultivated land in Hubei Province before and after the policy implementation, and the specific impacts of these changes on ecosystem services (habitat quality, carbon storage, soil conservation, and water yield). The main objectives of this study include the following: (1) Analyzing the spatiotemporal changes in the quantity and quality of cultivated land during the implementation of the cultivated land requisition–compensation balance policy in Hubei Province. (2) Assessing the impact of these changes on ecosystem service functions. (3) Conducting a spatiotemporal quantitative evaluation of the trade-off and synergy strength of ecosystem services in the requisition–compensation areas. (4) Evaluating the changes and interactions of ecosystem services under future climate scenarios in the study area and identifying issues in the policy implementation. It is hoped that this study will provide valuable references for policymakers, promote the coordinated development of cultivated land protection and ecological environment protection, and drive regional sustainable development.

2. Study Area

Hubei Province is located in the central heartland of China, in the middle reaches of the Yangtze River. The province's terrain is generally mountainous to the east, west, and north, with low plains in the middle, forming an incomplete basin that opens slightly to the south (as shown in Figure 1a). Of the province's total area, mountains account for 56%, hills for 24%, and plains and lake areas for 20%. Surrounding the central plains are the Dabie Mountains, Qinba Mountains, Wuling Mountains, and Mufu Mountains. The central plains have fertile cultivated land and diverse resources, with a dense network of rivers and lakes.

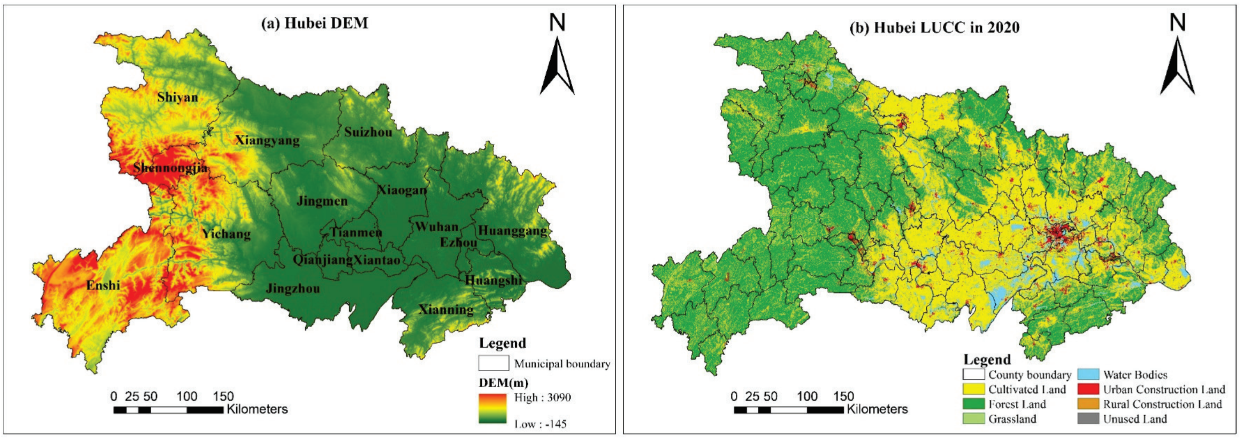

Figure 1. Land use and elevation map of Hubei Province.

Hubei Province is predominantly covered by forest land and cultivated land, with significant areas of urban and rural construction land and water bodies. According to the third national land survey of Hubei Province, the province has 4.7686 million hectares of cultivated land, mainly distributed in the plain and low hill areas. Forest land covers 9.2801 million hectares, grassland covers 0.0894 million hectares, urban and rural land and industrial and mining land covers 1.4115 million hectares, and water bodies and water conservancy facilities cover 1.9837 million hectares (spatial distribution is shown in Figure 1b). The overall land-use pattern of the province can be summarized as "five parts forest land, three parts farmland, one part urban and rural, and one part water".

3. Methods and Data

3.1. Research Framework

Figure 2 illustrates the technical route of this study. The research is divided into several key sections:

Implementation effects analysis: The initial phase involves analyzing the effects of the CLRCB by overlaying land-use maps from 2000, 2010, and 2020, the land-use transfer matrix is calculated to determine the quantity and spatial distribution of cultivated land requisition and compensation for the periods 2000–2010, 2010–2020, and 2000–2020. Subsequently, the cultivated land production potential model is utilized to assess the quality changes in requisitioned and compensated cultivated land.

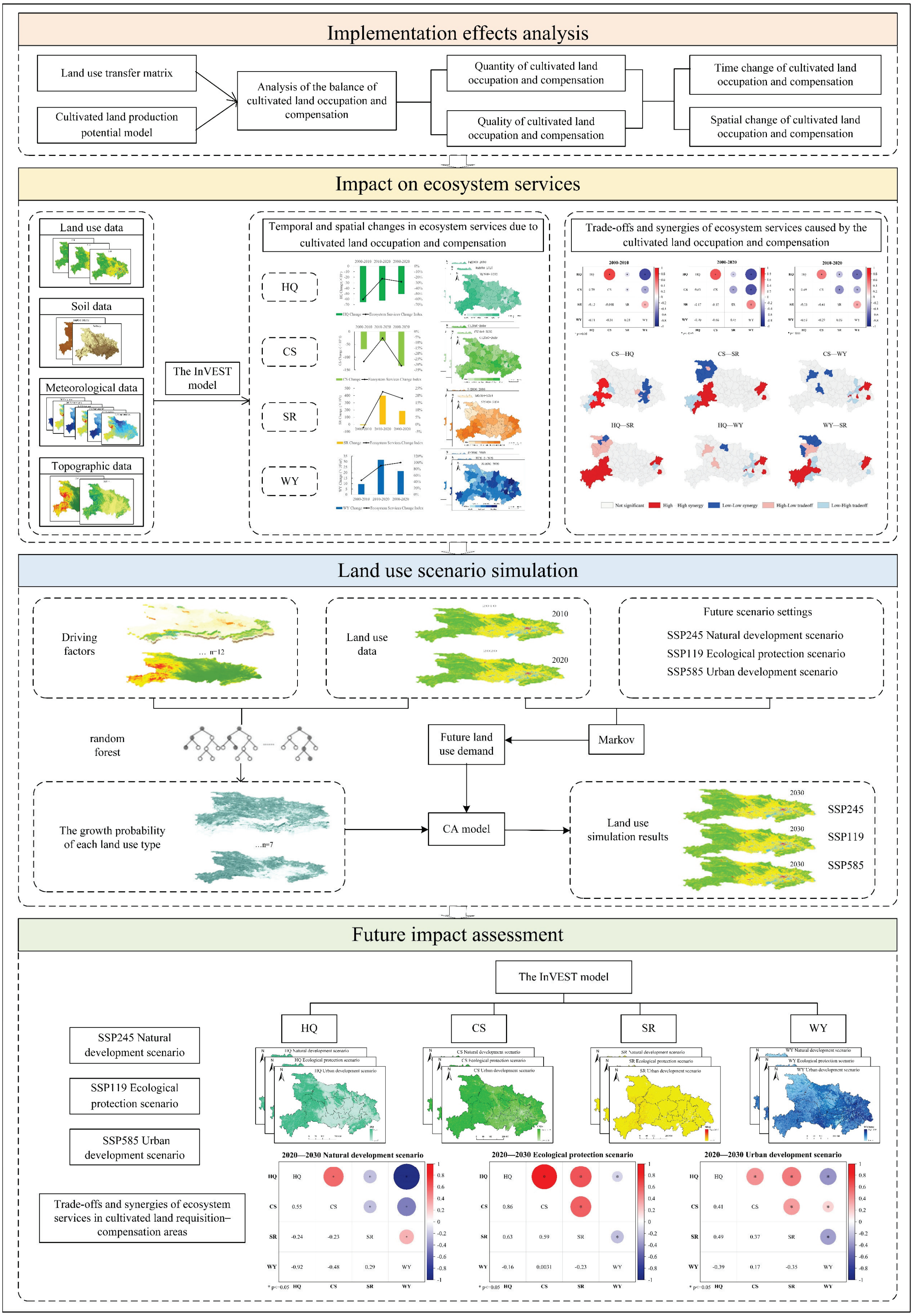

Figure 2. Technology roadmap. HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

Impact on ecosystem services: this phrase evaluates the policy's impact on ecosystem services and the trade-offs and synergies between various services. The InVEST model's habitat quality, carbon storage, soil retention, and water yield modules are employed to assess the quantity changes and spatial distribution of four ecosystem services in the study area [40,41]. Changes in ecosystem services on the requisitioned and compensated cultivated land plots are extracted and visualized spatially at the county level. The Spearman correlation coefficients among the ecosystem services in the requisition–compensation areas are calculated to analyze their trade-off and synergy strength. Bivariate spatial autocorrelation is used to calculate the spatial distribution of ecosystem service trade-offs and synergies.

Land-use scenario simulation: the following section simulates the land-use scenarios in the study area for 2030. Three scenarios are set: natural development, ecological protection, and urban development. The Markov model is applied to calculate future land-use demand, and the PLUS model is employed to simulate the spatial distribution of land use [42].

Future impact assessment: the final phase calculates the changes in ecosystem services under future land-use and climate scenarios, along with the changes in trade-offs and synergies in the cultivated land requisition–compensation areas.

3.2. Methods

3.2.1. Measurement of Cultivated Land Requisition and Compensation Quantity and Quality

1. Measurement of cultivated land quantity.

Land-use type maps of the study area from different periods are intersected to obtain the land-use transfer matrix. This matrix reveals the changes in the quantity of cultivated land requisition and compensation in Hubei Province for the periods 2000–2010, 2010–2020, and 2000–2020. The balance of cultivated land quantity is measured by calculating the cultivated land quantity balance index, using the following formula:

$$Q_C = \frac{A_{sup}}{A_{occ}} \tag{1}$$

where Q_C is the cultivated land quantity balance index, A_{sup} is the amount of compensated cultivated land, representing the area of forest land, grassland, water bodies, construction land, and unused land converted to cultivated land during the study period; and A_{occ} is the amount of requisitioned cultivated land, representing the area of cultivated land occupied by urban construction land during the study period. If $Q_C \geq 1$, it indicates that the study area has achieved a balance in the quantity of cultivated land requisition and compensation; otherwise, it has not achieved quantity balance.

2. Measurement of cultivated land quality.

The quality of cultivated land directly relates to its production potential, which refers to the biological yield or harvestable yield per unit area determined by natural factors such as light, temperature, water, soil, and nutrients. This study represents the quality change in requisitioned and compensated cultivated land by calculating the changes in their production potential. To minimize the impact of climate change, the average production potential over four years is used to focus on the impact of changes in requisition and compensation on the total productivity of cultivated land. The formula is as follows:

$$AP_i = \frac{\sum P_{j,i}}{m} \tag{2}$$

$$R_w = \frac{PA_w}{PB_w} \tag{3}$$

$$RU_w = \frac{UA_w}{UB_w} \tag{4}$$

where AP_i(kg/hm^2) represents the average production potential of grid cell i, $P_{j,i}$(kg/hm^2) represents the farmland production potential of grid cell i in the years j. The data are sourced from the Crop Potential Yield dataset of the Resource and Environment Science and Data Center, Chinese Academy of Sciences. PA_w(kg) and PB_w(kg) represent the total productivity of compensated and requisitioned cultivated land during period w, respectively, obtained by multiplying the area of compensated or requisitioned land plots by the farmland production potential of those plots. UA_w(kg/hm^2) and UB_w(kg/hm^2) represent the average potential yield of compensated and requisitioned cultivated land during period w, respectively. R_w and RU_w can be used to represent the cultivated land productivity balance index and the potential yield balance index for a specific period. If $R_w \geq 1$, it indicates that the productivity balance of CLRCB is achieved; otherwise, it is not met. If $RU_w \geq 1$, it indicates that the yield balance of CLRCB is achieved; otherwise, the yield balance is not met.

3.2.2. Measurement of Ecosystem Services before and after Cultivated Land Requisition and Compensation

There are numerous types of ecosystem services. Based on the specific conditions of Hubei Province, this study focuses on ecosystem services related to cultivated land, including habitat quality, carbon storage, soil retention, and water yield. The values of these ecosystem services are calculated using four corresponding modules of the InVEST model [43,44].

1. Habitat quality (HQ).

The InVEST habitat quality module estimates habitat quality by comprehensively considering factors such as the impact distance and intensity of threats and the sensitivity of different habitat types to these threats. This estimation reflects the state of biodiversity and the potential of the ecosystem to provide conditions for species survival and reproduction. The formula for calculating habitat quality is as follows:

$$HQ_{xj} = H_j \times \left[1 - \frac{D_{xj}^z}{D_{xj}^z + k^z}\right] \tag{5}$$

where HQ_{xj} is the habitat quality of grid cell x with land-use type j, ranging from [0,1]; higher values indicate better habitat quality. H_j is the habitat suitability of land-use type j. D_{xj}^z is the habitat stress level of grid cell x. k is the half-saturation constant. z is the scale constant.

2. Carbon storage (CS).

The basic assumption for calculating carbon storage in the InVEST model is that each land cover type corresponds to a total carbon density composed of belowground biomass carbon density, aboveground biomass carbon density, dead organic matter carbon density, and soil organic matter carbon density. Belowground biomass carbon density and aboveground biomass carbon density are collectively referred to as biomass carbon density. Due to the relative insignificance and difficulty of measuring dead organic matter carbon density, this form of carbon density is not considered in this study. The formula for calculating carbon storage is as follows:

$$C_i = C_{i_{above}} + C_{i_{below}} + C_{i_{soil}} \tag{6}$$

$$C_{i_{total}} = C_i \times A_i \tag{7}$$

where C_i is the total carbon density of land cover type i (t/hm^2). $C_{i_{\text{above}}}$ is the aboveground biomass carbon density of land cover type i (t/hm^2). $C_{i_{\text{below}}}$ is the belowground biomass carbon density of land cover type i (t/hm^2). $C_{i_{\text{soil}}}$ is the soil organic matter carbon density of land cover type i (t/hm^2). $C_{i_{\text{total}}}$ is the total carbon storage of land cover type i (t). A_i

is the area of land cover type i (hm^2). The carbon density values in this study are defined based on the referenced literature [31,45].

3. Soil retention (SR).

Soil retention (SR) describes the ability of different ecosystems to control soil erosion and prevent soil loss. The soil retention module in the InVEST model is based on the Universal Soil Loss Equation (USLE). It calculates the soil retention amount by determining the difference between potential and actual soil erosion, which reflects the amount of soil erosion increased or decreased due to vegetation cover or soil conservation measures. The calculation formulas are as follows:

$$RKLS_i = R_i \times K_i \times LS_i \tag{8}$$

$$ULSE_i = R_i \times K_i \times LS_i \times C_i \times P_i \tag{9}$$

where $RKLS_i$ represents the potential soil erosion amount of the i-th grid cell (t). $ULSE_i$ represents the actual soil erosion amount of the i-th grid cell (t). R_i, K_i, LS_i, C_i, and P_i are the rainfall erosivity factor (MJ mm hm^{-2} h^{-1} a^{-1}), soil erodibility factor (t h MJ^{-1} mm^{-1}), slope length and steepness factor, vegetation cover factor, and support practice factor of the i-th grid cell, respectively. The K_i factor is calculated using the method from the EPIC model, and the biophysical attribute table refers to Wang et al., 2020 [46].

4. Water yield (WY).

The calculation of water yield in the InVEST model is based on a simplified hydrological cycle model that uses a water balance approach. The water yield for each grid cell is calculated as the amount of rainfall minus the actual evapotranspiration. The more water yield, the greater the water provisioning service. The annual water yield Y(x) for different land-use type grid cells is calculated as follows:

$$Y(x) = \left(1 - \frac{AET(x)}{P(x)}\right) \times P(x) \tag{10}$$

where $Y(x)$ is the annual water yield of grid cell x (mm). $AET(x)$ is the annual actual evapotranspiration of grid cell x (mm). $P(x)$ is the annual precipitation of grid cell x (mm). Model parameters are referenced from the InVEST user guide.

3.2.3. Identification of Ecosystem Service Trade-Offs and Synergies

Trade-offs and synergies represent the interactions between different ecosystem services. Trade-offs occur when there is an inverse relationship between services, while synergies occur when services change in the same direction. If there is no apparent response relationship, the services are considered uncorrelated. This study uses the Spearman correlation coefficient method in SPSS 27 software to identify the trade-offs and synergies between ecosystem services resulting from CLRCB on a regional scale. Using a 5 × 5 km grid as the unit, the correlation coefficients of changes in ecosystem services caused by CLRCB during 2000–2010, 2010–2020, and 2000–2020 are calculated, followed by significance testing. If the correlation coefficient between two ecosystem services is negative and passes the significance test at the 0.05 confidence level, a significant trade-off relationship is considered to exist. Conversely, if the correlation is positive and significant, a significant synergy relationship is considered to exist. Bivariate spatial autocorrelation analysis is used to characterize the spatial clustering and differentiation of ecosystem services. The bivariate local Moran's I index is used to analyze the spatial distribution of trade-offs and synergies between pairs of ecosystem services at the county scale [47–50]. The bivariate local Moran's I index is calculated as follows:

$$I_i^{MN} = \frac{X_i^M - \overline{X}_M}{\sigma^M} \sum_{j=1}^{n} \left[W_{ij} \frac{X_i^N - \overline{X}_N}{\sigma^N} \right] \tag{11}$$

where I_i^{MN} is the bivariate local Moran's I index. X_i^M is the value of ecosystem service M in unit i. X_i^N is the value of ecosystem service N in unit j. $\overline{X}_M$ and $\overline{X}_N$ and σ^M and σ^N are the average and standard deviation of ecosystem service M and N. n is the number of units in the study area. W_{ij} is the weight matrix. The local spatial association patterns were divided into 5 types, including a high–high synergistic zone, low–low synergistic zone, high–low trade-offs zone, low–high trade-offs zone, and no significant zone ($p < 0.05$).

3.2.4. Simulation of Ecosystem Services under Future Climate Change Scenarios

This study simulates changes in ecosystem services in Hubei Province under different climate scenarios for the year 2030. Land-use types are categorized into seven types: cultivated land, forest land, grassland, water bodies, urban construction land, rural construction land, and unused land. First, the land-use changes for 2020 are simulated and validated for accuracy. Following this, the land-use changes and ecosystem services for Hubei Province in 2030 are simulated.

The sixth phase of the Coupled Model Intercomparison Project (CMIP6) provides richer global climate model data for climate change assessment. CMIP6 scenarios emphasize the impact of different socio-economic development patterns on climate change. This study selects three climate change scenarios from CMIP6 (SSP119, SSP245, and SSP585) to simulate future ecosystem services. SSP119 represents a sustainable development path with low greenhouse gas emissions; SSP245 represents a middle-path socio-economic development with moderate emissions; SSP585 represents a high-speed development path with extensive fossil fuel use and high emissions.

Three scenarios are set for this study: baseline development, ecological protection, and urban development.

Baseline development scenario: assumes land-use change is not influenced by human policies and evolves according to historical land-use transition characteristics, with no restrictions in the simulation. Climate data follow the SSP245 pathway.

Ecological protection scenario: emphasizes the protection of ecological land, assuming a 20% reduction in the probability of conversion from forest land, grassland, and water bodies to other land types and a 10% increase in the probability of conversion from cultivated land, rural construction land, and unused land to forest land, grassland, and water bodies. Climate data follow the SSP119 pathway.

Urban development scenario: assumes a 20% increase in the probability of converting cultivated land, forest land, grassland, and water bodies to construction land, and a 30% decrease in the probability of converting construction land to other land types. Climate data follow the SSP585 pathway.

Land-use demand is simulated using the Markov model, and the spatial distribution of land use is simulated using the PLUS model [51]. After simulating the land-use quantity and layout for 2030, the InVEST model is used to calculate changes in ecosystem services in Hubei Province under different future scenarios.

3.3. Data Sources

The data required for this study primarily include land-use data, soil data, meteorological data, watershed data, remote sensing data, and socio-economic data. Detailed information on data sources is provided in Table 1. The original land-use data are classified into 6 primary categories and 25 secondary categories. In this study, the definition of cultivated land requisition is the expansion of urban construction land occupying cultivated land. Therefore, for ease of data processing, construction land is subdivided into urban construction land and rural construction land. Thus, the land-use data are categorized into seven major types: cultivated land, forest land, grassland, water bodies, urban construction land, rural construction land, and unused land.

Table 1. Data source for this study.

Data Type	Description	Resolution	Source
Land-use data	Land-use data for the years 2000, 2010, and 2020	30 m	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (https://www.resdc.cn/)
Soil data	Depth-to-bedrock	1 km	https://doi.org/10.1038/s41597-019-0345-6
	Soil texture		World Soil Database (https://www.fao.org/soils-portal/en/, accessed on 29 September 2023)
	Soil type		Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (https://www.resdc.cn/)
Meteorological data	Monthly potential evapotranspiration for 2000, 2010, and 2020	1 km	National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/)
	Monthly precipitation for 2000, 2010, and 2020		
	Precipitation and evapotranspiration of future climate scenario		
Watershed data	Watershed and river network data extracted from DEM	/	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (https://www.resdc.cn/)
Topographic data	DEM data	30 m	Geospatial Data Cloud (https://www.gscloud.cn/)
	Slope data		Generated from elevation
Socio-economic data	GDP, population, roads, county government	/	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (https://www.resdc.cn/)
	Farmland Production Potential		

4. Results and Analysis

4.1. Spatial and Temporal Patterns of Cultivated Land Requisition and Compensation in Hubei Province

From 2000 to 2010, the amount of cultivated land requisitioned and supplemented in Hubei Province was basically balanced, with the amount of supplemented cultivated land slightly higher than the requisitioned land. The cultivated land balance index was 1.09. From 2010 to 2020, the amount of requisitioned cultivated land increased compared to the previous period, but the amount of supplemented cultivated land increased even more, resulting in a balance index of 2.97 (Table 2). Overall, from 2000 to 2020, urban construction land requisitioned 1553.87 km^2 of cultivated land, accounting for 33.13% of the total cultivated land loss, with 62.89% of new construction land coming from cultivated land. The area of supplemented cultivated land was 1971.86 km^2, with 67.93% of it coming from forest land, leading to a balance index of 1.27. In terms of quantity, the requisition and supplementation of cultivated land were balanced in all three periods, with forest land being the primary source of supplemented land, followed by water bodies and reclaimed construction land.

Table 2. Area of CLRCB and quantity–quality balance index in Hubei Province (2000–2020).

Period	Requisitioned Cultivated Land Area (km^2)	Supplemented Cultivated Land Area (km^2)	Quantity Balance Index	Potential Yield Balance Index	Productivity Balance Index
2000–2010	1209.06	1112.41	1.09	0.87	0.95
2010–2020	4540.30	1526.48	2.97	0.47	1.58
2000–2020	1971.86	1553.87	1.27	0.57	0.66

The potential yield balance index for cultivated land was less than 1 in the periods 2000–2010, 2010–2020, and 2000–2020, indicating that the potential yield of supplemented cultivated land was lower than that of the requisitioned land, reflecting a phenomenon of "replacing high-quality land with lower-quality land" in Hubei Province. However, the productivity balance index for 2010–2020 was greater than 1, due to the excess compensation of cultivated land (i.e., the balance index being greater than 1), which drove up the productivity balance index. This explains why the productivity balance index for 2010–2020 was lower than the corresponding quantity balance index. In contrast, for the periods 2000–2010 and 2000–2020, although the quantity balance index was greater than 1, it did not offset the yield losses caused by the quality differences between requisitioned and supplemented land, resulting in an imbalance in productivity.

Spatially, cultivated land in Hubei Province is mainly concentrated in the Jianghan Plain, Northern Hubei Hills, and Southeastern Hubei River Plains, with a high degree of concentration. However, these areas face high non-agricultural and non-grain risks due to flat terrain, dense population, and rapid economic development, leading to high demand for urban construction land. From 2000 to 2020, cultivated land requisition mainly occurred in the central and southern Jianghan Plain, particularly around Wuhan, Xiantao, and Ezhou, as well as along the Yangtze and Han Rivers, where social and economic development is rapid. Supplemented cultivated land was more dispersed, found in both the western mountainous areas and the central and eastern plain and hilly areas (as shown in Figure 3a). At the city level, from 2000 to 2020, 11 out of 17 cities in Hubei Province achieved a balance in the quantity of requisitioned and supplemented cultivated land. However, southeastern cities like Wuhan and Ezhou did not achieve this balance, with Wuhan having the lowest balance index of 0.24. Five cities reached a balance in potential yield of requisitioned and supplemented land, located in the western part of the province and central cities like Xiantao and Tianmen, where forest land or wetlands were used to supplement cultivated land, resulting in a higher potential yield for supplemented land. Only Tianmen achieved a balance in both the quantity, potential yield, and productivity of requisitioned and supplemented cultivated land (as shown in Figure 3b).

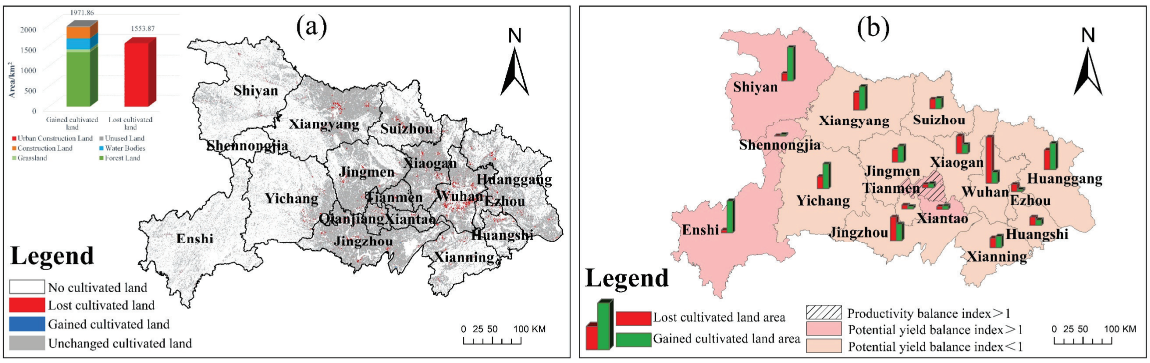

Figure 3. Spatial distribution of CLRCB in Hubei Province (2000–2020). (**a**) shows the spatial distribution of cultivated land occupation and compensation in Hubei Province, while (**b**) illustrates the distribution of cultivated land occupation and compensation area, quantity–quality balance index across various cities in Hubei Province.

4.2. Impact of CLRCB on Ecosystem Services

The balance policy of CLRCB has driven land-use changes, thereby impacting ecosystem services. The changes in four ecosystem services—habitat quality, carbon storage, soil retention, and water yield were—calculated for the balance areas, as well as their proportions of the total changes in the study area.

As shown in Figures 4 and 5, the balance of CLRCB negatively affected habitat quality. Habitat quality decreased in all three periods within the balance areas, with the most significant decline occurring from 2000 to 2010, reaching 60.66%. During this period, the change in habitat quality accounted for 123.74% of the total change in the study area, indicating the significant impact of CLRCB on habitat quality. In the subsequent two periods, the impact of habitat quality changes due to cultivated land requisition and compensation on the overall habitat quality of the study area gradually diminished. The balance of cultivated land requisition and compensation also negatively impacted carbon storage. From 2000 to 2020, carbon storage in the balance areas decreased by 31.19%, the most significant reduction among the three periods. The change in carbon storage accounted for between 39.16% and 63.77% of the total change in the study area. Soil retention in the balance areas slightly decreased from 2000 to 2010 but increased in both 2010–2020 and 2000–2020. The proportions of soil retention changes in the balance areas relative to the total changes in the study area were low in all three periods, indicating limited impact of CLRCB on the soil retention function of the study area. Water yield increased due to CLRCB, with an increase of 99.80% from 2000 to 2020. However, the proportion of water yield changes in the balance areas relative to the total changes in the study area was not as significant as that of habitat quality and carbon storage, ranging from 5.01% to 14.88%.

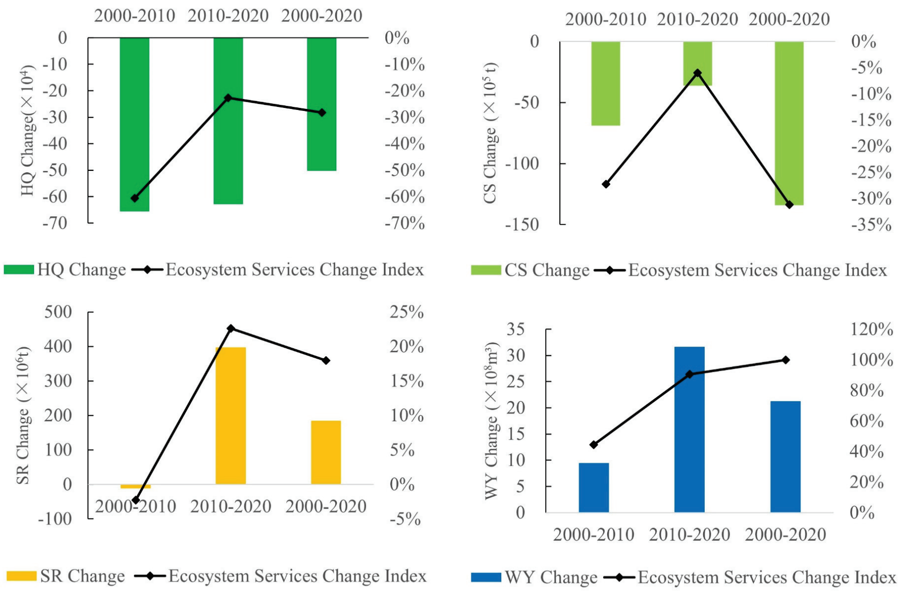

Figure 4. Changes in various ecosystem services due to CLRCB. HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

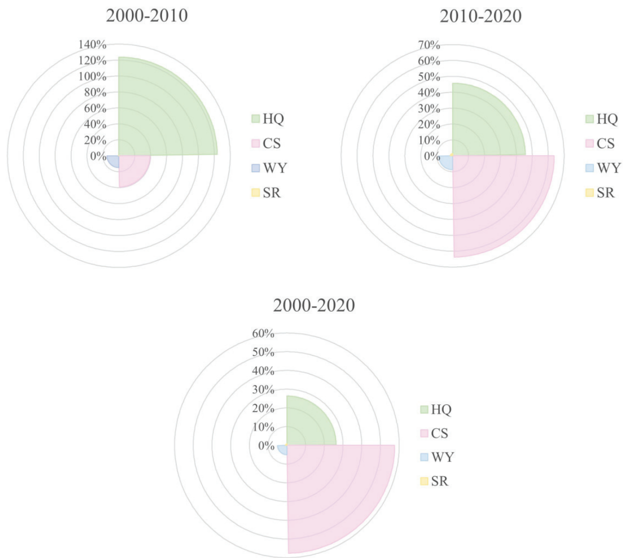

Figure 5. Proportion of ecosystem service changes in CLRCB areas relative to total changes in the study area. HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

4.3. Trade-Off/Synergy Relationships of Ecosystem Services in Cultivated Land Requisition and Compensation Areas

Using the administrative divisions of Hubei Province as a basis, a 5 km $\times$ 5 km grid dataset was established in ArcGIS 10.8. Spatial statistical tools were then used to calculate the changes in ecosystem services caused by cultivated land requisition and compensation for each grid over different time periods. The number of grids obtained was 5718 for the period from 2000 to 2010 and 7721 for the periods from 2010 to 2020 and from 2000 to 2020.

Using SPSS 27 software, a Spearman correlation analysis was conducted on the changes in four ecosystem services—habitat quality, carbon storage, soil retention, and water yield at the grid level. The correlations between these ecosystem services are shown in Figure 6. For the periods 2000–2010, 2010–2020, and 2000–2020, all ecosystem services passed the significance test at the 0.05 level, indicating varying degrees of correlation between them. From 2000 to 2010, habitat quality and carbon storage had a positive correlation coefficient, indicating a significant strong synergy. Habitat quality and water yield had a negative correlation coefficient, showing a significant strong trade-off, while habitat quality and soil retention had a significant weak trade-off relationship. Carbon storage and water yield exhibited a significant trade-off relationship, and carbon storage and soil retention had a significant weak trade-off relationship. Water yield and soil retention showed a significant synergy. From 2010 to 2020, the trade-off and synergy relationships between ecosystem services did not change. However, the synergy between habitat quality and carbon storage and the trade-off between habitat quality and water yield both weakened, while the trade-off relationships between soil retention and both carbon storage and habitat quality strengthened. Over the entire period from 2000 to 2020, the synergy between habitat quality and carbon storage and the trade-off relationships between water yield and both carbon storage and habitat quality were all strong. The trade-off relationship between soil retention and carbon storage, as well as the synergy between soil retention and water yield, were moderately strong, while the trade-off relationship between soil retention and habitat quality was relatively weak.

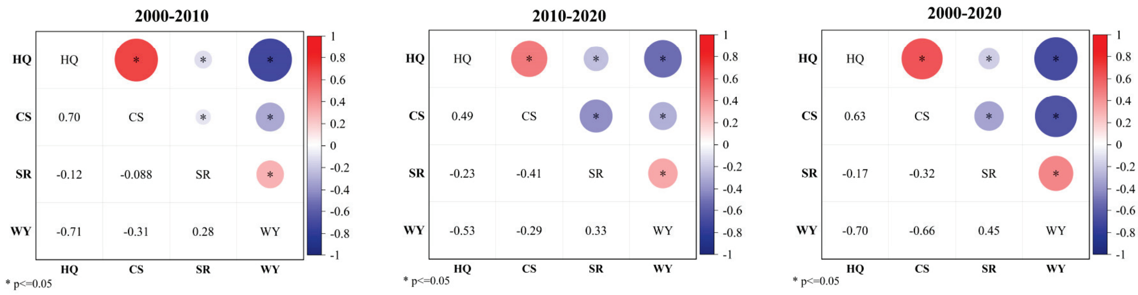

Figure 6. Correlation analysis of ecosystem service changes in CLRCB areas. HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

To understand the spatial trade-offs and synergies of various ecosystem services due to the CLRCB policy, this research used bivariate spatial autocorrelation to examine the spatial clustering and differentiation of these services. This research calculated the changes in ecosystem services from 2000 to 2020 for each county and city in Hubei Province using GeoDa 1.20 software and produced maps using bivariate Moran's I. High–high and low–low clusters indicate synergies, while high–low and low–high clusters indicate trade-offs.

As shown in Figure 7, between 2000 and 2020, the synergy between carbon storage and habitat quality was primarily found in the western Enshi Prefecture, eastern Yichang City, northern Xianning City, Wuhan City, and the Shennongjia Forest District. Trade-offs were mainly located in Xianfeng County, Enshi City, Yiling District of Yichang, Hannan District of Wuhan, and Liangzihu District of Ezhou, with other areas showing non-significant patterns. The synergy between carbon storage and soil retention appeared in central and southern Huanggang City, most of Shiyan City excluding Maojian and Zhangwan Districts, western Yichang City, and eastern Enshi Prefecture. Trade-offs were observed in the western and eastern parts of Enshi Prefecture and the Maojian and Zhangwan Districts of Shiyan City. Synergy between carbon storage and water yield was noted in Fang County of Shiyan City, Yiling District of Yichang City, Xiangzhou and Fancheng Districts of Xiangyang City, and parts of northeastern and southern Huanggang City. Trade-offs were evident in northern Xianning City, central Wuhan City, and Hong'an County. The synergy between habitat quality and soil retention was prevalent in southwestern Hubei, including Enshi Prefecture, western Yichang City, Yunyang District of Shiyan City, and parts of northeastern and southern Huanggang City. Trade-offs were found in most of Shiyan City, excluding Yunyang District, and in Xishui County. The spatial distribution of trade-offs and synergies between habitat quality and water yield was similar to that of carbon storage and water yield, but Fang County of Shiyan City and Yiling District of Yichang City shifted from synergy to trade-off. Finally, the synergy between water yield and soil retention was observed in most of Enshi Prefecture except for Laifeng and Hefeng Counties, northern and western Shiyan City, and central Huanggang City. Trade-offs were evident in Fang and Zhushan Counties of Shiyan City, Zigui, Xingshan, and Wufeng Counties of Yichang City, Laifeng and Hefeng Counties of Enshi Prefecture, and Tuanfeng County and Wuxue City of Huanggang City.

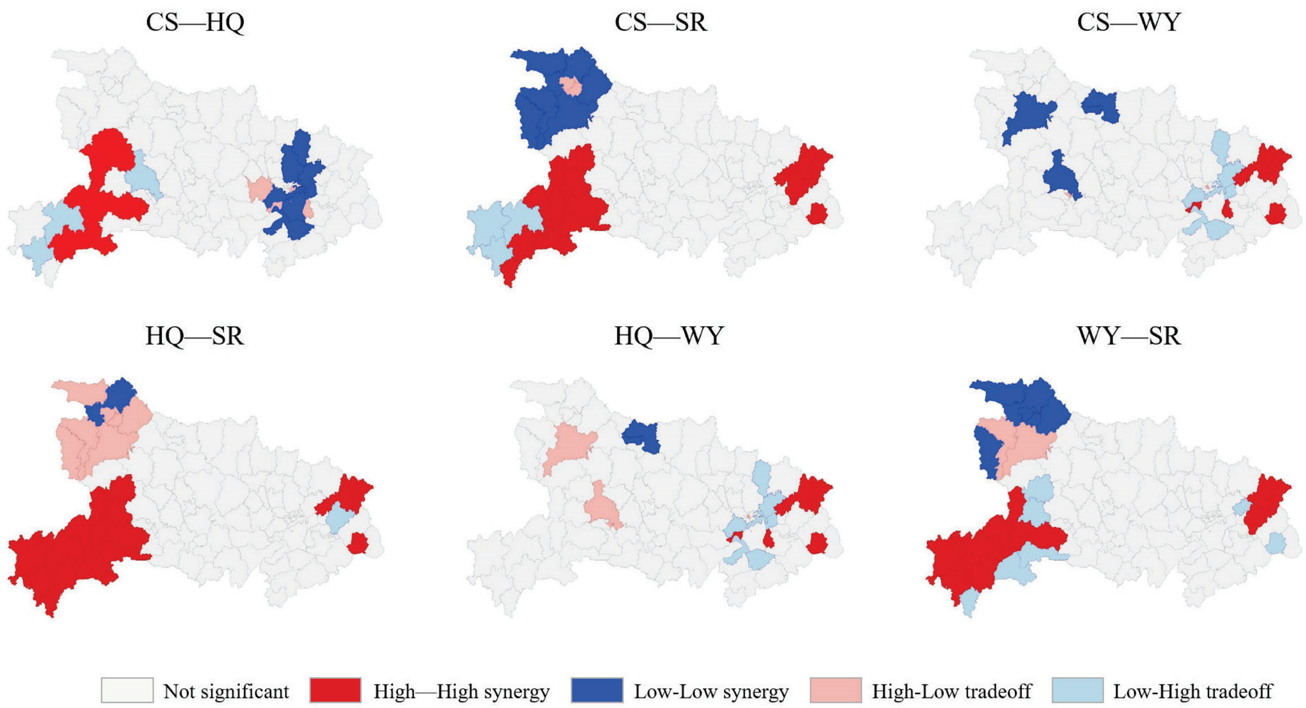

Figure 7. Spatial distribution of trade-offs and synergies of ecosystem services due to cultivated land requisition and compensation at the county level (2000–2020). HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

4.4. Simulation of Ecosystem Services and Trade-Offs/Synergies under Future Climate Scenarios in Hubei Province

Based on the land-use data from 2000, this research simulated the land-use changes for 2020. Comparing the simulated data with the actual data for 2020, the model showed an overall accuracy of 0.94 and a Kappa coefficient of 0.90, which is greater than 0.75. This indicates that the model's simulation performance is good and can be used to simulate land-use changes for 2030. Table 3 presents the simulated results of land-use changes in Hubei Province. In 2020, the primary land-use type in Hubei Province was forest land, covering 49.61% of the total area, followed by cultivated land (36.02%) and water bodies (6.26%). Under all three future scenarios, forest land remains the dominant land-use type.

Table 3. Simulated land use change results for Hubei Province.

Land-Use Scenario		Cultivated Land	Forest Land	Grassland	Water Bodies	Urban Construction Land	Rural Construction Land	Unused Land
Actual Scenario in 2020	Area	669.78	922.43	70.15	116.45	39.08	37.76	3.82
	Percentage	36.02%	49.61%	3.77%	6.26%	2.10%	2.03%	0.21%
Natural Development	Area	666.78	918.06	70.17	117.65	44.55	38.44	3.82
	Percentage	35.86%	49.37%	3.77%	6.33%	2.40%	2.07%	0.21%
Ecological Protection	Area	665.87	922.76	70.30	116.34	42.42	38.13	3.66
	Percentage	35.81%	49.62%	3.78%	6.26%	2.28%	2.05%	0.20%
Urban Development	Area	666.85	916.35	70.23	111.58	52.66	37.91	3.89
	Percentage	35.86%	49.28%	3.78%	6.00%	2.83%	2.04%	0.21%

Natural development scenario: both forest land and cultivated land slightly decrease, while water bodies and construction land increase. Grassland and unused land remain relatively stable, with minor changes. The majority of the increased construction land comes from converted cultivated land, followed by forest land.

Ecological protection scenario: there is a slight increase in forest land and grassland areas, along with an increase in construction land, though to the smallest extent among the three scenarios. Water body areas remain virtually unchanged. Cultivated land decreases the most in this scenario, with the converted land primarily becoming forest land, followed by urban construction land.

Urban development scenario: urban construction land sees the largest increase, while cultivated land, forest land, and water bodies decrease. Other land types show little change. The reduction in cultivated land primarily converts to urban construction land, and the reduction in forest land and water bodies is mainly used to supplement cultivated land.

Forest land and cultivated land are the most important land-use types in the study area. Changes in their areas directly affect the structure and function of ecosystem services. As population growth and economic development continue, urban construction land expands, often at the expense of cultivated land. This change not only reduces agricultural space but also leads to a decline in ecosystem services. Under three different future scenarios, the area changes for various land types differ, and varying climate conditions result in different trends in ecosystem services. The quantities and spatial distributions of four ecosystem service functions were calculated, as shown in Table 4 and Figure 8.

Table 4. Ecosystem services in Hubei Province under different scenarios.

Ecosystem Service	Actual Scenario by 2020	Natural Development Scenario by 2030	Ecological Protection Scenario by 2030	Urban Development Scenario by 2030
Habitat quality	0.552	0.542	0.543	0.534
Carbon storage (1×10^9 t)	2.308	2.302	2.306	2.298
Soil retention (1×10^{11} t)	1.471	1.521	1.253	1.274
Water yield (1×10^{11} m^3)	1.342	1.454	0.905	1.061

Each ecosystem service demonstrates different trends under various scenarios. Habitat quality and carbon storage show minimal changes, while soil retention and water yield experience significant variations. Habitat quality and carbon storage both decline in 2030 across all three scenarios, with the lowest values under the urban development scenario, followed by the natural development scenario, and the highest values under the ecological protection scenario. In the ecological protection scenario, although the areas of forest land and grassland increase compared to 2020, urban construction land also expands by 334 km^2, which is more than the combined increase in forest and grassland areas (47 km^2). This expansion of construction land negatively impacts habitat quality and carbon storage, causing them to decline even in the ecological protection scenario. Soil retention services increase by 3.39% under the natural development scenario but decrease by 14.82% under the ecological protection scenario and by 13.41% under the urban development scenario. Water yield increases by 8.39% under the natural development scenario but decreases by 32.58% under the ecological protection scenario and by 20.90% under the urban development scenario. Soil retention and water yield services are significantly influenced by climate conditions. In 2020, the annual precipitation in Hubei Province was 1439 mm. For 2030, under the natural development scenario using SSP245 climate data, the annual precipitation is projected to be 1547 mm. The ecological protection scenario, using SSP119 climate data, projects an annual precipitation of 1293 mm, while the urban development scenario, using SSP585 climate data, projects an annual precipitation of 1323 mm. These differences in precipitation under different climate pathways lead to corresponding increases or decreases in ecosystem service quantities.

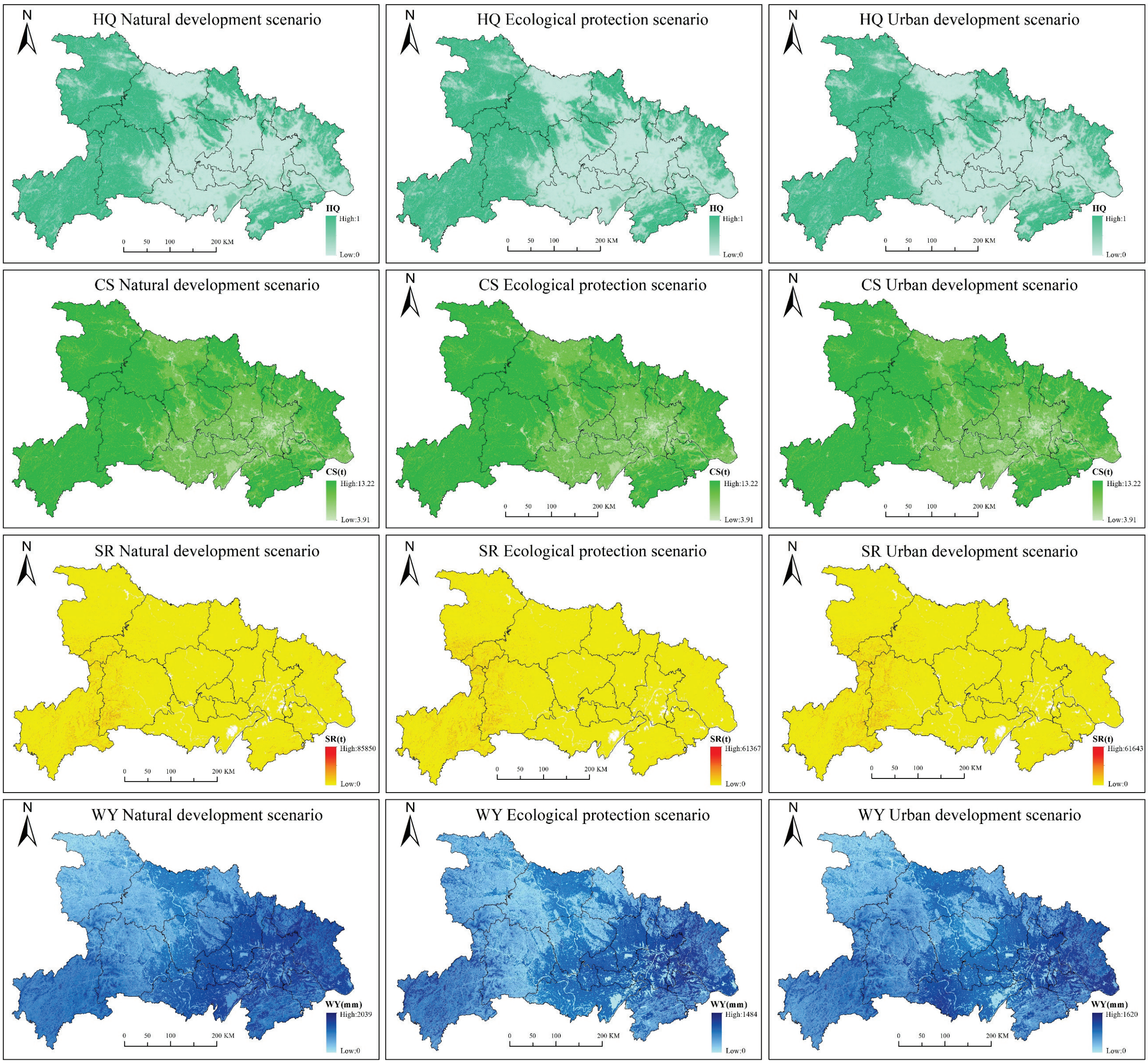

Figure 8. Spatial distribution of ecosystem services in Hubei Province under three future scenarios. HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

Figure 8 shows the spatial distribution of four future ecosystem services, each exhibiting different spatial patterns. Under future scenarios, the distribution of habitat quality and carbon storage is mainly influenced by land-use changes, with both showing lower values in the central region and higher values in the eastern and western regions. This pattern is related to the topography of Hubei Province, where the mountainous areas in the east and west are dominated by forests and grasslands, while the central plains are dominated by cultivated and construction land. Mountainous regions usually have higher ecosystem service values and biodiversity, whereas plains are more suitable for agricultural development. Agricultural activities and urban construction cause environmental pollution, which directly threatens habitat quality and carbon storage. For example, discharging wastewater into rivers can exceed a threshold, leading to eutrophication and a decline in aquatic species richness, thus threatening water ecological safety. The spatial distribution of soil retention services is relatively uniform, generally showing higher values in the west and lower values in the east. Under the natural development scenario in 2030, soil retention services increase in most areas except for the junction of Yichang, Xiangyang, and Shennongjia Forest District, where a decline is observed. In the ecological protection scenario, soil retention services decrease in most areas except for the northwestern parts of Shiyan City and Enshi Prefecture. Under the urban development scenario, soil retention services decrease in most areas except for the northern part of Shiyan City and the southwestern part of Jingzhou City. The spatial distribution of water yield contrasts with the other three ecosystem services, showing higher values in the central region and lower values around the periphery. Under the natural development scenario, water yield increases in most areas except for the junction of Yichang, Xiangyang, Jingmen, and Shennongjia Forest District, as well as central Suizhou. In the ecological protection scenario, water yield decreases in most areas except for the northwestern part of Shiyan City. Under the urban development scenario, water yield increases in the northern part of Shiyan City, southern Jingzhou City, and central Wuhan City, while it decreases in other regions.

The changes in ecosystem services in the cultivated land requisition and compensation areas under three future scenarios for 2030 were extracted, and correlation coefficients were further calculated to analyze the trade-offs and synergies of ecosystem services under different climate scenarios. The results are shown in Figure 9. Under the natural development scenario, the trade-offs and synergies of ecosystem services remained unchanged compared to the period from 2000 to 2020, and all passed the significance test at the 0.05 level. The synergy between habitat quality and carbon storage weakened, while the trade-offs between habitat quality and both soil retention and water yield strengthened. The trade-offs between carbon storage and both soil retention and water yield weakened, and the synergy between soil retention and water yield also weakened. In the ecological protection scenario, there were significant changes in the trade-offs and synergies of ecosystem services. The synergy between habitat quality and carbon storage significantly strengthened, increasing from 0.63 to 0.86. The trade-off between habitat quality and water yield weakened from -0.7 to -0.16, and the relationship between habitat quality and soil retention changed from a significant weak trade-off to a significant strong synergy. The relationship between carbon storage and soil retention changed from a trade-off to a synergy, and the relationship between carbon storage and water yield changed from a significant strong trade-off to an insignificant weak synergy. The relationship between soil retention and water yield changed from a synergy to a trade-off. Under the urban development scenario, the synergy between habitat quality and carbon storage weakened, as did the trade-off between habitat quality and water yield. The relationship between habitat quality and soil retention changed from a trade-off to a synergy. The relationship between carbon storage and soil retention also changed from a trade-off to a synergy, and the relationship between carbon storage and water yield changed from a significant strong trade-off to a significant weak synergy. The relationship between soil retention and water yield changed from a synergy to a trade-off.

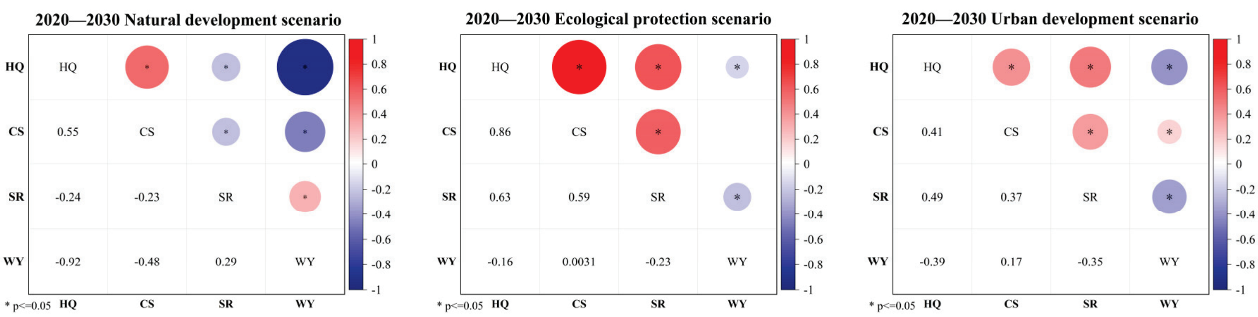

Figure 9. Trade-offs and synergies of ecosystem services due to cultivated land requisition and compensation under three future scenarios. HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

5. Discussion

5.1. Validation of Ecosystem Service

In this study, ecosystem services are composed of four aspects. This research recognizes that the accuracy of model parameters is crucial for the credibility of the calculation results. Due to the large geographic scope of Hubei Province, it is challenging to verify the calculation results through field surveys, and the ecosystem services calculated via the InVEST model are based on empirical values. Therefore, this research chose to validate soil retention and water yield because existing datasets or observational values are available for these services (Figure 10). However, there are no calculated data available for habitat quality and carbon storage for validation.

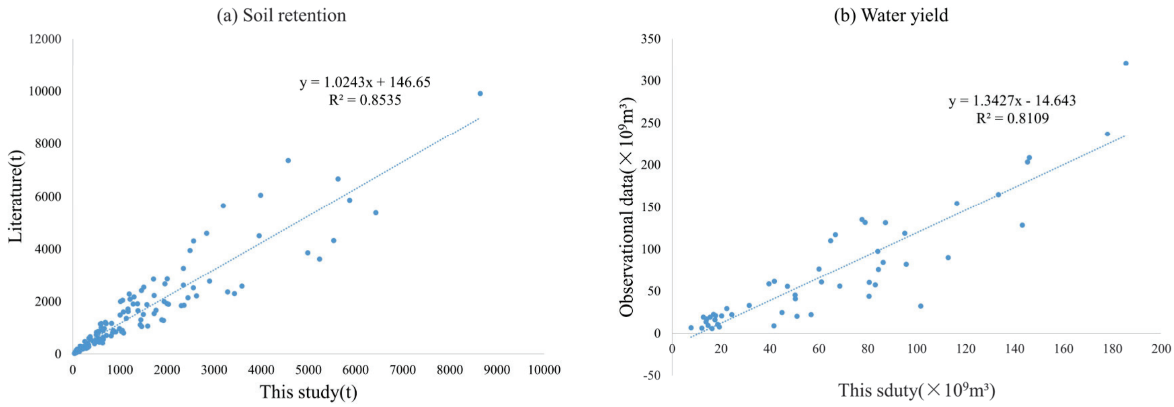

Figure 10. Validation of simulation accuracy for soil retention (**a**) and water yield (**b**).

To validate the soil retention data, this study employed a comparative analysis method, comparing the results with the "China Soil Erosion Conservation Dataset." This research established a 20 km fishnet in ArcGIS and used the "Extract Multi Values to Points" tool to extract grid values from both models for linear fitting. The results showed an R^2 of 0.85, indicating that the study results are reliable. To verify the accuracy of the water yield assessment, this study used the total water resources of each prefecture-level city in the "Hubei Water Resources Bulletin" as a reference, compared with the water yield calculated via the InVEST model, and calculated the coefficient of determination and the slope of the fitted least-squares regression line to evaluate the goodness of fit between the study results and the observational data. The results showed a high correlation, with an R^2 of 0.82, indicating that the simulation results can be used for water yield service analysis.

Through the above validation process, this research can conclude that the soil retention and water yield data calculated using the InVEST model in this study are reliable and accurate and can be used for further ecosystem service analysis and evaluation.

5.2. Impact of CLRCB on Ecosystem Services and Contribution

The average values of various ecosystem services for different land-use types in 2000, 2010, and 2020 were calculated, as shown in Figure 11. The changes in ecosystem services caused by the requisition and compensation of cultivated land were then calculated separately, as shown in Figure 12.

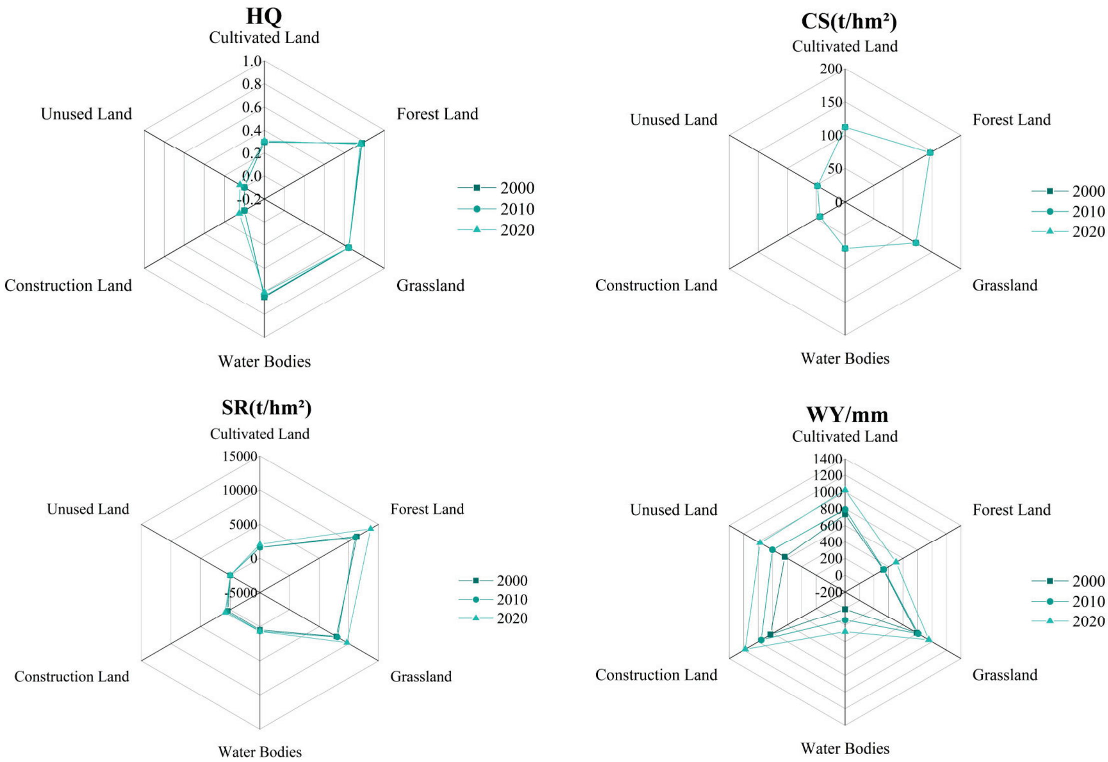

Figure 11. Average values of ecosystem services for different land-use types. HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

From Figure 11, it is evident that habitat quality is highest in forest land and grassland, followed by water bodies and cultivated land, with the lowest values in unused land and construction land. Forest land, grassland, and water bodies have complete ecosystems, making them ideal habitats for plant and animal communities, thus resulting in higher habitat quality [52]. In contrast, cultivated and construction lands have poorer habitat quality. Cultivated land, due to prolonged farming and fertilizer use, not only reduces soil quality but also causes agricultural non-point source pollution. Construction land, on the other hand, is threatened by production and domestic sewage discharge, resulting in lower habitat quality. Changes in the proportion, structure, and intensity of land use fundamentally alter the composition and configuration of ecosystems, ultimately affecting energy flow and material cycling between habitat patches [53]. Land-use changes can have positive or negative impacts on habitat quality. Generally, the outward conversion of forest land, grassland, and water bodies negatively impacts habitat quality, while the outward conversion of cultivated and construction land positively impacts habitat quality. This is consistent with the results of previous studies [15,33]. In the context of land-use changes due to cultivated land requisition and compensation, only the supplementation of cultivated land with construction and unused land positively impacts habitat quality, increasing it by 2851 and 3263 units from 2000 to 2020. However, due to the small area of these land-use changes, they are insufficient to offset the degradation in habitat quality caused by the conversion of other land types, leading to an overall decline in habitat quality in the study area by 501,862 units.

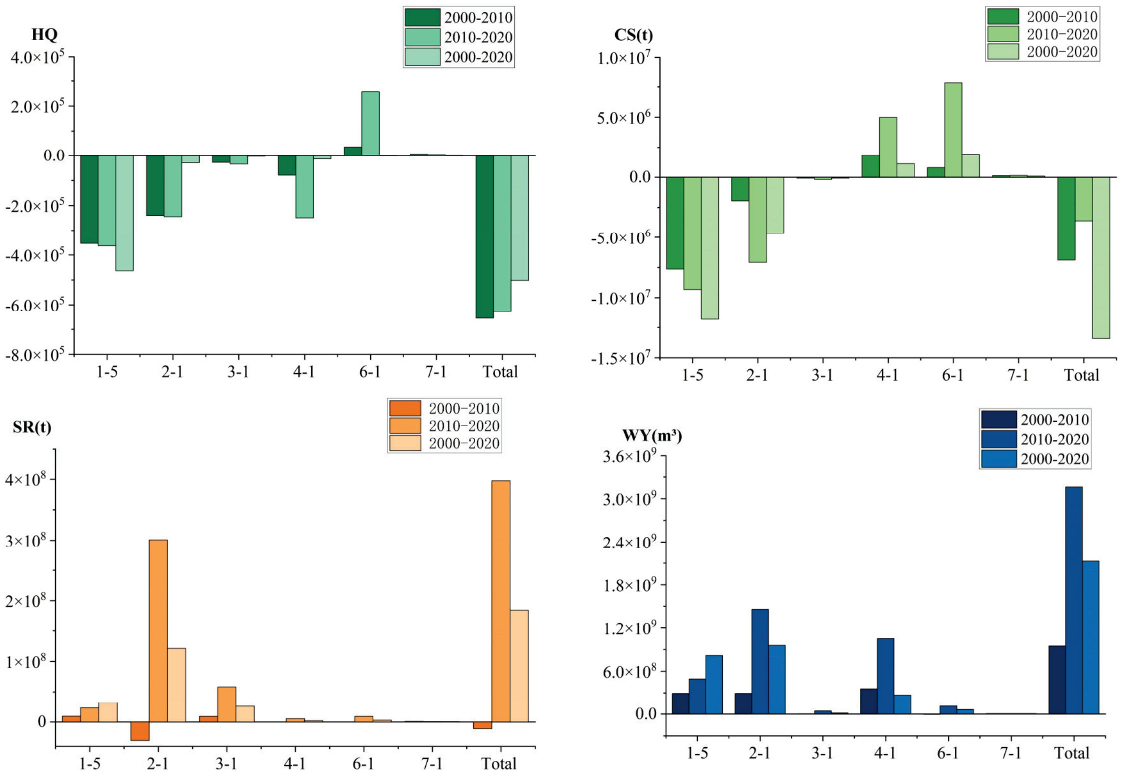

Figure 12. Changes in ecosystem services due to cultivated land requisition and compensation. Nos. 1–7 represent cultivated land, forest land, grassland, water bodies, urban construction land, construction land, and unused land, respectively. Code 1–2 represents cultivated land converted to forest land, and the other codes follow the same rule. HQ—habitat quality; CS—carbon storage; SR—soil retention; WY—water yield.

From Figure 11, it is also clear that carbon storage is highest in forest land and grassland, followed by cultivated land and water bodies, with the lowest values in unused land and construction land. Land-use changes have a profound impact on carbon storage in terrestrial ecosystems by altering the carbon sequestration capacity of soil and vegetation, affecting regional carbon budgets [27]. This study indicates that urban expansion into cultivated land is a major cause of carbon storage decline. To achieve a balance in cultivated land requisition and compensation, the supplementation of cultivated land with forest land, grassland, and other ecological lands further reduces carbon storage. Although the supplementation of cultivated land with water bodies, construction land, and unused land mitigates some carbon storage loss, the overall effect of the balance policy from 2000 to 2020 results in a loss of 13 million tons (1.3×10^7 t) of carbon storage in Hubei Province. This is consistent with the research results of some scholars. Tang et al. showed that cultivated land expansion in Hubei Province from 2000 to 2010 resulted in 1.76 Tg of carbon loss, and the loss of carbon storage caused by encroachment of forest land accounted for 81% of the total loss of cultivated land expansion [28]. Gao et al. showed that the loss of carbon storage in the compensation of cultivated land from 2010 to 2015 was mainly due to the inappropriate way of supplementing cultivated land with forest land. Although the area of supplementing cultivated land with forest land only accounted for 19.4% of the total amount of cultivated land, the resulting carbon storage loss even exceeded the carbon storage loss of cultivated land occupied by construction land [54].

Figure 11 shows that soil retention capacity is strongest in grassland and forest land, followed by cultivated land and water bodies, with the lowest values in construction land and unused land. Vegetation cover on grassland can reduce the impact of rainfall on the ground, slow down runoff, and decrease the likelihood of soil particles being carried away by water [55]. Forest land, with its complex vegetation structure and rich litter layer, can improve soil structure and increase soil porosity, thereby enhancing soil water retention capacity [56]. Unused land, with poorer soil physical and chemical properties and high surface runoff coefficients, is prone to soil erosion during heavy rainfall, resulting in the lowest soil retention capacity. Theoretically, without considering other factors, the outward conversion of grassland and forest land and the occupation of cultivated land by construction land would lead to a decrease in regional soil retention capacity [57].For example, converting forest to cropland could change the distribution of soil properties and compact deep soils, further resulting in a reduction in water infiltration and increases in surface runoff and the risk of soil erosion in top soils [58,59]. However, previous studies have shown that soil retention function is more sensitive to precipitation than to land-use types, with changes in soil retention function being more strongly controlled by climate change [60]. The study of Li et al. showed that the spatial and temporal variation of rainfall erosivity was basically consistent with the variation of soil erosion rate in western Hubei Province, and rainfall was the main factor leading to soil loss in western Hubei Province [61]. Therefore, the soil retention function within the cultivated land requisition and compensation areas in Hubei Province from 2000 to 2020 do not strictly follow the above change patterns. The average soil retention values for Hubei Province in 2000, 2010, and 2020 were 6778 t/hm^2, 6616 t/hm^2, and 8154 t/hm^2, respectively, showing a trend of initial decrease followed by an increase. This is consistent with the results of Li et al. [62,63]. Therefore, the soil retention function in the cultivated land requisition and compensation areas are affected by the combined effects of climate change and land-use changes, which are consistent with the overall change trend of Hubei Province.

Figure 11 also indicates significant differences in water yield across different land-use types, with the highest water yield in construction land, followed by grassland and cultivated land, then unused land, and the lowest in forest land and water bodies. The surfaces of construction land, typically composed of concrete, asphalt, and cement, form impermeable surfaces with almost zero infiltration, resulting in rainfall easily forming runoff and reducing soil water content, thus resulting in the highest water yield [64]. Grassland and cultivated land, with shallower root systems, have weaker rainfall interception capabilities, and crop growth on cultivated land consumes water, resulting in lower water yields compared to construction land [65]. Forest land, with deeper root systems, can absorb water from deep soil layers and has strong rainfall interception capabilities, while its dense canopy has significant transpiration [66]. Water bodies, being the most prone to runoff formation, have the lowest water yield when rainfall reaches the water surface, as evaporation directly forms runoff. Under unchanged climate conditions, the conversion of cultivated land to construction land, and the conversion of forest land, water bodies, and unused land to cultivated land increase water yield, while the conversion of grassland and construction land to cultivated land decreases water yield. However, previous studies have shown that climate change can significantly impact water yield by directly altering surface runoff, with precipitation having a more pronounced effect on regional water yield than land-use changes [63]. The average precipitation in Hubei Province was 1199.1 mm in 2000, 1279.3 mm in 2010, and 1439.6 mm in 2020. The increasing precipitation trend led to higher average water yields in cultivated land in 2020 compared to construction land in 2000 and 2010. Therefore, the conversion of construction land to cultivated land increased water yield from 2010 to 2020 and from 2000 to 2020. Similarly, due to the impact of precipitation, the average water yield in cultivated land in 2010 and 2020 was higher than that in grassland in 2000 and 2010, resulting in increased water yield from the conversion of grassland to cultivated land over the three time periods. Overall, the areas of construction land occupying cultivated land and forest land and water bodies supplementing cultivated land far exceed the changes in other land-use types. Since these three land type changes all lead to increased water yield, the cultivated land requisition and compensation balance policy results in an overall increase in regional water yield.

5.3. Trade-Off/Synergy Relationships of Ecosystem Services in Cultivated Land Requisition and Compensation Areas

This study investigates how ecosystem services—including habitat quality, carbon storage, soil retention, and water yield—have evolved over time in response to the trade-offs and synergies caused by land-use changes driven by cultivated land compensation policies. By employing Spearman correlation analysis across multiple time periods (2000–2010, 2010–2020, and 2000–2020), we identified significant correlations among these ESs, highlighting the intricate relationships between different ecosystem functions.

This research demonstrates that between 2000 and 2010, the relationship between habitat quality and carbon storage was strongly synergistic, suggesting that improvements in habitat conditions were closely linked to increases in carbon sequestration. This synergy aligns with prior research [67], which emphasizes that land-use practices promoting biodiversity conservation often enhance carbon storage due to increased vegetative cover and biomass. However, habitat quality exhibited a strong trade-off with water yield. This may be due to the increased reforestation or land restoration efforts enhancing habitat quality while reducing runoff, thus lowering water yield [68]. The weak trade-off between habitat quality and soil retention indicates that while some conservation actions may improve habitat conditions, they may not always benefit soil preservation. Carbon storage and water yield also displayed a notable trade-off, mirroring patterns observed in other studies where carbon sequestration efforts, such as reforestation, can lead to reduced water availability due to higher evapotranspiration rates [69]. A weak trade-off was also observed between carbon storage and soil retention, indicating that while these services can conflict, the interaction is not as significant as with water yield. Interestingly, water yield and soil retention were found to be strongly synergistic, suggesting that strategies promoting soil conservation, such as terracing or cover cropping, also enhance water regulation, corroborating findings from previous studies [70].

During the period 2010–2020, the fundamental trade-offs and synergies among ecosystem services remained consistent, but the intensity of these relationships shifted. The synergy between habitat quality and carbon storage weakened, as did the trade-off between habitat quality and water yield. This could be attributed to adjustments in land-use policies or changes in ecosystem management practices, where the marginal benefits of enhancing carbon storage or biodiversity may have decreased. On the other hand, the trade-offs between soil retention and both carbon storage and habitat quality became more pronounced, suggesting that in recent years, the actions taken to preserve soil may have come at a greater cost to biodiversity and carbon sequestration.

Looking at the entire period from 2000 to 2020, the strong synergy between habitat quality and carbon storage persisted, while the trade-off between carbon storage and water yield, as well as habitat quality and water yield, remained robust. These enduring patterns suggest that long-term land-use changes, such as forest expansion or changes in agricultural practices, consistently drive these ES dynamics. Moderate correlations between soil retention and other services—especially its trade-off with carbon storage and synergy with water yield—underscore the multifunctionality of land-use strategies that seek to balance soil conservation with other ESs. The relatively weak trade-off between habitat quality and soil retention also reflects the nuanced interactions among ESs that are shaped by localized environmental and policy contexts.

The results show that the effects of CLRCB on ecosystem services are complex and diverse, and multiple objectives need to be balanced in land management. For example, while enhancing biodiversity and carbon storage can reinforce each other, they may affect water availability. Weakening synergies and changing trade-offs over time suggest that policy needs to be flexible to avoid long-term negative effects. In future land-use planning, it is necessary to comprehensively consider water resources, soil conservation, and other factors to achieve balanced development of multiple services.

5.4. Limitations and Uncertainties

This study examines the effects of the cultivated land requisition–compensation balance (CLRCB) policy on ecosystem services in Hubei Province and projects future changes under different land-use scenarios for 2030. Despite its valuable insights, this study has several limitations and uncertainties that warrant attention.

First, the InVEST model, though widely used, simplifies complex ecological dynamics [71]. For instance, its habitat quality model assumes uniform distribution of threats, ignoring local variations in land-use intensity, while the carbon storage module overlooks nuanced impacts of land-use changes on soil and vegetation carbon fluxes. These simplifications may lead to inaccurate estimations of ecosystem services [72]. Additionally, the dynamic interactions among ecosystem services, such as trade-offs and synergies, are context dependent and could shift due to external factors like climate change or policy adjustments [37]. For example, while synergies between soil conservation and water production were observed, future climate extremes or policy shifts could alter these relationships, highlighting the need for continuous monitoring and adaptive management. The future land-use simulations, based on the Markov and PLUS models, also face uncertainties [51]. These models assume future patterns follow historical trends, which may not account for rapid urbanization or unanticipated changes. Moreover, the climate data used may not fully capture extreme events, complicating predictions of ecosystem service outcomes.

To address these limitations, future research should focus on improving modeling accuracy by integrating more advanced tools. For instance, combining InVEST with other models like SWAT could offer more detailed assessments, especially for hydrological services [73]. Incorporating more comprehensive climate change scenarios, including extreme events, would provide better insights into potential ecosystem responses [74]. Furthermore, future studies should explore the socio-economic dimensions of CLRCB, as land-use decisions driven by policy or economic incentives significantly influence ecosystem services outcomes. In conclusion, while this study offers important findings on the ecological impacts of CLRCB, significant uncertainties remain. Advancing modeling techniques, integrating climate projections, and addressing socio-economic drivers will be crucial for balancing food security with sustainable ecosystem management.

6. Conclusions

This study, focusing on Hubei Province, explored the impact of the cultivated land requisition and compensation policy on ecosystem services and simulated the changes in ecosystem services and their interactions for the year 2030. The findings indicate that from 2000 to 2020, the policy achieved a balance in cultivated land quantity through the excessive supplementation of cultivated land, with a balance index of 1.27. However, the prevalent issue of replacing high-quality land with lower-quality land resulted in suboptimal policy implementation, failing to achieve balance in land productivity and yield.

The balance policy negatively impacted habitat quality and carbon storage, leading to a decline in habitat quality by 501,862 and a loss of 13 million tons (1.3×10^7 t) of carbon storage during the study period. On the other hand, soil retention and water yield were more influenced by climate than by land use. The policy led to an increase in water yield by 2.129 billion cubic meters (21.29×10^8 m^3) and an increase in soil retention services by 184.2 million tons (184.2×10^6 t). Spatially, the policy caused the most significant decline in habitat quality in the eastern part of Hubei Province and the greatest decrease in carbon storage in the northern part. Soil retention service changes were highest in the southwest and northeast while lowest in the central region. Water yield changes showed a high east and low northwest distribution pattern. Within the cultivated land requisition and compensation areas, habitat quality and carbon storage, as well as soil retention and water yield, exhibited synergistic relationships, whereas trade-offs existed between the other pairs of ecosystem services.

The 2030 ecosystem service simulations indicate that soil retention and water yield are highest under the natural development scenario, while habitat quality and carbon storage are highest under the ecological protection scenario. Both scenarios perform better than the urban development scenario. When formulating policies, trade-off analyses can optimize land resources to maximize the comprehensive benefits of different ecosystem services.

The analysis reveals that while the cultivated land requisition and compensation policy has positive implications for food security, it also poses ecological risks and challenges that need to be addressed and improved in policy design. Future research should further investigate the specific impacts of different cultivated land supplementation models and technical measures on ecosystem services to find more balanced and sustainable solutions.

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References

1. Song, W.; Deng, X.; Liu, B.; Li, Z.; Jin, G. Impacts of Grain-for-Green and Grain-for-Blue Policies on Valued Ecosystem Services in Shandong Province, China. *Adv. Meteorol.* **2015**, *2015*, 213534. [CrossRef]
2. Wen, X.; Yang, F.; Chen, J.; Tu, Y.; Wang, H.; Chen, Z.; Dong, T.; Xu, G. Spatial patterns of urban expansion and cropland loss during 2017–2022 in Guangdong, China. *Heliyon* **2024**, *10*, e30548. [CrossRef] [PubMed]
3. Zhou, Y.; Zhong, Z.; Cheng, G. Cultivated land loss and construction land expansion in China: Evidence from national land surveys in 1996, 2009 and 2019. *Land Use Policy* **2023**, *125*, 106496. [CrossRef]
4. Song, W.; Pijanowski, B.C. The effects of China's cultivated land balance program on potential land productivity at a national scale. *Appl. Geogr.* **2014**, *46*, 158–170. [CrossRef]
5. Liu, C.; Song, C.; Ye, S.; Cheng, F.; Zhang, L.; Li, C. Estimate provincial-level effectiveness of the arable land requisition-compensation balance policy in mainland China in the last 20 years. *Land Use Policy* **2023**, *131*, 106733. [CrossRef]
6. Qie, L.; Pu, L.; Tang, P.; Liu, R.; Huang, S.; Xu, F.; Zhong, T. Gains and losses of farmland associated with farmland protection policy and urbanization in China: An integrated perspective based on goal orientation. *Land Use Policy* **2023**, *129*, 106643. [CrossRef]
7. Wang, C.; Zhang, D. The super-environmental effect of the westward shift of China's cultivated land patterns. *Environ. Earth Sci.* **2023**, *82*, 572. [CrossRef]
8. Costanza, R.; d'Arge, R.; de Groot, R.; Farber, S.; Grasso, M.; Hannon, B.; Limburg, K.; Naeem, S.; O'neill, R.V.; Paruelo, J.; et al. The value of the world's ecosystem services and natural capital. *Nature* **1997**, *387*, 253–260. [CrossRef]
9. Westman, W.E. How Much Are Nature's Services Worth? *Science* **1977**, *197*, 960–964. [CrossRef]
10. Daily, C.G. *Nature's Services. Societal Dependence on Natural Ecosystems*; Island Press: Washington, DC, USA, 1997.
11. Millennium ecosystem assessment. *Ecosystems and Human Well-Being*; Island press: Washington, DC, USA, 2005; Volume 5.
12. Hasan, S.S.; Zhen, L.; Miah, M.G.; Ahamed, T.; Samie, A. Impact of land use change on ecosystem services: A review. *Environ. Dev.* **2020**, *34*, 100527. [CrossRef]
13. Potapov, P.; Turubanova, S.; Hansen, M.C.; Tyukavina, A.; Zalles, V.; Khan, A.; Song, X.-P.; Pickens, A.; Shen, Q.; Cortez, J. Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. *Nat. Food* **2022**, *3*, 19–28. [CrossRef] [PubMed]
14. Schirpke, U.; Tasser, E.; Borsky, S.; Braun, M.; Eitzinger, J.; Gaube, V.; Getzner, M.; Glatzel, S.; Gschwantner, T.; Kirchner, M.; et al. Past and future impacts of land-use changes on ecosystem services in Austria. *J. Environ. Manag.* **2023**, *345*, 118728. [CrossRef]
15. Shifaw, E.; Sha, J.; Li, X.; Bao, Z.; Ji, J.; Ji, Z.; Kassaye, A.Y.; Lai, S.; Yang, Y. Ecosystem services dynamics and their influencing factors: Synergies/tradeoffs interactions and implications, the case of upper Blue Nile basin, Ethiopia. *Sci. Total Environ.* **2024**, *938*, 173524. [CrossRef]
16. Lawler, J.J.; Lewis, D.J.; Nelson, E.; Plantinga, A.J.; Polasky, S.; Withey, J.C.; Helmers, D.P.; Martinuzzi, S.; Pennington, D.; Radeloff, V.C. Projected land-use change impacts on ecosystem services in the United States. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 7492–7497. [CrossRef]
17. Song, W.; Pijanowski, B.C.; Tayyebi, A. Urban expansion and its consumption of high-quality farmland in Beijing, China. *Ecol. Indic.* **2015**, *54*, 60–70. [CrossRef]

18. 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]
19. Liu, Y.; Li, T.; Zhao, W.; Wang, S.; Fu, B. Landscape functional zoning at a county level based on ecosystem services bundle: Methods comparison and management indication. *J. Environ. Manag.* **2019**, *249*, 109315. [CrossRef]
20. Chen, W.; Chi, G.; Li, J. The spatial association of ecosystem services with land use and land cover change at the county level in China, 1995–2015. *Sci. Total Environ.* **2019**, *669*, 459–470. [CrossRef]
21. Gao, J.; Li, F.; Gao, H.; Zhou, C.; Zhang, X. The impact of land-use change on water-related ecosystem services: A study of the Guishui River Basin, Beijing, China. *J. Clean. Prod.* **2017**, *163*, S148–S155. [CrossRef]
22. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global consequences of land use. *Science* **2005**, *309*, 570–574. [CrossRef]
23. Liu, X.; Liu, Y.; Wang, Y.; Liu, Z. Evaluating potential impacts of land use changes on water supply-demand under multiple development scenarios in dryland region. *J. Hydrol.* **2022**, *610*, 127811. [CrossRef]
24. Qi, X.; Feng, K.; Sun, L.; Zhao, D.; Huang, X.; Zhang, D.; Liu, Z.; Baiocchi, G. Rising agricultural water scarcity in China is driven by expansion of irrigated cropland in water scarce regions. *One Earth* **2022**, *5*, 1139–1152. [CrossRef]
25. Chen, W.; Ye, X.; Li, J.; Fan, X.; Liu, Q.; Dong, W. Analyzing requisition-compensation balance of farmland policy in China through telecoupling: A case study in the middle reaches of Yangtze River Urban Agglomerations. *Land Use Policy* **2019**, *83*, 134–146. [CrossRef]
26. Shi, Z.; Ai, L.; Li, X.; Huang, X.; Wu, G.; Liao, W. Partial least-squares regression for linking land-cover patterns to soil erosion and sediment yield in watersheds. *J. Hydrol.* **2013**, *498*, 165–176. [CrossRef]
27. Poeplau, C.; Don, A.; Vesterdal, L.; Leifeld, J.; Van Wesemael, B.; Schumacher, J.; Gensior, A. Temporal dynamics of soil organic carbon after land-use change in the temperate zone—Carbon response functions as a model approach. *Glob. Chang. Biol.* **2011**, *17*, 2415–2427. [CrossRef]
28. Tang, L.; Ke, X.; Zhou, T.; Zheng, W.; Wang, L. Impacts of cropland expansion on carbon storage: A case study in Hubei, China. *J. Environ. Manag.* **2020**, *265*, 110515. [CrossRef]
29. Li, F.; Wu, S.; Liu, H.; Yan, D. Biodiversity loss through cropland displacement for urban expansion in China. *Sci. Total Environ.* **2024**, *907*, 167988. [CrossRef]
30. Tang, L.; Ke, X.; Chen, Y.; Wang, L.; Zhou, Q.; Zheng, W.; Xiao, B. Which impacts more seriously on natural habitat loss and degradation? Cropland expansion or urban expansion? *Land Degrad. Dev.* **2021**, *32*, 946–964. [CrossRef]
31. Zhang, B.; Li, L.; Xia, Q.; Dong, J. Land use change and its impact on carbon storage under the constraints of "three lines": A case study of Wuhan City circle. *Acta Ecol. Sin.* **2022**, *42*, 2265–2280.
32. Li, X.; Chen, Y. Projecting the future impacts of China's cropland balance policy on ecosystem services under the shared socioeconomic pathways. *J. Clean. Prod.* **2020**, *250*, 119489. [CrossRef]
33. Zheng, W.; Li, S.; Ke, X.; Li, X.; Zhang, B. The impacts of cropland balance policy on habitat quality in China: A multiscale administrative perspective. *J. Environ. Manag.* **2022**, *323*, 116182. [CrossRef] [PubMed]
34. Bradford, J.B.; D'Amato, A.W. Recognizing trade-offs in multi-objective land management. *Front. Ecol. Environ.* **2012**, *10*, 210–216. [CrossRef]
35. Howe, C.; Suich, H.; Vira, B.; Mace, G.M. Creating win-wins from trade-offs? Ecosystem services for human well-being: A meta-analysis of ecosystem service trade-offs and synergies in the real world. *Glob. Environ. Chang.* **2014**, *28*, 263–275. [CrossRef]
36. West, P.C.; Gibbs, H.K.; Monfreda, C.; Wagner, J.; Barford, C.C.; Carpenter, S.R.; Foley, J.A. Trading carbon for food: Global comparison of carbon stocks vs. crop yields on agricultural land. *Proc. Natl. Acad. Sci. USA* **2010**, *107*, 19645–19648. [CrossRef] [PubMed]
37. Nelson, E.; Mendoza, G.; Regetz, J.; Polasky, S.; Tallis, H.; Cameron, D.R.; Chan, K.M.A.; Daily, G.C.; Goldstein, J.; Kareiva, P.M.; et al. Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. *Front. Ecol. Environ.* **2009**, *7*, 4–11. [CrossRef]
38. Nigussie, S.; Mulatu, T.; Liu, L.; Yeshitela, K. The impact of land use/cover change on the supply, demand, and budgets of ecosystem services in the Little Akaki River catchment, Ethiopia. *Environ. Dev. Sustain.* **2023**, 1–32. [CrossRef]
39. Perschke, M.J.; Harris, L.R.; Sink, K.J.; Lombard, A.T. Using ecological infrastructure to comprehensively map ecosystem service demand, flow and capacity for spatial assessment and planning. *Ecosyst. Serv.* **2023**, *62*, 101536. [CrossRef]
40. Adem, E.; Chaabani, A.; Yilmaz, N.; Boteva, S.; Zhang, L.; Elhag, M. Assessing the impacts of precipitation on water yield estimation in arid environments: Case study in the southwestern part of Saudi Arabia. *Sustain. Chem. Pharm.* **2024**, *39*, 101539. [CrossRef]
41. Du, J.; Gong, Y.; Xi, X.; Liu, C.; Qian, C.; Ye, B. The study on the spatiotemporal changes in tradeoffs and synergies of ecosystem services and response to land use/land cover changes in the region around Taihu Lake. *Heliyon* **2024**, *10*, e33375. [CrossRef]
42. Reheman, R.; Kasimu, A.; Duolaiti, X.; Wei, B.; Zhao, Y. Research on the Change in Prediction of Water Production in Urban Agglomerations on the Northern Slopes of the Tianshan Mountains Based on the InVEST-PLUS Model. *Water* **2023**, *15*, 776. [CrossRef]
43. Zhang, X.; Li, Y.; Lyu, C.; Bi, R.; Xia, L.; Guo, Y.; Wang, Y.; Xu, C.; Sun, B. Research progress on application of ecosystem service functions based on InVEST model. *Ecol. Sci.* **2022**, *41*, 237–242.

44. Al Kafy, A.; Saha, M.; Fattah, M.A.; Rahman, M.T.; Duti, B.M.; Rahaman, Z.A.; Bakshi, A.; Kalaivani, S.; Rahaman, S.N.; Sattar, G.S. Integrating forest cover change and carbon storage dynamics: Leveraging Google Earth Engine and InVEST model to inform conservation in hilly regions. *Ecol. Indic.* **2023**, *152*, 110374. [CrossRef]
45. Yang, H.; Huang, J.; Liu, D. Linking climate change and socioeconomic development to urban land use simulation: Analysis of their concurrent effects on carbon storage. *Appl. Geogr.* **2020**, *115*, 102135. [CrossRef]
46. Wang, Y.; Dai, E. Spatial-temporal changes in ecosystem services and the trade-off relationship in mountain regions: A case study of Hengduan Mountain region in Southwest China. *J. Clean. Prod.* **2020**, *264*, 121573. [CrossRef]
47. Inacio, M.; Pinto, L.; Baltranaite, E.; Kalinauskas, M.; Burkhard, B.; Barcelo, D.; Pereira, P. Mapping and assessing marine ecosystem services supply in the Baltic Sea. *Sci. Total Environ.* **2024**, *950*, 175199. [CrossRef]
48. Roces-Diaz, J.V.; Burkhard, B.; Kruse, M.; Mueller, F.; Diaz-Varela, E.R.; Alvarez-Alvarez, P. Use of ecosystem information derived from forest thematic maps for spatial analysis of ecosystem services in northwestern Spain. *Landsc. Ecol. Eng.* **2017**, *13*, 45–57. [CrossRef]
49. Yuan, Y.; Bai, Z.; Zhang, J.; Huang, Y. Investigating the trade-offs between the supply and demand for ecosystem services for regional spatial management. *J. Environ. Manag.* **2023**, *325*, 116591. [CrossRef]
50. Ren, J.; Ma, R.; Huang, Y.; Wang, Q.; Guo, J.; Li, C.; Zhou, W. Identifying the trade-offs and synergies of land use functions and their influencing factors of Lanzhou-Xining urban agglomeration in the upper reaches of Yellow River Basin, China. *Ecol. Indic.* **2024**, *158*, 111279. [CrossRef]
51. Liang, X.; Guan, Q.; Clarke, K.C.; Liu, S.; Wang, B.; 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*, 101569. [CrossRef]
52. 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*, 104957. [CrossRef]
53. 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]
54. Gao, R.; Chuai, X.; Ge, J.; Wen, J.; Zhao, R.; Zuo, T. An integrated tele-coupling analysis for requisition-compensation balance and its influence on carbon storage in China. *Land Use Policy* **2022**, *116*, 106057. [CrossRef]
55. Hou, G.R.; Zheng, J.K.; Cui, X.L.; He, F.; Zhang, Y.Q.; Wang, Y.; Li, X.W.; Fan, C.; Tan, B. Suitable coverage and slope guided by soil and water conservation can prevent non-point source pollution diffusion: A case study of grassland. *Ecotoxicol. Environ. Saf.* **2022**, *241*, 113804. [CrossRef] [PubMed]
56. Nepstad, D.C.; De Carvalho, C.R.; Davidson, E.A.; Jipp, P.H.; Lefebvre, P.A.; Negreiros, G.H.; Da Silva, E.D.; Stone, T.A.; Trumbore, S.E.; Vieira, S. The role of deep roots in the hydrological and carbon cycles of amazonian forests and pastures. *Nature* **1994**, *372*, 666–669. [CrossRef]
57. Tang, Q.; Hua, L.; Cao, Y.; Jiang, L.; Cai, C. Human activities are the key driver of water erosion changes in northeastern China. *Land Degrad. Dev.* **2024**, *35*, 62–75. [CrossRef]
58. Jarvis, N.; Larsbo, M.; Koestel, J. Connectivity and percolation of structural pore networks in a cultivated silt loam soil quantified by X-ray tomography. *Geoderma* **2017**, *287*, 71–79. [CrossRef]
59. Ferro, N.D.; Sartori, L.; Simonetti, G.; Berti, A.; Morari, F. Soil macro- and microstructure as affected by different tillage systems and their effects on maize root growth. *Soil Tillage Res.* **2014**, *140*, 55–65. [CrossRef]
60. Peng, J.; Tian, L.; Zhang, Z.; Zhao, Y.; Green, S.M.; Quine, T.A.; Liu, H.; Meersmans, J. Distinguishing the impacts of land use and climate change on ecosystem services in a karst landscape in China. *Ecosyst. Serv.* **2020**, *46*, 101199. [CrossRef]
61. Li, J.; Zhou, Y.; Li, Q.; Yi, S.; Peng, L. Exploring the Effects of Land Use Changes on the Landscape Pattern and Soil Erosion of Western Hubei Province from 2000 to 2020. *Int. J. Environ. Res. Public Health* **2022**, *19*, 1571. [CrossRef]
62. Li, Q.; Zhou, Y.; Wang, L.; Zuo, Q.; Yi, S.; Liu, J.; Su, X.; Xu, T.; Jiang, Y. The Link between Landscape Characteristics and Soil Losses Rates over a Range of Spatiotemporal Scales: Hubei Province, China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 11044. [CrossRef]
63. López-Moreno, J.I.; Vicente-Serrano, S.M.; Moran-Tejeda, E.; Zabalza, J.; Lorenzo-Lacruz, J.; García-Ruiz, J.M. Impact of climate evolution and land use changes on water yield in the ebro basin. *Hydrol. Earth Syst. Sci.* **2011**, *15*, 311–322. [CrossRef]
64. Lee, Y.-C.; Ahern, J.; Yeh, C.-T. Ecosystem services in peri-urban landscapes: The effects of agricultural landscape change on ecosystem services in Taiwan's western coastal plain. *Landsc. Urban Plan.* **2015**, *139*, 137–148. [CrossRef]
65. Yohannes, H.; Soromessa, T.; Argaw, M.; Dewan, A. Impact of landscape pattern changes on hydrological ecosystem services in the Beressa watershed of the Blue Nile Basin in Ethiopia. *Sci. Total Environ.* **2021**, *793*, 148559. [CrossRef]
66. Mabuda, M.O.; Shoko, C.; Dube, T.; Mazvimavi, D. An analysis of the effects of changes in land use and land cover on runoff in the Luvuvhu catchment, South Africa. *Remote Sens. Appl. Soc. Environ.* **2024**, *33*, 101144. [CrossRef]
67. Deng, Z.-Y.; Cao, J.-S. Incorporating ecosystem services into functional zoning and adaptive management of natural protected areas as case study of the Shennongjia region in China. *Sci. Rep.* **2023**, *13*, 18870. [CrossRef]
68. Yan, K.; Zhao, B.; Li, Y.; Wang, X.; Jin, J.; Jiang, J.; Dong, W.; Wang, R.; Yang, H.; Wang, T.; et al. Effects of the Implementation Intensity of Ecological Engineering on Ecosystem Service Tradeoffs in Qinghai Province, China. *Land* **2024**, *13*, 848. [CrossRef]

69. Zubaida, M. Trade-offs and synergies between ecosystem services in Yutian County along the Keriya River Basin, Northwest China. *J. Arid Land* **2024**, *16*, 943–962. [CrossRef]
70. Han, H.; Gao, H.; Huang, Y.; Chen, X.; Chen, M.; Li, J. Effects of drought on freshwater ecosystem services in poverty-stricken mountain areas. *Glob. Ecol. Conserv.* **2019**, *17*, e00537. [CrossRef]
71. Gomes, E.; Inacio, M.; Bogdzevi, K.; Kalinauskas, M.; Karnauskait, D.; Pereira, P. Future land-use changes and its impacts on terrestrial ecosystem services: A review. *Sci. Total Environ.* **2021**, *781*, 146716. [CrossRef]
72. Agudelo, C.A.R.; Bustos, S.L.H.; Moreno, C.A.P. Modeling interactions among multiple ecosystem services. A critical review. *Ecol. Model.* **2020**, *429*, 109103. [CrossRef]
73. Azimi, M.; Barzali, M.; Abdolhosseini, M.; Lotfi, A. Examining the impact of rangeland condition on water conservation by using an integrated modelling approach. *Land Degrad. Dev.* **2021**, *32*, 3711–3719. [CrossRef]
74. Bastos, A.; Sippel, S.; Frank, D.; Mahecha, M.D.; Zaehle, S.; Zscheischler, J.; Reichstein, M. A joint framework for studying compound ecoclimatic events. *Nat. Rev. Earth Environ.* **2023**, *4*, 333–350. [CrossRef]

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Nonlinear Effects of Land-Use Conflicts in Xinjiang: Critical Thresholds and Implications for Optimal Zoning

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Abstract: Land-use conflicts (LUCs) are pivotal in assessing human–land interaction, reflecting the intricate interplay between natural and anthropogenic drivers. However, existing studies often overlook nuanced non-linear responses and critical threshold recognition, focusing solely on linear correlations between isolated factors and LUCs. This study, situated in Xinjiang, China's arid and semiarid region, introduces a novel analytical framework and threshold application model for LUCs. Integrating land-use and socioeconomic data, we quantified LUCs using Fragstats, correlation analysis, and restricted cubic spline (RCS) regression. Exploring non-linear dynamics between LUCs and 14 potential drivers, including natural and anthropogenic factors, we identified critical thresholds. LUC zones were delineated using a four-quadrant method, allowing tailored mitigation strategies. Our findings reveal Xinjiang's distinct LUC spatial pattern, with intense conflicts surrounding mountainous areas and milder conflicts in basin regions, showing marked diminishment from 2000 to 2020. RCS effectively identifies LUC thresholds, indicating persisting severity pre- or post-specific thresholds. Xinjiang's LUCs are categorized into key control areas, urgent regulation zones, elastic development territories, and moderate optimization regions, each with significant regional disparities. Tailored optimization suggestions mitigate linear analysis limitations, providing a fresh perspective on land zoning optimization. This research supports comprehensive land management and planning in Xinjiang, China.

Keywords: land-use conflicts; natural and anthropogenic driver; restricted cubic spline; critical threshold; land zoning

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1. Introduction

In the context of societal advancement and progress, the ever-growing human aspiration for wealth accumulation and the pressing need for development exert considerable pressure on finite land resources. This escalation intensifies tensions within the human–land interaction, exacerbating conflicts between humanity and the land. Since the Industrial Revolution, these contradictions and conflicts have rapidly transcended local boundaries to a global scale. Common challenges such as climate change, energy crises, and food shortages underscore the imbalance in the human–land system. Land-use conflicts (LUCs), arising from disparities in interests and needs among different stakeholders, epitomize the concentrated manifestation of these contradictions. Defined as spatial disputes and rights conflicts among stakeholders engaged in land resource utilization, LUCs encompass disputes arising from differences in land-use modes and the natural environment [1]. As a scarce resource integrating economic, social, and ecological values, land becomes a focal point of conflicts when stakeholders, driven by diverse value orientations and interest demands, engage in the land utilization process. These conflicts manifest as economic disputes among land-use subjects and as conflicts between economic interests, ecological protection, and social development [2]. LUC is a complex process characterized by the "land–land" conflict (imbalance between land-use quantity and function), with the "man–land" conflict (mismatch between land-use subject and function) at its core, and the "man–man" conflict (mismatch between land-use subject and spatial benefit distribution) as its essence. The "man–land" conflict originates from the evolution of regional human–land relationships influenced by external factors such as systems and markets. Throughout this evolution, the spatial interest game among various stakeholders forms a "man–man" conflict, aiming to achieve coordinated human–land relationships. However, constrained by external policies, systems, and internal economic and social factors, the evolution often falls short of achieving coordinated human–land relationships, resulting in a "land–land" conflict. This cyclic process persists. In essence, the root cause of LUC lies in the imbalance of the human–land relationship, a consequence of the structural and inherent spatial competition stemming from the ever-growing demand for limited land. This demand arises from the interplay between human activities, various land-use modes, and natural ecological processes [3]. Consequently, implementing appropriate control measures becomes imperative to effectively mitigate LUC [4]. Exploring the complex mechanisms influencing LUC, such as urbanization–ecological environment interactions [5], the economy–environment relationship [6], and the population–land–industry interplay [7], along with coordinating multiple land-use functions [8], optimizing and controlling the spatial pattern of the national territory [9,10], are essential measures that can contribute to the alleviation of LUC.

LUCs stand as a sensitive indicator of the intricate interaction between humans and the land. The continual escalation of human activities amplifies the conflict between economic growth and the natural environment, resulting in heightened competition and LUCs across diverse regions [11]. These conflicts manifest through the conversion of ecological land into cultivated or construction areas and the frequent mismatch and overlap between agricultural or industrial zones and ecological conservation spaces [12,13]. These competitions and contradictions represent complex disputes that, if not addressed promptly, often give rise to challenging environmental and social problems, potentially diminishing economic, ecological, or social benefits [14]. Furthermore, they pose a substantial hazard to sustainable development [15]. The occurrence and development of LUCs result from multi-dimensional internal and external factors, encompassing the natural environment, economy, society, and policy system. This intricate interplay shapes a complex mechanism driving the development and evolution of LUCs. As natural and human factors jointly exert their influence, the scope and intensity of LUCs gradually expand and intensify [16]. Firstly, as LUCs stem from the scarcity and multiple suitability of resources, natural environmental conditions significantly impact conflicts by determining the scarcity and multiple suitability of land resources. Hence, natural conditions serve as long-term factors influencing the formation of conflicts [17,18]. Secondly, LUCs are closely linked to economic and social factors. In the realm of socioeconomics, the burgeoning population and its demands act as primary catalysts for conflict development [19]. The overlapping interests of land-use subjects, shaped by human personality characteristics and group behavior, and the ensuing contradictions in land-use objectives are commonly regarded as the root causes of conflicts [20,21]. Thirdly, the noteworthy influence of policy and institutional environments on LUC is indirect and reliant. Essentially, it primarily exerts its influence indirectly by regulating the process of regional economic and social development [22,23]. This holds great significance for a thorough scientific exploration and effective comprehension of the role played by policy and institutional factors in LUC. To mitigate LUC more effectively and prevent its negative effects from spreading further, a clear understanding of the impact of natural and anthropogenic drivers on LUC is essential.

Certain studies have emphasized that LUC can be construed as the outcome of the interplay between economic driving forces, policy and institutional influences, and social and cultural factors [24]. Consequently, both natural and human factors exert an influence on LUC [19,21]. Typically, the intensity of regional LUC hinges on local background conditions and the extent of human development and land resource utilization in subsequent stages. The level of urbanization among dynamic drivers and terrain constraints among static factors have been identified as significant drivers affecting LUC [25]. Specifically, a high degree of coupling and coordination has been observed between the level of urbanization, terrain relief, and LUC. Notably, the intensity of LUC undergoes changes when the urbanization level and topographic relief index reach a certain threshold [26]. This implies that natural and anthropogenic drivers affecting LUC exhibit non-linearity, suggesting the potential for a threshold effect between LUC and these drivers. In recent decades, the proliferation of studies related to LUC has been evident with current research focusing on understanding conflicts between different subjects of interest through participatory surveys [27,28]. Quantitative identification of the effects of regional urbanization levels, population density, and topographic conditions on LUC has also been a key aspect of contemporary research [26,29]. In conclusion, existing studies have primarily centered on examining the effect of a single driver on LUC, lacking the analysis of the integrated impact of multiple factors on LUC. Moreover, there is a dearth of studies considering the nonlinear effects of different drivers on LUC intensity and the potential existence of thresholds, and where these thresholds might be applied. The diversity and complexity inherent in LUC are often overlooked since they result from a combination of anthropogenic activities [25], potentially leading to a lack of specificity in proposing control measures to mitigate LUC. Restricted cubic splines (RCS) have proven effective for modeling nonlinear relationships between explanatory variables and outcomes [30]. However, limited research has been conducted on the application of RCS in the environmental field, with most existing studies focused on other areas, such as virology research and family business science [31,32]. Consequently, more research is warranted to explore the potential application of RCS in other studies.

To effectively bridge this research gap, we applied RCS to the study of LUC and investigated their nonlinear relationship in Xinjiang. Positioned in the heartland of the Asia-Europe continent and located within the arid zone of northwestern China, this region represents a distinctive natural geographic unit. It features interspersed mountain ranges and basins, with coexisting oases and deserts that together form a unique mountain-oasis-desert ecosystem. The region contends with harsh natural conditions and relatively fragile ecosystems, influenced by climatic and hydrological factors. Xinjiang faces substantial challenges related to water resources and ecology, acting as impediments to economic development and posing threats to ecological health [33,34]. Furthermore, uncertainties such as rising temperatures and soil erosion impact the regional ecosystem [35]. In conjunction with these challenges, the rapid expansion of the Silk Road Economic Belt has escalated the demand for land resources in the region [36]. Consequently, human activities' impact on the environment has intensified gradually, accentuating the conflict between the scarcity of land resources and unrefined land-use practices. This paradoxical relationship between people and the land emerges as a critical constraint on the regional ecosystem and sustainable societal development [37], further exacerbating LUC [38]. Regional land construction and development have become primary concerns [39]. However, current research on LUC in Xinjiang primarily focuses on specific oasis areas, such as Urumqi city and the Ili River Valley [3], with less attention paid to LUC on the overall Xinjiang scale. Therefore, investigating the drivers of LUC in arid and semi-arid regions and zoning of land-use patterns hold significant importance. This research aims to support the rational development and utilization of land resources, protection of the ecological environment, optimization of the spatial pattern of the national territory, harmonization of human–land relations, and achievement of sustainable development. In this article, we quantitatively measured the intensity of LUC in Xinjiang from 2000 to 2020, analyzed its spatial and temporal pattern characteristics, conducted a correlation analysis of 14 typical natural and anthropogenic driving factors on LUC, and, based on threshold recognition results, classified the land-use pattern in Xinjiang into four types using an LUC pattern optimization model. Suggestions were then presented. In summary, the scientific issues addressed in this study include the following:

(1) Do different natural and anthropogenic drivers exhibit thresholds that influence LUC in Xinjiang?
(2) If thresholds exist, how can we effectively identify them?
(3) How can the defined thresholds be used practically for land management zoning?

2. Theoretical Framework

2.1. Threshold Analysis of Drivers of Land-Use Conflicts (LUCs)

From a general understanding, assuming no human intervention, nature will form an orderly natural pattern and maintain the relative stability of the ecosystem [38]. When human development is taken into account, the initial natural pattern often fails to meet human demand for production and living space, and human beings are bound to carry out long-term and cyclical management and governance activities on land in accordance with a certain pursuit of interests and development goals, forming land-use behavior [40]. With the concentration of population and industry in a given area, the entire layout of natural ecosystems is often disrupted by the intrusion of human activities, including the expansion of land for construction and agriculture and a reduction in ecological land. Furthermore, the increasing frequency of land development intensifies the conflict in land utilization. It has been found that human activities have both positive and negative impacts on land resources [41,42]. Since the 1980s, the concept of sustainable development has gradually spread globally, and people have begun to take action to protect the ecological environment. Consequently, by considering their available resources and development objectives, LUCs are continuously mitigated, ultimately giving rise to a spatial arrangement of land utilization that aligns with the local natural resources and socio-economic conditions.

The emergence and progression of LUCs stem from the interplay of multidimensional endogenous and exogenous factors, with the natural environment and human activities as primary components [24]. On one hand, land resources, influenced by their inherent conditions such as topography, distinct spatial characteristics (e.g., parcel geometry, etc.), and their own physical conditions (soil texture, etc.), as well as unexpected changes in LUCs due to sea level fluctuations triggered by climate change and natural disasters like heavy rainfall and drought disrupt the harmony of the LUC structure, consequently inciting and intensifying LUCs [43,44]. On the other hand, LUCs are closely linked to human factors. Previous research indicates that population growth and associated demands are primary drivers of conflict development [11,13,19,45]. Conflicts often arise from overlapping interests among land-use stakeholders due to individual and collective behavior traits, resulting in land-use goal conflicts [20,21]. Cultural differences, diverse political viewpoints within communities, and variations in education levels may also exacerbate LUCs [46]. Urbanization, as a core process in contemporary socioeconomic development, profoundly influences LUCs. Disorderly urban expansion, accelerated reduction in agricultural land, and deterioration of land ecological environments contribute to a decrease in arable land quantity and quality, land degradation, sudden changes in land use, and increased likelihood of conflict occurrence. In summary, the root cause of LUC lies in the imbalance between human–land relationships, resulting from the escalating demand for limited land resources, structural and elemental contradictions formed by spatial competition, and interactions among natural ecological processes, human activities, and different land-use practices [47]. Natural conditions determine the bottom line of LUC intensity, and human factors determine the upper limit of conflict intensity [24]. Based on this, we make an assumption that there are thresholds for the drivers of LUC, and the thresholds of natural drivers are called natural thresholds, and the thresholds of anthropogenic drivers are called anthropogenic thresholds. When the natural threshold and the anthropogenic threshold intersect at a certain point, there will be a turning point in the evolution of LUC; this pivotal moment marks a shift in the impact of human activities on land use, with a transition from negative to positive impacts. In addition, land-use patterns have experienced a shift from structural imbalance to pattern optimization [18]. Simultaneously, the dynamic between individuals and the land experiences a transition from a state characterized by LUC to a state of coordination (Figure 1a).

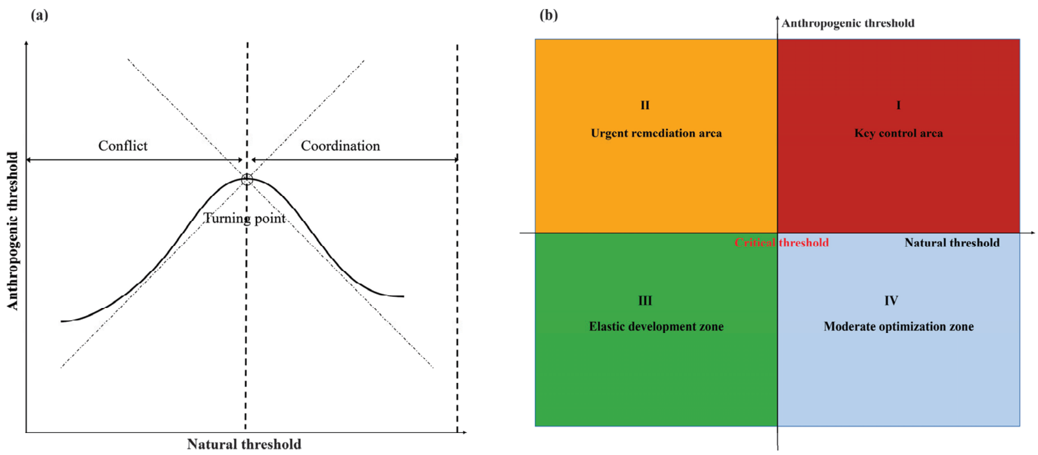

Figure 1. Theoretical analysis and the four-quadrant diagram approach. (**a**) Macroscopic evolution of temporal dimension; (**b**) types of optimized zoning in the spatial dimension.

2.2. Threshold Application of Drivers of LUC

The evolution of LUC is a dynamic process, and the overall parabola shows an inverted "U-shape", which is in line with the characteristics of the conflict curve model [48] (Figure 1a). With the passage of time, when the conflict breaks through the critical value of the controllable level, the invisible conflict will be transformed into an open conflict, and all kinds of conflict problems are becoming more and more prominent, and the controllability level of the conflict can be categorized into four levels, namely, stable and controllable, basically controllable, basically out of control, and seriously out of control [49]. In the stable and controllable stage, regional development will not suffer from LUC. With the gradual escalation of the conflict, the intensity of its role is increasing, and it begins to gradually affect the sustainable coordination of the region, and the conflict is upgraded to the basic controllable level, but its negative effects are not yet obvious, and this stage is the most critical period for the regulation of the conflict. When the conflict breaks through the critical value of the controllable level, the stability of the region begins to be broken, the conflict develops to the basic uncontrolled level, and the impact effect of the conflict tends to be unstable, with all kinds of conflict problems becoming more and more prominent. If the conflict further deteriorates, the negative effects of the conflict will have a great impact on regional development, and if favorable measures are not taken to curb the conflict at this time, the critical value of the regional crisis will be broken, and regional development will be imbalanced, and the conflict will rise to the level of serious out of control, and the conflict will completely break out [25]. After the outbreak of the conflict, all stakeholders will be harmed to different degrees, and all kinds of compulsory regulatory measures begin to intervene to curb the adverse effects of spatial conflict, and then gradually resolve the conflict, so that the regional development is able to restore stability [3,10,11]. From the analysis of the conflict curve model, different conflict control strategies should be adopted at different stages of conflict development, and the latent stage is an important stage of spatial conflict control, where efforts should be made to maintain the level of spatial conflict at a controllable level in order to avoid regional imbalance.

In view of this, in order to identify the inflection point of the dynamic evolution of LUC under the influence of anthropogenic and natural factors on the inverted "U" curve in a specific region, and the role of this inflection point in the regulation of LUC, we drew a four-quadrant map using the identified critical threshold as the origin, natural conditions as the horizontal coordinates, and anthropogenic influences as the vertical coordinates. We drew a four-quadrant diagram from the perspective of the dynamic evolution of

LUC, taking the identified critical threshold as the origin, the natural conditions as the horizontal coordinate, and the anthropogenic influences as the vertical coordinate. Since the background conditions of the natural environment are the result of the long-term and stable formation of nature, while the anthropogenic factors can be changed through policy guidance and human behavior, the anthropogenic factors are more controllable than the natural conditions. Combining the identification results of natural and anthropogenic thresholds, the land-use pattern can be classified into four categories based on the four-quadrant method, and corresponding regulatory measures can be taken (Figure 1b).

$$
\begin{aligned}
&(\text{Natural threshold, Anthropogenic threshold})\\
&\qquad = \begin{cases} (+,+), \text{ first quadrant, key control area} \\ (-,+), \text{ second quadrant, urgent remediation area} \\ (-,-), \text{ third quadrant, elastic development zone} \\ (+,-), \text{ fourth quadrant, moderate optimization zone} \end{cases}
\end{aligned}
$$

Quadrant I is the area that exceeds the natural and anthropogenic thresholds, where the risk of conflict is serious and timely intervention is needed to contain the adverse effects of the conflict, which is defined as the key control area. Quadrant II is the area that does not exceed the natural thresholds, but exceeds the anthropogenic thresholds, where favorable measures are needed to contain the conflict, which is defined as the urgent remediation area. Quadrant III is an area that has not exceeded the natural and anthropogenic thresholds, and the land pattern remains stable, and is defined as elastic development zone. Quadrant IV is an area that has exceeded the natural thresholds but has not exceeded the anthropogenic thresholds, and the conflict has escalated to a basically controllable level due to the restricted natural conditions of the region's background, but its negative effects are not yet obvious, and can be appropriately controlled. Negative effects are not yet obvious, and human development activities can be moderately optimized. This stage is the most critical period for conflict regulation, and this zone is defined as the moderate optimization zone (Note: When spatial overlap occurs, the higher the risk, the more attention should be paid to the overlapping area, and the overlapping area is defined as the priority control area, such as the moderate optimization zone and urgent remediation zone overlapping with the urgent remediation zone, thus the overlapping zone is preferentially defined as the urgent remediation zone). Here, Quadrant III and Quadrant IV are considered sustainable, while Quadrant I and Quadrant II are unsustainable and need to be controlled and optimized in time.

3. Materials and Methods

3.1. Study Area

Xinjiang (73°40′ E–96°23′ E, 34°25′ N–49°10′ N) is located on China's northwestern border and shares borders with China's provinces, namely Tibet, Qinghai, and Gansu, in addition to eight neighboring countries: Russia, India, Kazakhstan, Mongolia, Tajikistan, Pakistan, Afghanistan, and Kyrgyzstan. This vast province covers an expansive area of approximately 166.49×10^4 square kilometers, which represents about one-sixth of China's total land area. Consequently, Xinjiang stands as the largest province in China, characterized by its extensive land borders and its diverse range of neighboring countries (Figure 2). Xinjiang boasts a distinctive mountain and basin landscape, characterized by what can be described as a three mountain peaks and two basins' topography. This geographic configuration includes the Altai Mountains, Junggar Basin, Tianshan Mountains, Tarim Basin, and Kunlun Mountains, listed in descending order of prominence. Xinjiang's geographical location, distant from the sea and surrounded by mountains, poses a challenge for oceanic air currents to reach the region. This results in an average annual precipitation of merely 130 mm, while annual evaporation surpasses 1000 mm [50]. This climatic condition characterizes Xinjiang as a typical arid and semi-arid region, fraught with ecological and environmental issues, including drought, soil erosion, and land desertification. Over the past two decades, Xinjiang has witnessed significant changes in Land Use and Land Cover (LULC) due to the intensification of human activities [51,52]. The ecological environment can face significant pressure due to the unsustainable development of land [53]. As Xinjiang experiences rapid urbanization, there is a rapid expansion of construction land, accompanied by a gradual decline in grassland area [54]. The expanding built-up area and the increasing conflicts between various land-use types introduce substantial stress and challenges to regional land use, ultimately posing a severe threat to the sustainable development of socio-economic elements in the region. In addition, Xinjiang, an autonomous region of the People's Republic of China, has historically been a multi-ethnic region with unique strategic significance and challenges. Previous studies have indicated that such borderland regions, due to facing multiple "border exclusion" predicaments [55], exhibit relatively complex land-use conflict issues, making them focal areas of spatial governance disorder and spatial contradictions [56]. Therefore, conducting research on land-use conflicts in Xinjiang is of paramount importance for comprehensive regional land management.

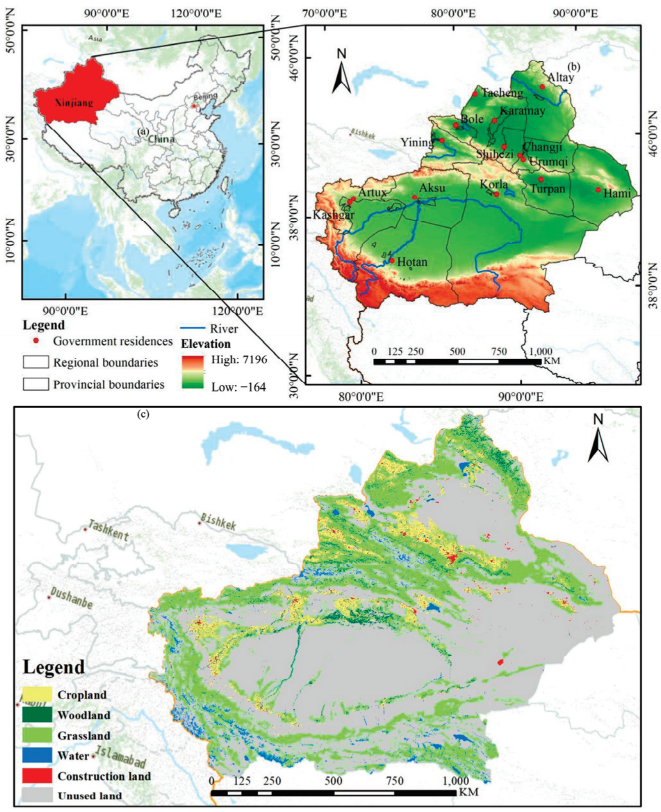

Figure 2. Study area. (**a**) Geographical location of Xinjiang in China; (**b**) elevation distribution; (**c**) land-use types in 2020.

3.2. Research Framework

This study mainly includes four main steps in Figure 3: (1) Diagnosing LUC intensity. Constructing LUC measurements by utilizing the risk source–risk receptor–risk effect theory. (2) Correlation analysis. Correlation analysis and curve fitting are utilized to identify the main drivers and drivers with nonlinear relationships. (3) Threshold identification. Natural factor thresholds and human factor thresholds affecting LUC are identified separately by RCS regression. (4) Threshold application. The intersection area identified by the natural and anthropogenic threshold conditions is delineated as potential high-risk areas of land use and is discussed in relation to zoning of land-use patterns.

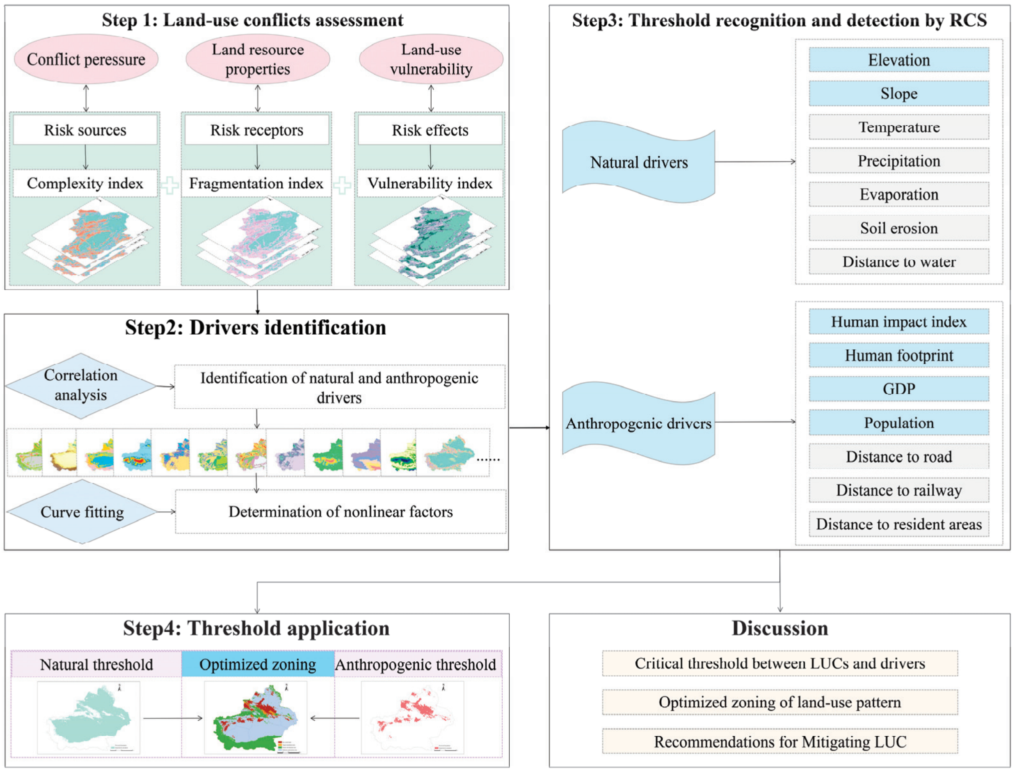

Figure 3. The research framework.

3.3. Data Processing

In terms of their mode and intensity of influence, natural factors represent long-term influencing factors in the formation of LUCs [17,47], whereas human factors exhibit a more pronounced impact on regional land-use conflicts in the short term and at large spatial scales [53,57], with the policy and institutional environment demonstrating indirect and dependent characteristics in its influence on LUCs [22,23]. Drawing on relevant studies [11,19,25,29,44,54], and based on the theoretical framework outlined in Section 2 and data availability, a total of seven natural drivers and seven anthropogenic drivers were selected, all of which are theoretically and empirically known to influence LUCs [24]. Natural drivers include elevation (abbreviated as ELE), slope (abbreviated as SLO), temperature (abbreviated as TEM), precipitation (abbreviated as PRE), evaporation (abbreviated as EVA), soil erosion (abbreviated as SE), and distance from water systems (abbreviated as Water). Anthropogenic drivers included human influence index (abbreviated as HII), human footprint (abbreviated as HF), GDP, population (abbreviated as POP), distance from roads (abbreviated as Road), distance from railroads (abbreviated as Rail), and distance from residents (abbreviated as Resident). The specifics of the data are outlined in Table 1. All data underwent rigorous preprocessing, with spatialization conducted for metrics such as GDP and POP using ArcGIS software.

Table 1. Overview of the data, resolution, and data source.

Date	Resolution	Source
Xinjiang administrative boundaries	-	China National Geographic Information Directory Service http://www.webmap.cn (accessed on 1 September 2023)
Road network water	- -	https://www.openstreetmap.org (accessed on 1 September 2023)

Table 1. *Cont.*

Date	Resolution	Source
Land-use data	30 m	Resource and Environmental Science Data Center of the Chinese Academy of Sciences http://www.resdc.cn (accessed on 1 September 2023)
Precipitation	1 km	
Evaporation	1 km	
Temperature	1 km	
Soil erosion	1 km	
Population data	1 km	
GDP data	1 km	
DEM data	1 km	
Human influence index	1 km	Socio-economic data and application center https://sedac.ciesin.columbia.edu (accessed on 1 September 2023)
Human footprint	1 km	

3.4. Evaluation Model for LUC

In accordance with the theory of human–land relationship, the issue of LUC emerges as a spatial competition and a clash of rights and interests between people and land. The resulting imbalance in land-use pattern and spatial relationship is a crucial reflection of the level of coordination within the human–land system [18]. Although the essence of the conflict lies in the interest game of many subjects, it is an objective geographical phenomenon manifested by conflicting elements (the contradiction between the quantity of land-use allocation and the allocation structure). In this paper, an ecological risk evaluation model was established to measure the LUC. This model is grounded in the conceptual framework of ecological risk assessment and incorporates key principles from landscape ecology [19,49]. The complexity index, vulnerability index, and fragmentation index of the landscape were used as three indicators reflecting the risk sources, risk receptors, and risk effects in ecological risk, respectively, and thus diagnosing the intensity of LUC. We chose to select this model because it treats land use as a complex system including natural geosystems and socioeconomics, which allows us to analyze the causal relationships among the elements affecting the system [58], while the results of this study can be presented in more detail at the grid scale.

3.4.1. Risk Sources

Landscape complexity is a vital risk source (S) indicator, gauging the extent of neighboring landscapes to the target landscape unit. It is defined by the area-weighted average patch fractal index, expressed by the following formula:

$$S = CI = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\frac{2\ln(0.25 p_{ij})}{\ln(a_{ij})} \left(\frac{a_{ij}}{A} \right) \right] \quad (1)$$

where CI is the complex index; p_{ij} signifies the patch perimeter; a_{ij} represents the patch area; and A stands for the total landscape area. This index has been shown to be effective in describing the degree of anthropogenic disturbance in the context of landscape pattern complexity [59]. The index has proved to be effective to describe the complexity of landscape pattern under human disturbances [36]. A larger value often indicates more complex landscape patterns, and more intense land-use conflict interfered by human activities [10,48].

3.4.2. Risk Receptors

The landscape vulnerability reflects the risk receptors (R), and is used to describe the capability of land system to external disturbances. It is often intricately linked to land use. Based on prior research and data [60], the vulnerability of land-use types was determined by considering the natural characteristics and diversion rates in Xinjiang from 2000 to 2020. Specifically, the diversion rates of cropland, woodland, grassland, water, construction land,

and unused land during the study period were 0.52%, 0.28%, 0.01%, 0.33%, 1.07%, and 0.02%, respectively. The vulnerability scores order of landscape types in this study, from weak to strong, was as follows: grassland, unused land, woodland, water, cropland, and construction land. Then, we calculated the landscape vulnerability using the following formula [10,11]:

$$R = VI = \sum_{i=1}^{n} F_i \times \frac{a_i}{S} \tag{2}$$

where VI is the vulnerability index, F_i represents the vulnerability score of land-use type i, a_i stands for the area of land-use type i, and S indicates the total area. In our research, a high vulnerability score of an assessment unit indicated the weaker ability of land-use structure to resist human disturbances, and then LUC tends to be more intense.

3.4.3. Risk Effects

The landscape fragmentation, an indicator of the risk response (E), reflects how spatial units react to disturbances such as urbanization and land reclamation. The more fragmented landscape suggests high competition among different land-use stakeholders and intense LUC. Here we characterized landscape fragmentation with patch density which was calculated as shown below:

$$E = FI = \frac{n_i}{A_i} \tag{3}$$

where FI is the fragmentation index, n_i stands for the number of patches in landscape unit i, and A represents the area of the landscape unit. The higher the index value, the more fragmented the landscape. The fragmented land-use structure often indicates the lack of land-use stability, which tends to increase land-use conflict.

3.4.4. Land-Use Conflict Index

The intensity of the LUC is characterized using the land-use conflict index ($LUCI$), which is calculated by summing the risk source, risk receptor, and risk response using the following formula:

$$LUCI = S + R + E \tag{4}$$

Considering the scale of the study area and data accessibility, by comparing the scale effects of 6 km, 8 km, and 10 km, conflict effects were most fully and effectively demonstrated at the 8 km scale. Therefore, we finally selected the 8 km fishing net as the basic spatial analysis unit, and set the image size of all raster data to 8 km × 8 km, resulting in a division of the study area into a total of 26,062 grids. In addition, all three indicators and the final calculated LUC were normalized to the range of 0 to 1 in order to allow aggregation of the indicators. Larger index indicates more intense LUC.

3.5. Correlation Analysis of Drivers

The strength of the correlation between LUC and drivers was tested by the Pearson correlation coefficient (r). To determine whether there is a threshold between the response variable (LUC) and the independent variable (driver) and what the threshold is, we constructed a correlation analysis between the response variable and the independent variable based on a scattered point cloud. To minimize the effect of outliers [61], we applied a local density-based approach to detect and eliminate them [62]. Subsequently, the potential relationship between LUC and drivers was analyzed by performing curve fitting, focusing on optimizing the regression model's performance ($p < 0.05$). Curve-fitting analysis is a powerful tool for representing the nonlinear relationship of variables and gaining insights into their intrinsic links [63].

3.6. Threshold Recognition and Detection

In addressing the non-linear association between independent and dependent variables, we employ restricted cubic spline (RCS) for the purpose of characterizing this intricate relationship and ascertaining potential thresholds [64,65]. To maintain a smooth curve, these splines, resembling segmented polynomials, must be continuous and exhibit second-order differentiability at each threshold point [66]. The conditions under which splines are applicable include the following: (1) the relationship between the data x and y does not satisfy the linear or generalized linear premise; (2) the data multivariate regression R^2 is low; and (3) the trend changes significantly before and after a knot. RCS conforms to the spline function, RCS (X), which renders a smooth curve of a continuous variable, X, over the entire range of values by choosing the location and number of nodes. When visualizing curvilinear relationships using RCS, it is essential to set the number and position of the spline function nodes. Typically, the placement of nodes exerts minimal influence on the fit of the restricted cubic spline, whereas the number of nodes determines the curve's shape and quantity [67]. In our study, we determined the number of nodes for variable X after evaluating different options. We performed RCS regression analysis using R software, version 4.2.2, along with the use of rms package [68] and MSTATA software.

3.7. Four-Quadrant Method

The four-quadrant method, also known as the two-dimensional quadrant method, is a time management theory proposed by Stephen R. Covey, an American management scientist. In the process of analysis, the evaluation unit is analyzed and weighed by two attributes, and then the evaluation unit is filled into each quadrant box one by one, and finally the four quadrants are sorted according to different goal orientation.

3.8. Threshold Application

Thresholds were determined by constructing an RCS between the drivers and LUC. Most of the drivers can cause the LUC maximally within specific ranges. LUC intensity remained consistently high within these threshold limits. Drawing upon the results of threshold identification for both LUC and driver factors, the four-quadrant method was used to combine the threshold values to determine the partition of LUC.

4. Results

4.1. Spatial-Temporal Patterns of LUC

From 2000 to 2020, landscape complexity in Xinjiang shows a trend of first decreasing and then increasing, with CI having increased by 0.1353% overall (Table 2). The spatial CI distribution of different regions in 2000 shows that high-value areas are near the northern slope of Tianshan Mountain city cluster, the southern Xinjiang city cluster, and the core urban areas of various cities. Conversely, the low-value CI areas are distributed in the Tarim Basin in the south of Xinjiang, the Junggar Basin in the north of Xinjiang, and the eastern region, which includes the three major deserts of Xinjiang, namely Gurbantunggut Desert, Taklamakan Desert, and Kumutage Desert (Figure 4a1). In 2020, the distribution pattern of CI high-value areas is basically the same as that in 2000, and they are concentrated in the central region of Xinjiang, with dense distribution of construction land and large population, industry, and human disturbance (Figure 4a3). Analyzing the trends over the past two decades, counties experiencing increased CI value are mainly located in the built-up areas around the three mountains, the areas with decreased CI value are mainly scattered in the areas with increased CI value, and the CI value remains unchanged in the desert areas near the Tarim Basin and Junge Basin. In general, the spatial complexity of Xinjiang in the past two decades shows the characteristics of higher spatial pattern around three mountains and lower spatial pattern around two basins.

Table 2. Index value of land-use conflicts (LUCs) in Xinjiang from 2000 to 2020.

Year	Risk Sources (S)	Risk Receptors (R)	Risk Effects (E)	Land-Use Conflicts Index (LUCI)
2000	1.0344	0.3537	0.9793	2.3673
2010	1.0352	0.3142	0.9782	2.3276
2020	1.0358	0.3178	0.9779	2.3315
2000–2020	0.1353% ↑	0.1498% ↓	0.1430% ↑	1.5123% ↓

(Note: "↑ "represents increases, "↓ "represents decreases).

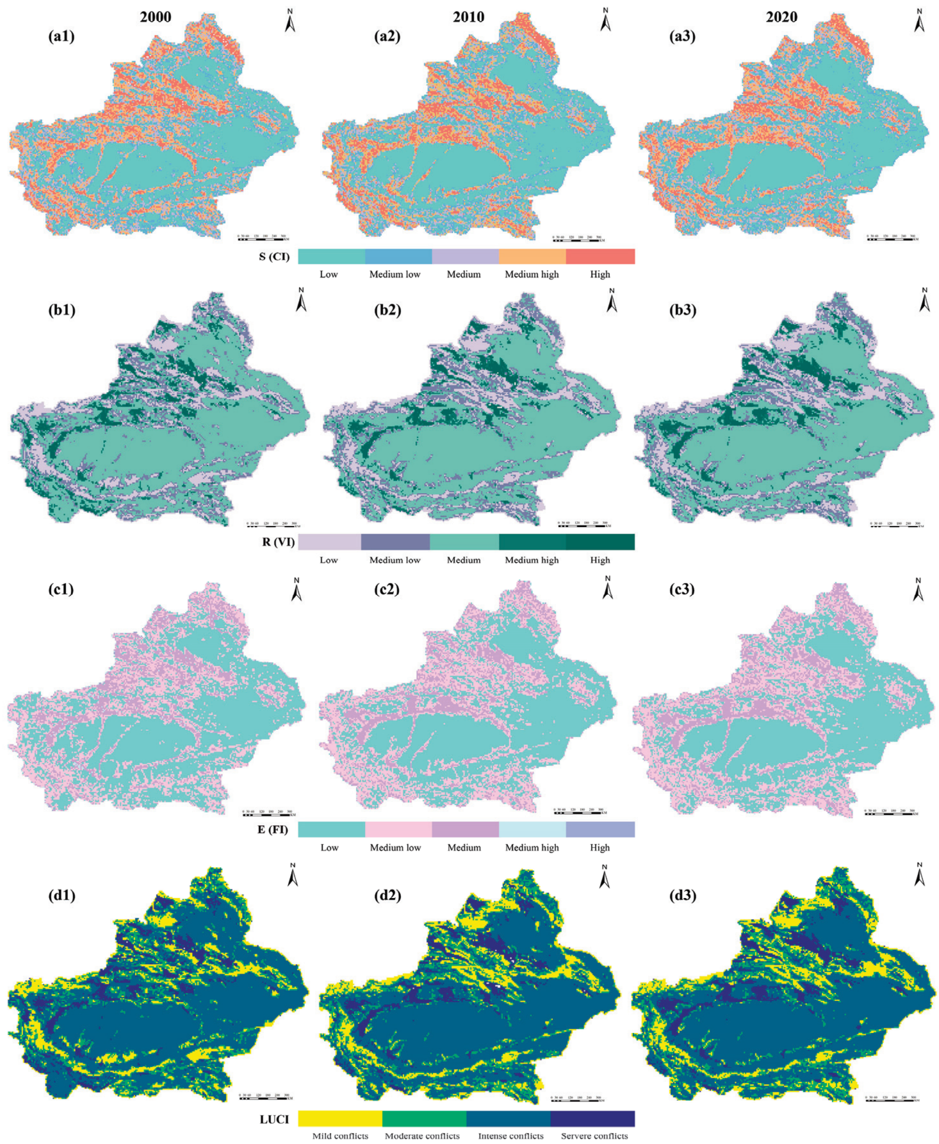

Figure 4. The spatial distribution of land-use conflicts (LUCs) from 2000 to 2020. (**a1**–**a3**) Risk sources (S); (**b1**–**b3**) risk receptors (R); (**c1**–**c3**) risk effects (E); (**d1**–**d3**) land-use conflicts index (LUCI).

From 2000 to 2020, landscape vulnerability in Xinjiang also shows a trend of first decreasing and then increasing, with VI having been down 0.1498% overall (Table 2). The spatial distribution of the fragility of the land system shows that the distribution of vulnerability in the recent 20 years has exhibited a consistent pattern, characterized by higher values in the northwest and lower values in the southeast. The VI high-value areas in both 2000 and 2020 are concentrated in the centers of cities in various states, and the vulnerability in 2020 is significantly higher than in 2000. Low-value areas of VI were distributed in Hami City, Turpan City, and Bayingol Mongol Autonomous Prefecture (Figure 4b1–b3). From the trend change in the past 20 years, we have noted increased VI in many districts and counties across Xinjiang, mainly situated along the urban development axis, such as the Urumqi–Altai development axis, the Lanzhou–Xin Line development axis, the southern Xinjiang railway development axis, and the Kashi–Hotan–Ruoqiang development axis. As a result, production and living space encroachment on ecological space and agricultural space leads to a gradual increase in the landscape vulnerability.

The spatial distribution of landscape fragmentation reveals a consistent pattern over the past two decades, with the high-value and low-value regions exhibiting an inverse relationship to spatial stability. High FI value areas were primarily situated in urban development areas in central, northern, and southern Xinjiang (Figure 4c1), while areas with low FI value were predominantly found in Tarim Basin in southern Xinjiang, Junggar Basin in northern Xinjiang, and desert areas in eastern Xinjiang (Figure 4c3). The FI value was related to the fragmentation degree of landscape patches, and increased human activities tend to elevate this fragmentation degree, leading to a decrease in stability. According to the trend of change in the past two decades, counties witnessing an increase in FI values primarily clustered around the three mountains, exhibiting a trend analogous to the changes observed in CI values. Meanwhile, landscape fragmentation remained relatively constant in the desert areas near the Tarim Basin and the Junge Basin.

From 2000 to 2020, the spatial distribution patterns of landscape complexity and fragmentation in Xinjiang were basically consistent (Figure 4a1–a3,c1–c3). Regions with higher levels of human activity exhibited greater patch fragmentation consistent with previous spatial analysis. High-value areas of LUC are distributed on a certain scale in the northern, central, and southern parts of Xinjiang, mainly in the oasis areas near the Altai Mountains, Tian Shan, and Kunlun Mountains. In contrast, low-value regions are primarily found near the Junggar Basin and Tarim Basin, resulting in a clear spatial distribution pattern that extends from northwest to southeast. The distribution of landscape vulnerability followed a similar pattern, with high-value regions clustering near the urban agglomeration in the northern slope of the Tianshan Mountain and the northern and southern Tarim Basin, while the low-value regions were scattered around the three mountains (Figure 4b1–b3).

The assessment of LUC in Xinjiang was conducted through a comprehensive approach involving the integration of complexity, vulnerability, and landscape fragmentation indices. By applying the natural break point method, supported by ArcGIS, the study area was categorized into mild conflicts area, moderate conflicts area, intense conflicts area, and severe conflicts area. The average LUC values of Xinjiang in 2000, 2010, and 2020 were 2.3673, 2.3276, and 2.3315, respectively, reflecting an overarching declining trend, with LUCI as a whole down 1.5123% (Table 2). The area of mild conflicts increased from 13.58% in 2000 to 14.35% in 2020, and the area of intense and above conflict areas decreased from 70.59% in 2000 to 69.74% in 2020, indicating that Xinjiang has embarked on addressing the issue of LUC over the past two decades, implementing effective mitigation measures. Severe conflict areas in Xinjiang were primarily distributed in the oasis areas along the northern foothills of the Tianshan Mountains and at the northern edge of the Tarim Basin during the study period. In contrast, intense conflict areas were prevalent in the vicinity of the Junggar Basin, Tarim Basin, and Tuha Basin, attributed to their relative landscape vulnerability despite lower levels of anthropogenic impact. Meanwhile, mild and moderate conflict areas were dispersed across regions marked by high-covered grasslands and woodlands surrounding the three mountains (Figure 4d1–d3). In general, from 2000 to 2020, the LUC in Xinjiang presented a spatial pattern of "strong conflicts around the three mountains and weak conflicts around the two basins", which was the result of the comprehensive impact of the regional geographic environment and human activities on the ecosystem.

4.2. Relationship between LUC and Key Drivers

By employing the Spearman correlation coefficient, we delved into the connection between LUCs and their driving factors, as illustrated in Figure 5a. As a whole, the correlation between LUCs and anthropogenic driving factors was stronger than that of natural driving factors. Notably, significant positive correlations were observed with POP, HII, HF, and GDP, while there were marked negative correlations with ELE and SLO. To further examine the degree of fit between LUCs and the drivers, we conducted a curve-fitting analysis through the mean values of LUCs and the key drivers for 2000, 2010, and 2020 (Figure 5b1–c7), and the results of the fitted curves showed a potential pattern between LUCs and the key drivers ($p < 0.01$). The correlation between LUCs and EVP, ERO, Water, Rail, Road, and Resident drivers showed a linear monotonic trend. However, not all relationships between LUCs and other factors were linear and the best-fit curve was significantly quadratic ($p < 0.05$). The fitted curves had significant Inverted U or U-shaped trends alongside monotonic relationships. In the study area, the fitted curves of LUCs with ELE, SLO, TEM, PRE, HII, and HF all exhibited a U-shaped pattern, whereas the fitted curves with GDP and POP were an Inverted U. This further indicates a nonlinear relationship between LUCs and natural and anthropogenic drivers.

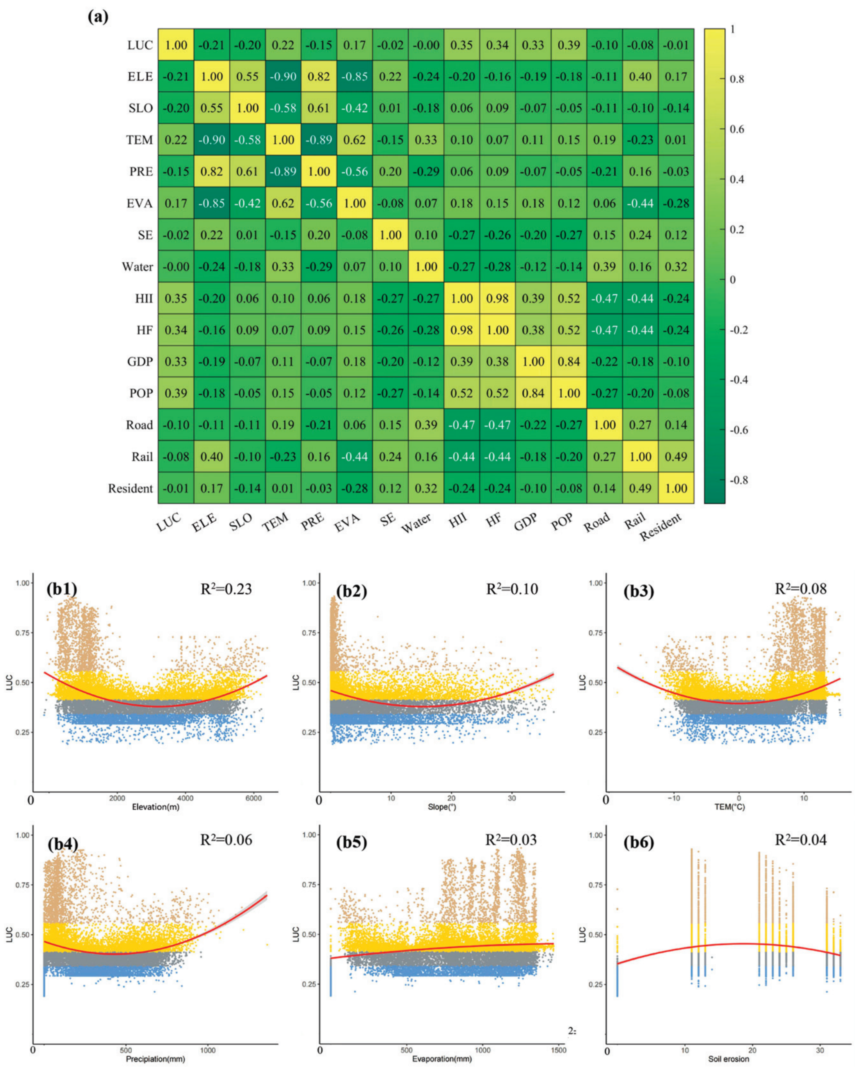

Figure 5. *Cont.*

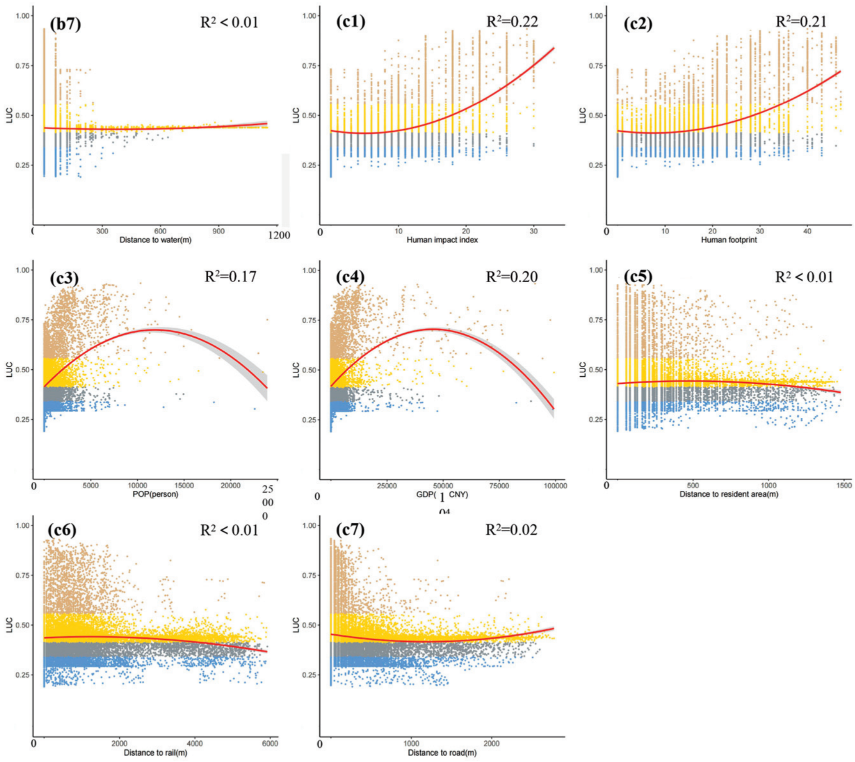

Figure 5. (**a**) Correlation analysis of LUC and its driving factors in Xinjiang from 2000 to 2020; (**b**) scatter plots of LUC versus different key drivers (**b1**–**c7**). The data used for curve fitting are averages for 2000, 2010, and 2020.

4.3. Thresholds of LUC

4.3.1. The Natural Key Drivers and Their Thresholds

The combination of LUC and natural driver correlation analysis and curve fitting showed that LUC had strong correlation with ELE and SLO, some correlation with TEM, PRE, and EVA climatic factors, and no correlation with distance from water. Figure 4 clearly illustrates that some driving factors have relatively small R^2 values, such as distance to water, distance to rail, and distance to resident ($R^2 < 0.01$). In our study, considering the suitability of RCS curves for polynomial regression with low R^2 values in the data [67,68], we ultimately selected natural drivers with relatively good fit ($R^2 > 0.1$) for RCS curve analysis to identify thresholds. The results show that the intensity of LUC varies greatly due to different elevations and slopes (Figure 5b1–b7). The smaller the slope and the flatter the terrain, the more severe the LUC intensity, i.e., low elevation and low slope areas are the key areas for LUC occurrence. Concerning the specific values of thresholds, in Xinjiang, areas with ELE < 2845 m and slope < 9° tend to have higher LUC (Figure 6a,b), and the trend of LUC change gradually slows down when ELE and slope exceed the thresholds.

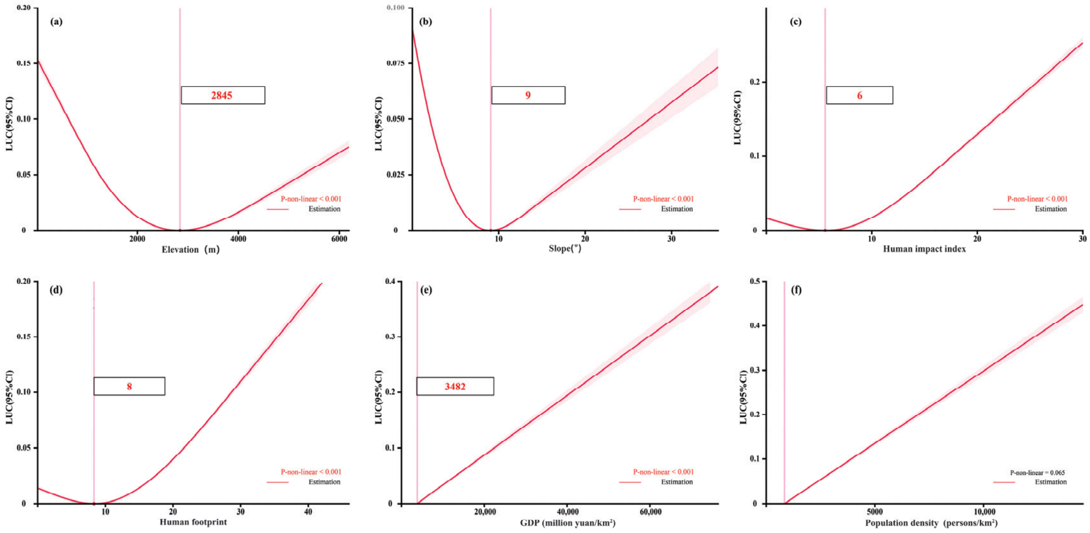

Figure 6. Restricted cubic splines for predicted LUC according to driving factors. (**a**) Elevation; (**b**) slope; (**c**) human impact index; (**d**) human footprint; (**e**) GDP; (**f**) population density.

4.3.2. The Anthropogenic Key Drivers and Their Thresholds

The combination of LUC and anthropogenic driver correlation analysis and curve fitting unveiled that LUC was positively correlated (albeit somewhat negatively correlated within the threshold range) with all anthropogenic drivers as a whole (Figure 5c1–c7). Among them, the highest correlation with LUC is with HII and HF, followed by POP and GDP, and weakly correlated with the distance to rail, road, and resident. LUC increases with the intensity of human activities and land-use intensity (Figure 6c–6f). Regarding the specific values of thresholds, LUC intensity gradually increases when HII exceeds 6 (Figure 6c). The LUC intensity gradually increases when HF exceeds 8 (Figure 6d).The effects of GDP and POP on the LUC are generally consistent. With the economic development and population growth, the LUC rises sharply. When GDP exceeds CNY 3482 million/km^2, the intensity of LUC gradually increases (Figure 6e). Although the R^2 >0.1 between LUC and POP, the two did not show a nonlinear relationship, i.e., the P for non-linear was 0.065 (Figure 6f), so the threshold was not significant.

In conclusion, the LUC in Xinjiang shows an environmental gradient effect, and the analysis of the RCS curve shows that the LUC and the driving factors such as ELE, SLO, HII, and HF show a "U-shaped" trend. With the increase in the driving altitude, the trend is decreasing and then increasing, but when the ELE exceeds 2845 m and the slope reaches about 9°, the increasing trend gradually slows down. From the relationship between LUC and HII and HF, LUC increases slowly at the beginning, but when HII exceeds 6 and HF exceeds 8, the increase speed is gradually accelerated. The LUC and GDP are in "L-shape", and when GDP exceeds CNY 3482 million/km^2, the LUC rises sharply.

4.4. Zoning of Land-Use Patterns Identified by Thresholds

Utilizing the identified thresholds, areas characterized by ELE $\leq$ 2845 m, Slope $\leq$ 9°, HII $\geq$ 6, HF $\geq$ 8, and GDP $\geq$ CNY 3482 million/km^2 were identified as potentially high-risk areas of land use (Table 3). Figure 7a,b show the spatial distribution of areas in Xinjiang that exceed the natural and anthropogenic thresholds for LUC, respectively. The natural thresholds for LUC are exceeded in most regions of Xinjiang, except for the central and southern fringe regions, which account for about 70% of the area of Xinjiang. The area exceeding the anthropogenic threshold for LUC accounts for about 12% of the area of Xinjiang, mainly distributed in the built-up areas of the four prefectures in the center and south. According to the four-quadrant diagram of Figure 1b, these threshold combinations were classified, and the resulting land-optimization zoning is shown in Figure 7c. Quantitatively (Figure 7d), the area ratio of moderate optimization zone is the largest, followed by elastic development zone, and the area ratio of urgent remediation area is the smallest; the key control area is the one that exceeds both the natural threshold and the anthropogenic threshold determined by the intersection area, with a cumulative area of 172,800 km^2, equivalent to about 10% of Xinjiang. In terms of spatial distribution, the key control area is mainly distributed in urban agglomeration in the northern slope of Tianshan Mountains and the agricultural development belt on the southern slope of Tianshan Mountain, including Urumqi metropolitan area, Kashgar urban area, Ili River Valley, Aksu Prefecture, etc., which are densely populated areas in Xinjiang where economic and social development are more centralized, these areas are all densely populated areas with more concentrated economic and social development in Xinjiang. The urgent remediation area is mainly distributed in the central cities of Xinjiang, such as Urumqi City, Khorgos City, Hami City, Kuqa county, etc. And the elastic development zone is mainly distributed in the fringe areas in the central and southern parts of Xinjiang, including the Altai Mountains, Tian Shan mountains, and Kunlun mountains, which are the three main areas of Xinjiang. The elastic development area is mainly distributed in the edge area of central and southern Xinjiang, including the Altai Mountains, Tian Shan mountains, and Kunlun mountains. The moderate optimization zone is mainly distributed around Junggar Basin, Turpan-Hami Basin, and Tarim Basin.

Table 3. Natural and anthropogenic thresholds used for identifying areas with potential high land-use risk.

Type	Drivers	Used Thresholds
Natural	Elevation (m)	≤-2845
	Slope (°)	≤9
Anthropogenic	Human influence index	≥6
	Human footprint	≥8
	GDP (million yuan/km^2)	≥3482

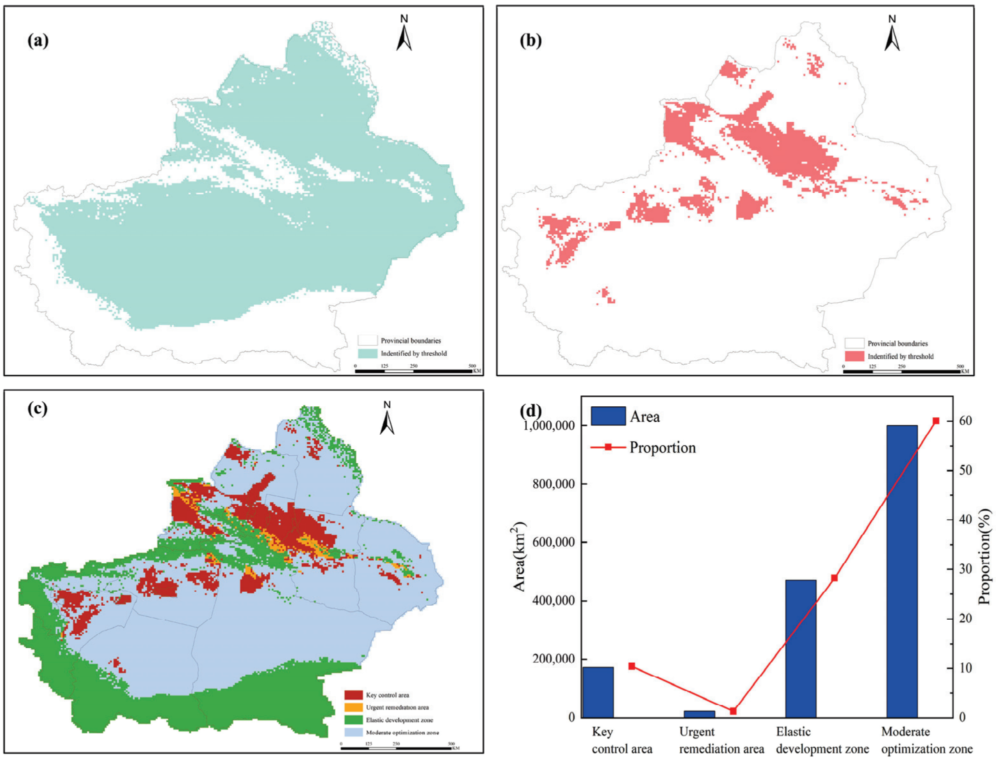

Figure 7. The potential LUC areas that are identified by threshold and pattern zoning. (**a**) Natural threshold; (**b**) anthropogenic threshold; (**c**) zoning of LUC pattern; (**d**) area and proportion.

5. Discussion

5.1. Critical Thresholds between LUC and Drivers

Our study provided a comprehensive analysis of the threshold identification of natural and anthropogenic drivers on the LUCs in Xinjiang, China. Overall, among the selected 14 drivers, factors such as elevation, human influence index, and human footprint were found to have significant impacts on LUCs, while factors like distance to water, resident, and rail had relatively smaller impacts. However, due to the regional variability of LUC, the influence of these drivers may vary across different areas [48,58]. This study shows that by considering these factors and using RCS, it is possible to determine thresholds between the various drivers of LUCs, substantiating the validity of the hypothesis proposed in Section 2.1. Within our investigation, we found the presence of pivotal impact thresholds among these drivers. Notably, the RCS spline function plot shows that, in terms of natural drivers, LUCs exhibit a decline as terrain slope increases, with the acceleration of LUCs subsiding when the ELE exceeds 2845 m and the slope reaches about 9° above; the increase in LUCs gradually slows down. This phenomenon may be explained by the fact that the oasis plain in the center concentrates most of the cropland and construction land in the study area, which is characterized by flatter terrain and relatively abundant water resources. The high coverage rate of cultivated land and the rapid expansion of construction land in this area inevitably contribute to a higher likelihood of LUCs. Consequently, the distinctive geomorphological characteristics of the study area play a crucial role in shaping the spatial pattern of LUCs, aligning with previous findings that highlight the significant negative influence of ELE on LUCs, with higher elevations corresponding to reduced intensity [19]. The preference for lower, flatter locales for urban development, industrial expansion, and agricultural utilization amplifies the demand for diverse land-use types, thereby compounding the challenges posed by LUCs in these areas [69]. Regarding anthropogenic drivers, LUCs increase with the increase in human influence, and gradually rise when HII exceeds 6, HF exceeds 8, and GDP exceeds CNY 3482 million/km^2. These findings are consistent with prior research demonstrating the positive correlation between population density and LUCs [70]. Furthermore, they support that social advancement contributes to the encroachment of land-use types [71]. Regions exhibiting high land-use change correspond to areas of intensified LUCs, a consequence of elevated human activities that induce significant fragmentation of landscape patches and pattern instability. These outcomes align with the conclusions of previous studies [9]. We also found that the risk of LUC is more pronounced in northern Xinjiang than in its southern counterpart. This is likely due to the substantial growth in regional economic co-operation over the past two decades, predominantly concentrated in the northern areas [72]. The rapid economic growth in the north has led to an increase in population and land for construction, accelerating the urbanization process. This, in turn, has resulted in the appropriation of the regional ecological land, thus exacerbating LUCs. In contrast, southern Xinjiang, characterized by challenging natural conditions and slower economic development, exhibits a relatively lower risk of LUCs. Once again, it shows that the spatial pattern of LUC is the result of a combination of natural and socio-economic factors, consistent with previous research [73]. Therefore, there is an imperative need to comprehensively consider the combination of multiple thresholds when delineating potential conflicts areas of land use. Therefore, we use RCS to explore the nonlinear characteristics of LUC in this paper, which can better reflect its nonlinear relationship and provide a new perspective for the previous research on the driving factors of LUC.

5.2. Optimal Zoning of Land-Use Pattern

In this study, a threshold detection method was employed to identify potential high-risk areas of land-use conflicts (LUCs), where changes in LUC intensity occur only when driving factors reach specific thresholds. Our threshold identification method, incorporating multiple natural and anthropogenic thresholds, effectively captures the dynamic processes of natural and anthropogenic drivers on LUC. To further validate the effectiveness of applying LUC thresholds, we compared the optimized land-use pattern zoning map (Figure 6d) with Xinjiang Uygur Autonomous Region Territorial Spatial Planning (2021–2035). As a guideline for national spatial development and a blueprint for sustainable development, the land spatial planning strictly adheres to the principles of the "Three zones and Three lines" (Three Zones represent ecological space, agricultural space, and urban space; Three Lines represent ecological conservation redline, permanent capital farmland, and urban development boundary) [53], aiming to rationalize land resource allocation, meet diverse human needs, and mitigate land-use conflicts. The comparison results demonstrate a high degree of consistency between the land-use pattern delineated by conflict thresholds and the land spatial development and protection pattern and "Three zones and Three lines." On one hand, the zoning pattern aligns closely with the overall pattern of "two belts, two rings, and three barriers". For instance, the "two belts" (agricultural development belts on the northern and southern slopes of the Tianshan Mountains) correspond to Key Control Areas, the "two rings" (two oasis ecological rings distributed along the Tarim Basin and Junggar Basin) correspond to Moderate Optimization Zones, and the "three barriers " (ecological barriers formed by the Altai Mountains, Tianshan Mountains, and Kunlun Mountains–Alataw Mountains) correspond to Elastic Development Zones. Additionally, Urgent Remediation Areas are primarily located within the planned urban centers, such as the central city of Urumqi and the sub-central city of Yining. On the other hand, overlaying the "three control lines" on the optimized land-use zoning map (Figure 6d) reveals extensive permanent basic farmland in Key Control Areas, where land-use conflicts primarily stem from competition between residential and agricultural land uses. Urgent Remediation Areas encompass most urban development boundaries, highlighting the conflict between human land demand and baseline constraints, necessitating urgent rectification. Elastic Development Zones contain large areas of ecological protection redlines, with concentrated distribution of woodland, grassland, and other ecological lands, posing relatively low risks of land-use conflicts and thus conducive to flexible development. In summary, the comparison with existing planning demonstrates the scientific validity of the land-use pattern optimization zoning based on thresholds. Moreover, this zoning approach complements planning schemes, particularly facilitating the validation or optimization of delineation outcomes.

5.3. Recommendations for Mitigating LUC through Pattern Zoning

Identifying potential high-risk areas becomes crucial for effectively warning against LUC and enabling decision makers to preemptively address risks. However, the geographical variations in the extent of LUC necessitate the implementation of differentiated policies and measures for land-use planning and management in Xinjiang. This targeted approach aims to address conflicts effectively and promote sustainable regional development. Based on the outcomes of the four types of zoning for land-use pattern optimization (Figure 8) and in alignment with current regional planning, the following recommendations are proposed:

(1) Key control area. The optimization suggestion for this region is a focus on control, emphasizing the need to reasonably manage city scale, promote the consolidation of inefficient construction land, enhance construction land-use efficiency, and optimize the spatial layout within the national territory. Taking the urban agglomeration in the northern slope of Tianshan Mountains as an example (Figure 8a), this area plays a pivotal role in supporting Xinjiang's economic growth. Policy and financial support should prioritize revitalizing existing land, strictly controlling construction land expansion, and implementing measures such as renovating the old city and optimizing land layouts in built-up areas. Simultaneously, strict protection of arable land and permanent basic farmland is crucial to maintain both quantity and quality.

(2) Urgent regulation area. The optimization suggestion for this region emphasizes the need for urgent regulation, vigilance against urban sprawl, and rational adjustment of land-use patterns for living, production, and ecology. Taking the Ili River Valley as an example (Figure 8b), with the implementation of the "Two Ho and Two yi" integration development

strategy, the regional population has increased, and the demand for land resources has increased, especially in Yining City and Horgos City as the two core cities in the region. The influence of human factors on land-use changes has deepened gradually, and the built-up areas of the cities will continue to spread outward, encroaching on the agricultural and ecological land in the vicinity of them. The urban built-up areas will continue to spread and expand outward, encroaching upon nearby agricultural and ecological land. Consequently, it becomes imperative to strictly enforce the restriction known as the "Three Zones and Three Lines" policy, which pertains to ecological, agricultural, and urban functions. The "three lines" consist of the permanent basic farmland, urban development boundary line, and ecological protection red line [53], to coordinate the arrangement of the three spaces, control the scale of urban expansion, reduce the load pressure on the land and ecological environment caused by overpopulation and overgathering, alleviate the pressure on the bearing of land resources, and promote the optimal matching of population size, economic development, and land resources in the region. Simultaneously, it becomes essential to control the direction of urban expansion and preserve the continuity and integrity of the remaining natural land. By doing so, the degradation of the ecosystem can be mitigated to some extent, facilitating sustainable socio-economic development.

(3) Elastic development zone. The optimization proposal for this region is elastic development, acting as a "blank zone" for transferring excess land-use demand to ensure regional land space security and stability. Mainly located near ecological barriers such as the Altai Mountains, Tianshan Mountains, and Kunlun Mountains, this region requires a stringent ecological protection system. Illustrated by Kashgar Prefecture (Figure 8c), strengthening ecological construction, protection, and conversion of farmland to forests can alleviate ecological pressures. This approach supports the development of cities, towns, and agriculture, maximizing ecological benefits for social and economic advancement.

(4) Moderate optimization zone. The optimization proposal for the land-use pattern in this region is to moderately optimize, coordinate, and harmonize agricultural land use, and control and slow down land sanding. This type of zone is predominantly distributed around Xinjiang's basins. Taking Bortala Mongol Autonomous Prefecture as an example (Figure 8d), the region is mainly a large homogeneous territory of arable land and waters, which can strengthen the development and transformation of barren and unutilized land, improve the utilization of land resources, and gradually change the land-use mode from rough to fine. At the same time, the region is an ecological protection zone, so it is necessary to reasonably avoid permanent basic farmland and the ecological protection red line, strengthen ecological monitoring, protect and repair ecological corridors, and reduce the crowding out of ecological and agricultural land by human development activities.

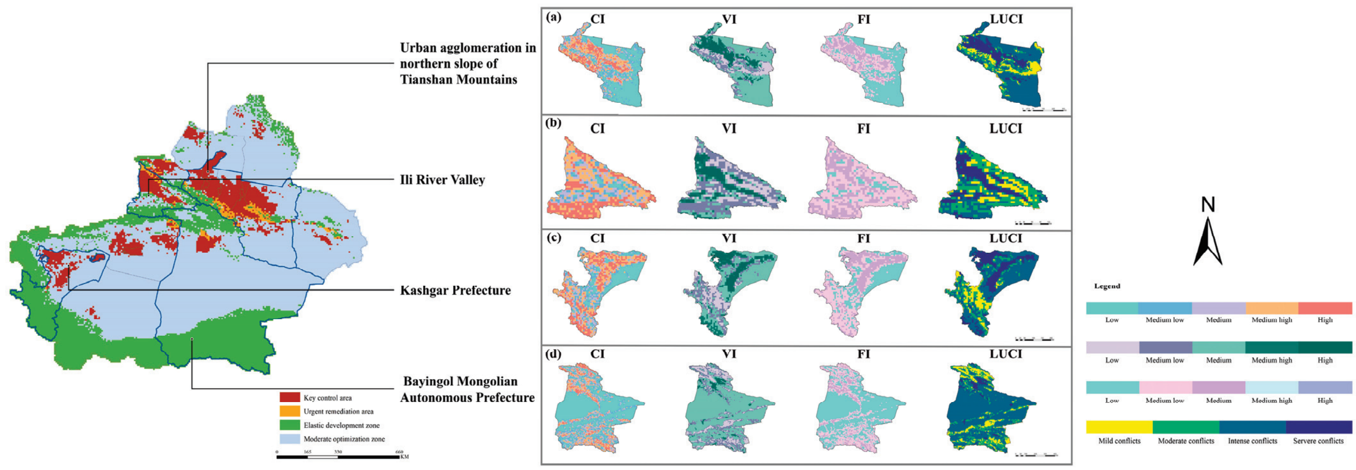

Figure 8. Land-use spatial optimization zone and typical cases in Xinjiang.

5.4. Limitations and Future Research Directions

While our study provides novel insights, we acknowledge several limitations that warrant consideration. Firstly, we evaluated the LUCs using a landscape ecological model, and although this method is currently a common method for LUC evaluation [25,48,49] and its effectiveness has been demonstrated by relevant studies [73], the method still has some limitations. For example, in addition to altering landscape patterns, LUC leads to the generation of social, economic, and ecological negative effects [3], and it is necessary to consider multiple dimensions in the assessment of LUCs. Secondly, our focus on constructing correlations between LUCs and the identified 14 drivers, while informative, may not capture the full array of influences contributing to LUCs. Land suitability, resource scarcity [17], and socio-economic elements such as urban expansion, policies, and institutions [23] play crucial roles in shaping LUCs. In Xinjiang, where water resources are intricately linked to land-use patterns [73], coupled with the region's developmental complexity and strategic importance, our study, regrettably, did not delve into the impact of water resources, policies, and historical factors. Additionally, while all driving factors may exhibit linear relationships with LUCs [26,73], our consideration was limited to nonlinear impacts, which could potentially affect the research outcomes. Future research endeavors should strive for a more comprehensive inclusion of these factors, ensuring a holistic understanding of the key drivers of LUCs in Xinjiang. Moreover, our study, while providing a valuable perspective on delineating potential LUC areas, does not prescribe specific development and protection strategies for these identified conflict zones. Addressing this gap requires refining and expanding our recommendations in future research endeavors. In forthcoming studies, we plan to explore the nonlinear relationships of additional factors, including policies, history, and institutions, on LUCs. Our intention is to integrate the thresholds of both natural and anthropogenic drivers into land-use monitoring practices. By doing so, we aim to enhance the precision of our control suggestions for potential conflict zones, contributing to effective mitigation strategies for regional LUCs.

6. Conclusions

In conclusion, this study employed a comprehensive LUC analysis framework and a threshold application model to quantitatively assess LUCs in Xinjiang, China, spanning the period from 2000 to 2020. Spatial and temporal patterns of LUCs were analyzed, and correlation analyses and RCS curves were employed to identify key natural and anthropogenic drivers as well as critical thresholds affecting LUCs. Incorporating the results of conflicts threshold recognition, this study applied a four-quadrant method to partition the LUC pattern. Differentiated land comprehensive regulation strategies were subsequently proposed based on this partitioning. This study revealed a distinct spatial pattern of LUCs in Xinjiang, characterized by "strong conflicts around the three mountains and weak conflicts around the two basins." Significantly, the extent of LUCs exhibited a noticeable mitigation trend from 2000 to 2020. The application of RCS proved effective in capturing the nonlinear effects of both natural and anthropogenic drivers on LUCs, unveiling critical thresholds such as ELE (2845 m), slope (9°), human influence index (6), human footprint (8), and Gross Domestic Product (CNY 3482 million/ km^2). Furthermore, based on threshold recognition results, the land-use pattern in Xinjiang was categorized into key control areas, urgent remediation areas, elastic development zones, and moderate optimization zones. Notably, key control areas were predominantly situated in urban agglomeration in the northern slope of Tianshan Mountains and the south slope of the Tianshan agricultural development belt, constituting approximately 10% of Xinjiang's total area. This study introduces an innovative and pragmatic framework for identifying potential LUC areas, particularly in response to evolving natural and anthropogenic conditions. The identified potential LUCs serve as early warning indicators for land-use planning, contribute valuable information for spatial development initiatives, and guide the comprehensive integration and zoning of land use in Xinjiang, China.

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References

1. Stanley, T.A.; David, N.B.; Keith, W.; Kristen, C.N. Diagnostic reframing of intractable environmental problems: Case of a contested multiparty public land-use conflict. *J. Environ. Manag.* **2012**, *108*, 108–119.
2. Andrew, J.S. Potential application of mediation to land use conflicts in small-scale mining. *J. Clean. Prod.* **2003**, *11*, 117–130. [CrossRef]
3. Wang, C.; Wang, H.; Wu, J.; He, X.; Luo, K.; Yi, S. Identifying and warning against spatial conflicts of land use from an ecological environment perspective: A case study of the Ili River Valley, China. *J. Environ. Manag.* **2024**, *351*, 119757. [CrossRef] [PubMed]
4. Hong, W.; Guo, R.; Wang, W. A diagrammatic method for the identification and resolution of urban spatial conflicts. *J. Environ. Manag.* **2022**, *316*, 115297. [CrossRef] [PubMed]
5. 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**, *780*, 637–638. [CrossRef] [PubMed]
6. Bertinelli, L.; Strobl, E.; Zou, B. Economic development and environmental quality: A reassessment in light of nature's self. *Ecol. Econ.* **2008**, *66*, 371–378. [CrossRef]
7. Yang, R.; Liu, Y.; Long, H. The study on non-agricultural transformation coevolution characteristics of "population-land-industry": Case study of the Bohai Rim in China. *Geogr. Res.* **2015**, *34*, 475–486.
8. de Groot, R. Function-analysis and valuation as a tool to assess land use conflicts in planning for sustainable, multi-functional landscapes. *Landsc. Urban Plan.* **2006**, *75*, 175–186. [CrossRef]
9. Li, S.; Zhao, X.; Pu, J.; Miao, P.; Wang, Q.; Tan, K. Optimize and control territorial spatial functional areas to improve the ecological stability and total environment in karst areas of Southwest China. *Land Use Pol.* **2021**, *100*, 104940. [CrossRef]
10. Zhou, D.; Xu, J.; Lin, Z. Conflict or coordination? Assessing land use multi-functionalization using production-living-ecology analysis. *Sci. Total Environ.* **2016**, *577*, 136–147. [CrossRef]
11. Zou, L.; Liu, Y.; Wang, J.; Yang, Y.; Wang, Y. Land use conflict identification and sustainable development scenario simulation on China's southeast coast. *J. Clean. prod.* **2019**, *238*, 117899. [CrossRef]
12. Shan, L.; Yu, A.T.W.; Wu, Y. Strategies for risk management in urban-rural conflict: Two case studies of land acquisition in urbanizing China. *Habitat Int.* **2017**, *59*, 90e100. [CrossRef] [PubMed]
13. Yu, A.T.W.; Wu, Y.; Zheng, B.; Zhang, X.; Shen, L. Identifying risk factors of urban-rural conflict in urbanization: A case of China. *Habitat Int.* **2014**, *44*, 177–185. [CrossRef]
14. Godschalk, D.R. Land use planning challenges: Coping with conflicts in visions of sustainable development and livable communities. *J. Am. Plan. Assoc.* **2004**, *70*, 5–13. [CrossRef]
15. Zhang, Y.; Long, H.; Tu, S.; Ge, D.; Ma, L.; Wang, L. Spatial identification of land use functions and their tradeoffs/synergies in China: Implications for sustainable land management. *Ecol. Ind.* **2019**, *107*, 105550. [CrossRef]
16. Zhang, Y.; Hu, Y.; Zhang, B.; Li, Y.; Zhang, X.; Xie, Y. Conflict between nature reserves and surrounding communities in China: An empirical study based on a social and ecological system framework. *Glob. Ecol. Convers.* **2020**, *21*, e00804. [CrossRef]
17. Yu, B.; Lv, C. The progress and prospect of land use conflicts. *Prog. Geogr.* **2006**, *25*, 106–115.
18. Wang, J.; Liu, X. Recognizing and measuring spatial conflict of land use via "risk-effect". *Trans. Chin. Soc. Agric. Eng.* **2022**, *38*, 291–300.
19. Zhou, D.; Lin, Z.; Lim, S. Spatial characteristics and risk factor identification for land use spatial conflicts in a rapid urbanization region in China. *Environ. Monit. Assess.* **2019**, *191*, 677.1–677.22. [CrossRef]
20. Henderson, S.R. Managing land-use conflict around urban centres: Australian poultry farmer attitudes towards relocation. *Appl. Geogr.* **2005**, *25*, 97–119. [CrossRef]
21. Brown, G.; Raymond, C.M. Methods for identifying land use conflict potentialusing participatory mapping. *Landsc. Urban Plann.* **2014**, *122*, 196–208. [CrossRef]
22. Dominika, M.; Katarzyna, Z. Land-use conflicts and the common agricultural policy: Evidence from Poland. *Land Use Pol.* **2018**, *73*, 423–433.

23. Campbell, D.J.; Gichohi, H.; Mwangi, A.; Chege, L. Land use conflict in kajiado district, Kenya. *Land Use Pol.* **2000**, *17*, 337–348. [CrossRef]
24. Tian, J.; Wang, B.; Wang, S. The paradigms and main content of land use conflict research. *Resour. Sci.* **2023**, *45*, 465–479. [CrossRef]
25. Ma, W.; Jiang, G.; Chen, Y.; Qu, Y.; Zhou, T.; Li, W. How feasible is regional integration for reconciling land use conflicts across the urban-rural interface? —Evidence from Beijing-Tianjin-Hebei metropolitan region in China. *Land Use Pol.* **2020**, *92*, 104433. [CrossRef]
26. 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. A scenario-based study in the Beijing-Tianjin-Hebei region, China. *J. Environ. Manag.* **2021**, *296*, 113168. [CrossRef] [PubMed]
27. Álvarez De Andrés, E.; Fernández Güell, J.M.; Smith, H. Instruments for analysing urban conflicts in the global south: The case of urban transformation processes in Dakar. *Habitat Int.* **2015**, *49*, 187–196. [CrossRef]
28. Chitonge, H.; Mfune, O. The urban land question in Africa: The case of urban land conflicts in the City of Lusaka, 100 years after its founding. *Habitat Int.* **2015**, *48*, 209–218. [CrossRef]
29. Cieslak, I. Identification of areas exposed to land use conflict with the use of multiple-criteria decision-making methods. *Land Use Pol.* **2019**, *89*, 104225. [CrossRef]
30. Lara, L.; Ahlin, C. Restricted cubic splines for modelling periodic data. *PLoS ONE* **2020**, *15*, e0241364.
31. Akshay, K.; Ammothum, K.; Eddie, W.; Bálint, A.; Peter, B.; Jolla, K. Curvature Constrained Splines for DFTB Repulsive Potential Parametrization. *J. Chem. Theory Comput.* **2021**, *17*, 1771–1781.
32. Aris, P.; Willi, S.; Michal, A.; Matthias, S. A review of spline function procedures in R. *BMC Medical Res. Methodol.* **2019**, *19*.
33. Xu, C.; Chen, Y.; Yang, Y.; Hao, X.; Shen, Y. Hydrology and water resources variation and its response to regional climate change in Xinjiang. *J. Geogr. Sci.* **2010**, *20*, 599–612. [CrossRef]
34. Liu, Y.; Yuan, X.; Li, J.; Qian, K.; Yan, W.; Yang, X.; Ma, X. Trade-offs and synergistic relationships of ecosystem services under land use change in Xinjiang from 1990 to 2020: A Bayesian network analysis. *Sci. Total Environ.* **2023**, *858*, 160015. [CrossRef]
35. Ishida, K.; Ohara, N.; Ercan, A.; Jang, S.; Trinh, T.; Kavvas, M.L.; Carr, K.; Anderson, M.L. Impacts of climate change on snow accumulation and melting processes over mountainous regions in Northern California during the 21st century. *Sci. Total Environ.* **2019**, *685*, 104–115. [CrossRef] [PubMed]
36. Zhou, C.; Wang, S.; Wang, J. Examining the influences of urbanization on carbon dioxide emissions in the Yangtze River Delta, China: Kuznets curve relationship. *Sci. Total Environ.* **2019**, *675*, 472–482. [CrossRef]
37. Evans, G.W.; Kantrowitz, E. Socioeconomic status and health: The potential role of environmental risk exposure. *Annu. Rev. Publ. Health.* **2002**, *23*, 303–331. [CrossRef]
38. Fan, J. The scientific foundation of major function oriented zoning in China. *Acta Geogr. Sin.* **2007**, *62*, 339–350. [CrossRef]
39. Liu, H.; Willems, P.; Bao, A.; Wang, L.; Chen, X. Effect of climate change on the vulnerability of a socio-ecological system in an arid area. *Glob Planet Chang.* **2016**, *137*, 1–9. [CrossRef]
40. Fu, B.; Zhang, L. Land-use change and ecosystem services: Concepts, methods and progress. *Prog. Phys. Geogr.* **2014**, *33*, 441–446.
41. Chi, Y.; Liu, D.; Wang, J.; Wang, E. Human negative, positive, and net influences on an estuarine area with intensive human activity based on land covers and ecological indices: An empirical study in Chongming Island, China. *Land Use Pol.* **2020**, *99*, 104846. [CrossRef]
42. Huimin, L. The impact of human behavior on ecological threshold: Positive or negative? Grey relational analysis of ecological footprint, energy consumption and environmental protection. *Energy Policy* **2013**, *56*, 711–719. [CrossRef]
43. Cieślak, I. Spatial conflicts: Analyzing a burden created by differing land use. *Acta Geogr. Sin.* **2019**, *59*, 44–57. [CrossRef]
44. Von der Dunk, A.; Grêt-Regamey, A.; Dalang, T.; Hersperger, A.M. Defining a typology of peri-urban land-use conflicts—A case study from Switzerland. *Landsc. Urban Plann.* **2011**, *101*, 149–156. [CrossRef]
45. Zong, S.; Hu, Y.; Bai, Y.; Guo, Z.; Wang, J. Analysis of the distribution characteristics and driving factors of land use conflict potentials in the Bohai Rim coastal zone. *Ocean Coast. Manag.* **2022**, *226*, 106260. [CrossRef]
46. Dietz, K.; Engels, B. Analysing land conflicts in times of global crises. *Geoforum* **2020**, *111*, 208–217. [CrossRef]
47. Wang, Y.; Li, W.; Zeng, X.; Li, P.; Xue, B. The spatial multi-scale mechanism of land use elemental conflicts in Shenyang economic zone. *Econ. Geogr.* **2022**, *42*, 231–239.
48. Zhou, G.; Peng, J. The evolution characteristics and influence effect of spatial conflict: A case study of Changsha-Zhuzhou-Xiangtan urban agglomeration. *Prog. Phys. Geogr.* **2012**, *31*, 717–723.
49. Peng, J.; Zhou, G.; Tang, C.; He, Y. The analysis of spatial conflict measurement in fast urbanization region based on ecological security: A case study of Changsha-Zhuzhou-Xiangtan urban agglomeration. *Agric. Nat. Resour.* **2012**, *27*, 1507–1519.
50. Gao, F.; Zhang, Y.; Chen, Q.; Wang, P.; Yang, H.; Yao, Y.; Cai, W. Comparison of two long-term and high-resolution satellite precipitation datasets in Xinjiang, China. *Atmos. Res.* **2018**, *212*, 150–157. [CrossRef]
51. Zhang, F.; Kung, H.; Johnson, V.C. Assessment of land-cover/land-use change and landscape patterns in the two national nature reserves of Ebinur Lake Watershed, Xinjiang, China. *Sustainability* **2017**, *9*, 724. [CrossRef]
52. Zhao, R.; Chen, Y.; Shi, P.; Zhang, L.; Pan, J.; Zhao, H. Land use and land cover change and driving mechanism in the arid inland river basin: A case study of Tarim River, Xinjiang, China. *Environ. Earth Sci.* **2013**, *68*, 591–604. [CrossRef]
53. Wang, Y.; Fan, J.; Zhou, K. Territorial function optimization regionalization based on the integration of "double evaluation". *Geogr. Res.* **2019**, *38*, 2415–2429.

54. Liu, Q.; Yang, Z.; Wang, C.; Han, F. Temporal-spatial variations and influencing factor of land use change in Xinjiang, central Asia, from 1995 to 2015. *Sustainability* **2019**, *11*, 696. [CrossRef]
55. Chen, L. Study on the predicament in boundary exclusion and cross- border linkage mechanism of regional governance of the urban agglomeration. *Inn. Mong. Soc. Sci.* **2019**, *40*, 55–62.
56. Wang, Z.; Yang, Q.; Li, J.; Wang, Y., Shixuan; Yang, H. Optimization strategy of rural settlement layout in mountainous urban fringe area: A case study of Sichuan Town in Yubei District of Chongqing. *Econ. Geogr.* **2019**, *39*, 182–190.
57. Jiang, S.; Meng, J.; Zhu, L. Spatial and temporal analyses of potential land use conflict under the constraints of water resources in the middle reaches of the Heihe River. *Land Use Pol.* **2020**, *97*, 104773. [CrossRef]
58. Jiang, S.; Meng, J. Process of land use conflict research: Contents and methods. *Arid. Land Geogr.* **2021**, *44*, 877–887.
59. Hu, S.; Cheng, Q.; Wang, L.; Xie, S. Multifractal characterization of urban residential land price in space and time. *Appl. Geogr.* **2012**, *34*, 161–170. [CrossRef]
60. Liao, L.; Dai, W.; Chen, J.; Huang, W.; Jiang, F.; Hu, Q. Spatial conflict between ecological-production-living spaces on Pingtan Island during rapid urbanization. *Resour. Sci.* **2017**, *39*, 1823–1833.
61. Fearnhead, P.; Rigaill, G. Change point detection in the presence of outliers. *J. Am. Stat. Assoc.* **2019**, *114*, 169–183. [CrossRef]
62. Tang, B.; He, H. A local density-based approach for outlier detection. *Neurocomputing* **2017**, *241*, 171–180. [CrossRef]
63. Chen, W.; Gu, T.; Zeng, J. Urbanisation and ecosystem health in the Middle Reaches of the Yangtze River urban agglomerations, China: A U-curve relationship. *J. Environ. Manag.* **2022**, *318*, 115565. [CrossRef] [PubMed]
64. Dahlgren, J.P.; García, M.B.; Ehrl'en, J. Nonlinear relationships between vital rates and state variables in demographic models. *J. Ecol.* **2011**, *92*, 1181–1187. [CrossRef] [PubMed]
65. Bhaskaran, K.; dos-Santos-Silva, I.; Leon, D.A.; Douglas, I.J.; Smeeth, L. Association of BMI with overall and cause-specific mortality: A population-based cohort study of 3.6 million adults in the UK. *Lancet Diabetes Endo.* **2018**, *6*, 944–953. [CrossRef] [PubMed]
66. Li, D.; Cao, W.; Dou, Y.; Wu, S.; Liu, J.; Li, S. Non-linear effects of natural and anthropogenic drivers on ecosystem: Services: Integrating thresholds into conservation planning. *J. Environ. Manag.* **2022**, *321*, 116047. [CrossRef]
67. Stone, C.J. generalized additive models: Comment. *Stat. Sci.* **1986**, *1*, 312–331. [CrossRef]
68. Fong, Y.; Huang, Y.; Gilbert, P.B.; Permar, S. chngpt: Threshold regression model estimation and inference. *BMC Bioinf.* **2017**, *18*, 454. [CrossRef] [PubMed]
69. Huang, C.; Huang, X.; Peng, C.; Zhou, Z.; Teng, M.; Wang, P. Land use/cover change in the Three Gorges Reservoir area, China: Reconciling the land use conflicts between development and protection. *Catena* **2021**, *175*, 388–399. [CrossRef]
70. Jang, S.; Meng, J.; Zhu, L.; Cheng, H. Spatial-temporal pattern of land use conflict in China and its multilevel driving mechanisms. *Sci. Total Environ.* **2021**, *801*, 149697. [CrossRef]
71. Zhou, C.; Jin, W.; Zhang, G.; Li, M. Spatio-temporal characteristics and influencing factors of state-owned construction land supply in China. *Acta Geogr. Sin.* **2019**, *74*, 16–31.
72. Han, C.; Zheng, J.; Guan, J.; Yu, D.; Lu, B. Evaluating and simulating resource and environmental carrying capacity in arid and semiarid regions: A case study of Xinjiang, China. semiarid regions: A case study of Xinjiang, China. *J. Clean. Prod.* **2022**, *338*, 130646. [CrossRef]
73. Guo, H.; Ling, H.; Xu, H.; Guo, B. Study of suitable oasis scales based on water resource availability in an arid region of China: A case study of Hotan River Basin. *Environ. Earth Sci.* **2016**, *75*, 984. [CrossRef]

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Dynamics of the Oasis–Desert–Impervious Surface System and Its Mechanisms in the Northern Region of Egypt

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Abstract: Arid oasis ecosystems are susceptible and fragile ecosystems on Earth. Studying the interaction between deserts, oases, and impervious surfaces is an essential breakthrough for the harmonious and sustainable development of people and land in drylands. Based on gridded data such as land use and NDVI, this article analyzes the interaction characteristics between oases, deserts, and impervious surfaces in northern Egypt and examines their dynamics using modeling and geographic information mapping methods. The results show the following: In terms of the interaction between deserts and oases, the primary manifestation was the expansion of oases and the reduction of deserts. During the study period, the oases in the Nile Delta and Fayoum District increased significantly, with the area of oases in 2020 being 1.19 times the area in 2000, which shows a clear trend of advance of people and retreat of sand. The interaction between oases and impervious surfaces was mainly observed in the form of the spread of impervious surfaces on arable land into oases. During the study period, the area of impervious surfaces increased 2.32 times. The impervious surface expanded over 1903.70 km^2 of arable land, accounting for 66.67% of the expanded area. The central phenomenon between the impervious surface and the desert was the encroachment of the covered area of the impervious surface into the desert, especially around the city of Cairo. Population growth and urbanization are the two central drivers between northern Egypt's oases, deserts, and impervious surfaces. The need for increased food production due to population growth has forced oases to move deeper into the desert, and occupation of arable land due to urbanization has led to increasing pressure on arable land, creating a pressure-conducting dynamic mechanism. Finally, countermeasures for sustainable regional development are suggested.

Keywords: desert; oasis; northern Egypt; interaction characterization; dynamical mechanisms

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1. Introduction

Oases are natural geographical landscapes found in dry areas around the world. On a global scale, oases are mainly distributed in the middle and low latitudes controlled by subtropical high pressure, where there is little rainfall, the climate is dry, and the habitat is fragile, and it is the world's leading distribution area of deserts. Since the 1970s, environment and development have become two significant issues of concern to the international community, and the interrelationship between population, environment, and development in drylands has received considerable attention [1]. Oasis formation and desertification are the two most fundamental geographical processes in dryland zones [2]. With a deeper understanding of global terrestrial ecosystems and sustainable development, land use, and terrestrial desertification in dry areas, the development of oases has received significant attention from scientists at home and abroad [3]. Oases are mainly the result of a combination of anthropogenic factors in dry areas disturbed by human activities and natural factors aimed at increasing the productivity of the land [4]. Oasis formation directly manifests environmental change in drylands and positively stabilizes oases, preventing desertification and maintaining ecological stability [5]. Among other things, Sun et al. [6]

investigated the spatial and temporal patterns, structural changes, and their causes of oases in the Shule River Basin from 1975 to 2020, based on Landsat series data and a combination of object-oriented random forests and visual interpretation methods. Sun et al. [7] analyzed the relationship between the expansion of arable land and the ability of vegetation to sequester carbon within the oasis, using the Weiku Oasis in Xinjiang as the study area. Liu et al. [8] used a coupled deep learning model to simulate the value of ecological services in the Wuwei arid oasis in the next ten years and analyzed the driving factors. The process of mutual transformation between oasis and desert has essential functions, such as preventing the spread of deserts, maintaining the ecological security of oases, and occupying a special status in the dry zone [9,10]. For oases, desertification is characterized by poor water quality, severe soil salinization, the destruction of vegetation cover, and limitations on ecosystem productivity [11]. In particular, in the last hundred years, due to the unique water, soil, and gas conversion processes and the intervention of human activities on the oasis in the dry zone, the changes in the transition zone between the oasis and the desert have been particularly highlighted [12]. At the same time, the oasis is the most critical activity site for human production and life in the dry zone, and human activities disrupt the development of the oasis to some extent. Some scientists have also conducted extensive research on this topic, including Yin et al. [13], who analyzed the expansion of construction land in Urumqi, an oasis city in Li, based on three Landsat remote sensing images from 2000, 2010, and 2018. Zhang et al. [14] used dynamic change, focal point, and coordination analysis to examine the relationship between urban expansion and people–land coordination in 13 cities in Xinjiang, China. Pai et al. [15] selected two typical oasis cities, Urumqi and Kashgar, and studied the changes between the development of oasis cities and the ecological environment. However, few scientists have studied the small-scale interaction in typical oasis–desert–impervious surface systems and their pressure-transmitting dynamic mechanism.

The delta region is a vital oasis ecosystem that provides an essential source of fresh water and food for a growing population [16]. The Nile Delta and Fayoum District are typical dry-zone oases that occupy an important position in global oasis research, and the rich water resources and fertile sediments of the Nile Delta, as well as the favorable transportation conditions, have had a significant impact on Egypt's agriculture, economy, culture and religion [17]. The Nile Delta accounts for only 3% of Egypt's land area but is home to more than 90% of Egypt's population, living in the fertile lands along the Nile and the Nile Delta, the birthplace of ancient Egyptian civilization [18]. The Nile Delta accounts for about two-thirds of Egypt's total arable land, and it is the center of Egypt's agricultural production and an area that has been subject to very significant changes due to human activities [19]. With this in mind, this article analyzes the interaction characteristics of the oasis–desert–impervious surface system in northern Egypt. It examines the dynamics and mechanisms using the modeling and geomorphological information mapping methods to provide a basis for optimizing human–land relationships in drylands and the sustainable development of the region. The purpose of this study was to (1) characterize the spatial and temporal evolution of deserts, oases, and impervious surfaces in northern Egypt from 2000 to 2020; (2) analyze the characteristics of deserts, oases, and impervious surfaces in the northern region of Egypt from 2000 to 2020 using geomorphological information mapping; and (3) explore the dynamics of oasis–desert–impervious surface interaction in northern Egypt.

2. Methods and Data

2.1. Study Area

The northern part of Egypt was selected as the study area, which is located between 28°51′~33°7′ E longitude and 28°27′~31°35′ N latitude (Figure 1). The northern region of Egypt is mainly dominated by the Nile Delta, characterized by solid sunlight; abundant water; flat terrain; fertile land; and a Mediterranean climate with hot, dry summers and mild, rainy winters. Cairo is located in the delta, which has one of Egypt's highest population densities and numbers. The spread of agriculture has not only impacted the Egyptian desert, but the eastward expansion of Cairo's cities has further exacerbated environmental problems. Many of the Egyptian government's desert restoration programs have been implemented over the past 50 years in response to increasing food shortages and urban population density [20].

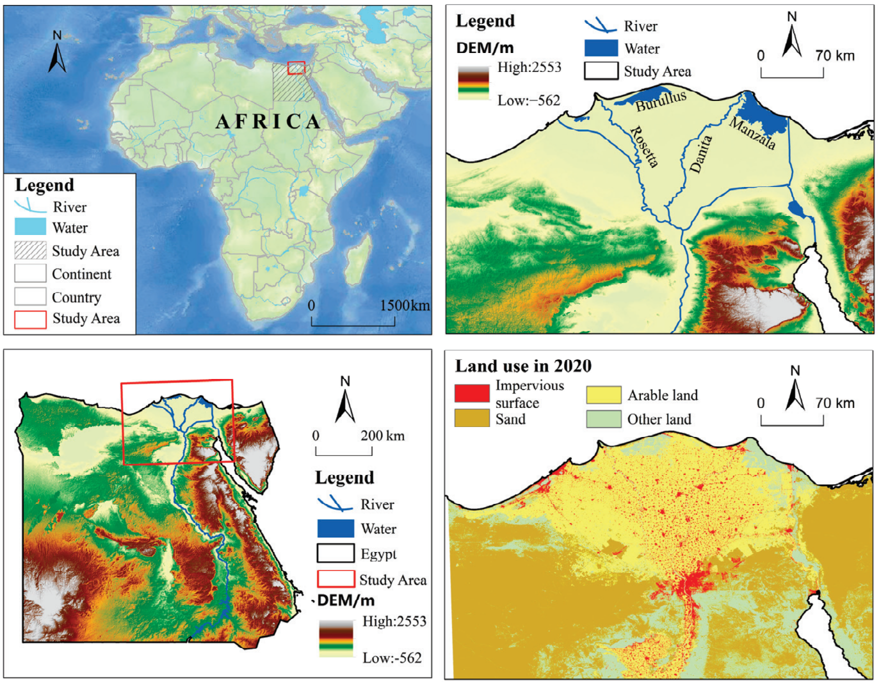

Figure 1. Scope of the study area (produced based on the base map of a standard map with the Remote Sensing and Geographic Information Cloud Service Platform website. (https://engine.piesat.cn/dataset-list (accessed on 5 December 2023)). No modifications were made to the base map, the same for maps at the bottom.

2.2. Methodology

2.2.1. Model Analysis Method

(a) Single land use dynamics: Single land use dynamics is the frequency of changes in land types over time, quantified using land use dynamics [21,22]. The formula is as follows:

$$N = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%$$

In the above formula, N is the annual rate of change of a land use type in the study area, and U_a and U_b are the areas of land use types at the beginning and the end of the study period; the larger the N is, the more the land type is converted out, and the greater the relative degree of change is. T is the study period $\mathrm{t_b} - \mathrm{t_a}$ in years.

(b) Comprehensive land use dynamics: Comprehensive land use dynamics are used to reflect changes in the overall land use in the study area [23]. The formula is as follows:

$$LC = \frac{\sum_{i=1}^{n} \Delta LU_{i-k}}{2\sum_{i=1}^{n} LU_i} \times \frac{1}{T} \times 100\%$$

In the above formula, LC is the combined land use dynamics; $\Delta LU_{i\text{-}j}$ is the absolute value of the area of land use type I that was converted to land use type j during the study period; LUi is the area of land use type I in the initial period; T is the study period $\mathrm{t_b} - \mathrm{t_a}$ in years.

(c) Land use transfer matrix: Land use transfer matrices can not only quantify the transformation between different land use types but also reveal the rate of transfer between different land use types [24]. The formula is as follows:

$$K = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1\mathrm{n}} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix}$$

In the above formula, K is the area of the initial land use type converted to the terminal land use type; n is the number of land use types; in the transfer matrix, the rows are the initial land use types, and the columns are the terminal land use types.

2.2.2. Methods for Analyzing Geographical Information Mapping

Geographic information mapping is a geospatial–temporal composite analysis method that can simultaneously express spatial structural features and practice dynamic changes [25]. The map has the dual nature of graph and spectrum; graphrepresents the spatial location characteristics, and spectrumrepresents the process change information; the combination of map and spectrum and analysis can solve the complex problem of spatial and process integration research. The mapping unit is the basic unit of the geological information map, which contains information about the spatial variability of geographical units and phenomena, as well as information about the temporal changes of geographical processes, and it represents a combination of geographical and temporal units with internal homogeneous characteristics [26]. Based on raster data, geographic information system (GIS), and spatial analysis methods, impervious surfaces and arable land areas in the study area were extracted, and change information on impervious surfaces and arable land areas was determined.

2.3. Data Source

The primary data sources used were land use/cover data, digital elevation model (DEM) data, roads, water systems, etc. (Table 1), and some vector data were obtained by vectorization based on the literature. Among others, the land use data were derived from the Global 30 m Land Cover Change Dataset from 1985 to 2020 (GLC_FCS30D) [27], developed by Liu Liangyun's group, which has an overall accuracy of 80.88% for land cover types. Land use types were categorized into arable land, impervious land, sand, and other land use types based on ArcGIS 10.8 software, which is the version released in 2020 by ESRI Corporation of United States (Redlands, CA, USA). The space reference was GCS_WGS_1984.

Table 1. Information about the different types of data used in this study.

Data Name	Source	Resolution
Land-use/cover change raster data for 2000 and 2020	https://essd.copernicus.org/articles/16/1353/2024/ [27] (accessed on 28 December 2023)	90 m
Digital elevation model data	https://download.gebco.net (accessed on 31 December 2022)	30 m
Water systems and global continental boundary data	https://gaohr.win/site/blogs/2017/2017-04-18-GIS-basic-data-of-China.html (accessed on 15 April 2024)	1:1,000,000
Normalized difference vegetation index	https:/www.earthdata.nasa.gov (accessed on 16 July 2024)	250 m
Vector data	https://engine.piesat.cn/dataset-list (accessed on 5 December 2023)	1:1,000,000

3. Results

3.1. Characterization of Oasis–Desert–Impervious Surface Interaction Dynamics in Northern Egypt

3.1.1. Oasis–Desert–Impervious Surface Mass Structure Change

Significant changes were found in land types in northern Egypt from 2000 to 2020. The largest area is sand, which accounts for about 50 percent of the total study area, followed by more extensive arable land and a smaller proportion of impervious surfaces. The northern region of Egypt is flat and fertile, and long-term stable water sources provide unique conditions for agriculture. In 2010, the arable land reached a maximum of 28,900 km^2, and then, with the strong population growth, which puts pressure on arable land and natural resources, the arable land decreased, and the overall arable land growth in the northern part of the Egyptian region was reduced to 2.5 percent. Egypt is a typical arid zone with many sand areas and scarce water resources, and the area of sand has decreased from 53,400 km^2 to 50,500 km^2, indicating a decrease of 2900 km^2, which corresponds to 5.34%. Impervious surfaces have expanded with the increase in population, and the area has increased by 2900 km^2, up to 2.3 times (Figure 2).

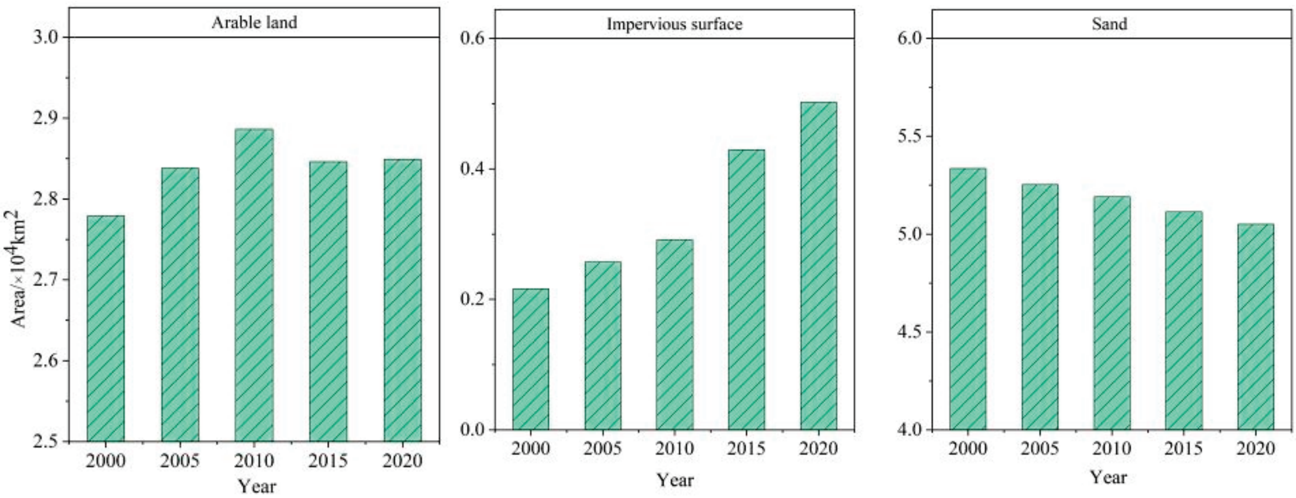

Figure 2. Statistical map of changes in the area of arable land–impervious surface–sand in the northern region of Egypt from 2000 to 2020.

3.1.2. Basic Characteristics of the Oasis–Desert–Impervious Surface Dynamics

Significant differences were observed in the dynamics of individual land use between categories in the northern region of Egypt from 2000 to 2020. The single land use dynamics values for impervious surfaces were highest between 2010 and 2015, reaching 9.47 percent, indicating a dramatic expansion of impervious surfaces. The single land use dynamic for sand has been shrinking; arable land had the most significant single dynamic of 0.42% from 2000 to 2005, which reduced to 0.28% from 2010 to 2015. Arable land, sand, and impervious surfaces combined with the land use dynamic exhibited positive values from 2010 to 2015. The combined dynamic was the largest, amounting to 0.003%, indicating that the changes in arable land, sand, and impervious surface were drastic from 2000 to 2010. The smallest combined dynamic was from 2015 to 2020, amounting to 0.0017%, indicating that the trend of change in the land, sand, and impervious surface from 2005 to 2010 was relatively stable (Figure 3).

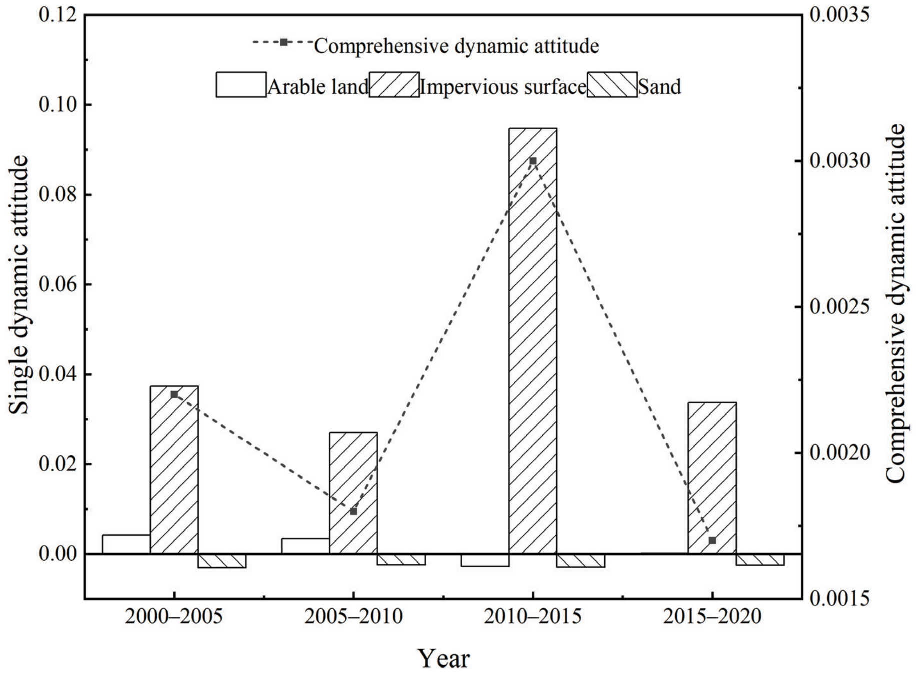

Figure 3. Dynamic map of single and integrated land use in the northern region of Egypt from 2000 to 2020.

3.1.3. The Transfer Flow Characteristics of the Oasis–Desert–Impervious Surface Interaction

Land use transfer flow is one of the proposed methods by Ma Caihong et al. for tracking land use changes [28,29]. It was found that there are significant phase differences in the transformation of arable land, sand, and impervious surface interactions in the northern part of Egypt. From 2000 to 2005, the most extensive arable land was converted to impervious surfaces, with 0.76% of the total area transferred. The largest area of sand was converted to arable land, with 1.34% of the total area transferred, indicating a more significant demand for arable land and a more drastic trend of change from arable land to sand. From 2005 to 2010, the sand area was converted into arable land. The land area was 665.8 km^2, with the transferred area accounting for 1.27% of the total area, while the area of arable land converted into impervious areas was 210.2 km^2, with the transferred area accounting for 0.74% of the total area. From 2010 to 2015, the arable land converted to impervious areas accounted for 3.49% of the total area, indicating that human activities were more disruptive to the land during this study period. From 2015 to 2020, the area of arable land converted into impervious areas was 499.42 km^2, and the sand area converted into arable land was 564.1 km^2. Impervious areas continued to increase throughout the study period without any shifts across land types (Figure 4).

3.2. Spatial Characterization of Oasis–Desert–Impervious Surface Interactions in Northern Egypt

3.2.1. Spatial Characterization of Oasis and Desert Change

Vegetation cover in northern Egypt generally improved from 2000 to 2020, but there were significant spatial differences (Figure 5). Every five years, the mean spectrogram of NDVI was calculated. The results indicate that as the Nile flows through the delta area, which is well irrigated and suitable for plant growth, the mean NDVI value is in the high-value range [0.4, 1). The NDVI value in the transition zone increased from [0.003, 0.2) to [0.4, 0.8], mainly due to the disturbance of human activities, which resulted in significantly increased NDVI. At each 5-year interval, the difference spectrogram of NDVI was calculated, and it was found that the NDVI differences in the Nile Delta and Fayoum District from 2000 to 2005 and from 2015 to 2020 were mainly in the range of [0.02, 0.11), indicating that the condition of the vegetation cover in the Nile Delta is gradually improving.

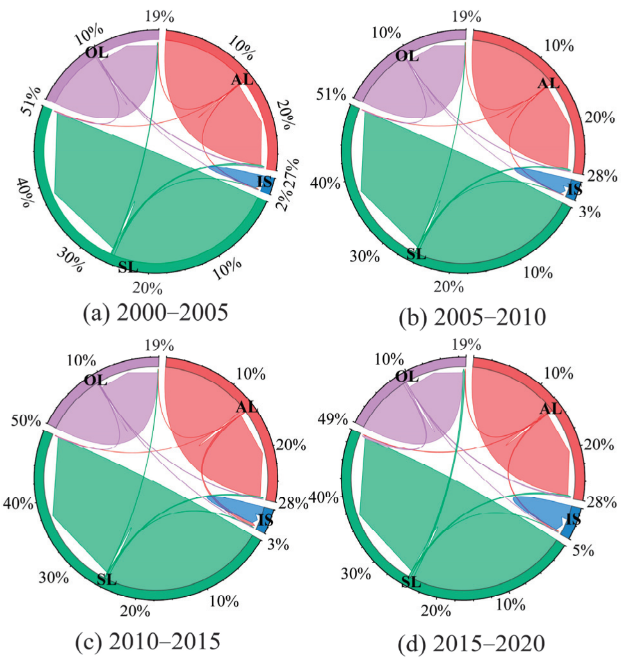

Figure 4. Arable land–impervious surface–sand-other transfer flow chords in northern Egypt from 2000 to 2020.

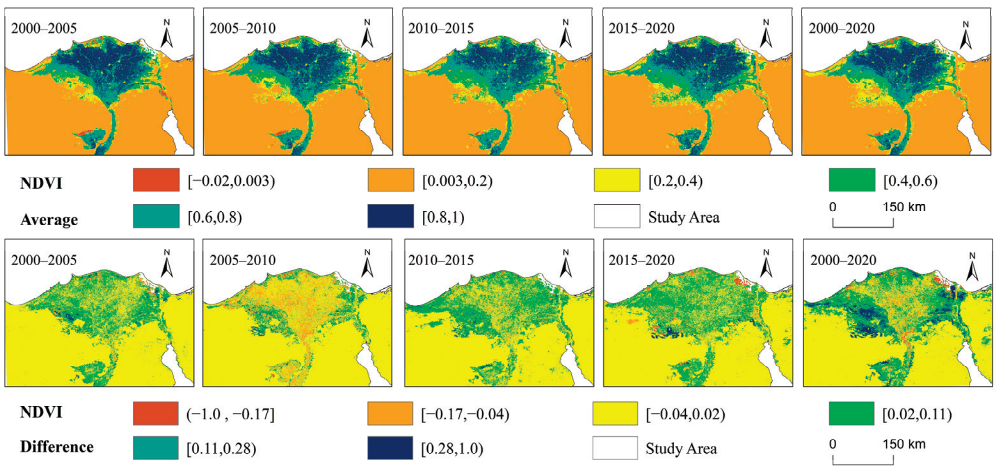

Figure 5. Spatial distribution of normalized vegetation index (NDVI) in northern Egypt from 2000 to 2020.

From 2000 to 2020, land use types in the Nile Delta and Fayoum District were dominated by arable land (Figure 6). The large expanses of water in the Nile Delta are more suitable for agricultural land. The arable land in 2020 was estimated to be 1.19 times larger than that in 2000, with the most significant expansion occurring in the southwestern part of the Nile Delta.

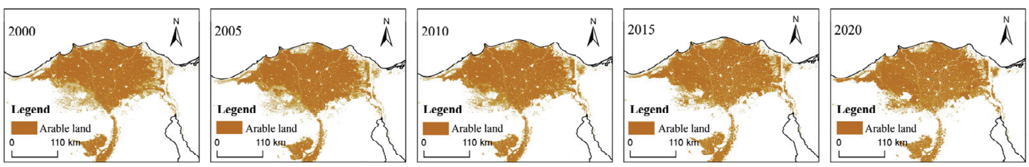

Figure 6. Changes in arable land in northern Egypt from 2000 to 2020.

3.2.2. Characterization of Spatial Variation in Impervious Surfaces

From 2000 to 2020, the impervious surfaces and arable lands in the northern region of Egypt changed significantly due to rapid economic development, generally showing a trend of rapid expansion of impervious surface encroachments on arable land towards the delta region and an increase in arable encroachment on sand in the west(Figure 7). The population proliferated over the study period, with population growth in 2020 being 0.98 times that in 2000. The demand for population growth drives the expansion of the impervious area, with the impervious area in 2020 being 2.32 times the area in 2000, representing a discrepancy between both growth rates and suggesting weak population intensification in northern Egypt. The nighttime light index is an index that reflects the degree of change in human activities. The nighttime light index from 2000 to 2020 indicates that people mainly concentrated in Cairo and then expanded to the Nile Delta and Fayoum District, which is consistent with the general characteristics of urbanization development [30].

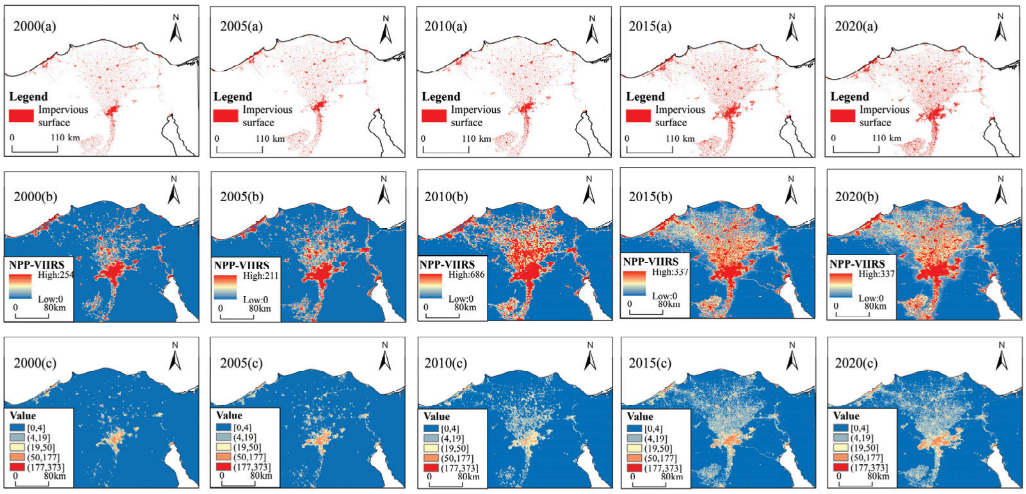

Figure 7. Map of impervious surface and nighttime light index in northern Egypt from 2000 to 2020: (**a**) change in impervious surface; (**b**) genealogy of nighttime light index; (**c**) change in nighttime light index.

3.3. Study of Drivers of Oasis–Desert–Impervious Surface Interaction Evolution

3.3.1. Characteristics of Spatial Changes in Oasis–Desert Interaction Lines

The northern region of Egypt is a typical agricultural desert oasis area. To investigate the extension of the oasis in the southwest direction, we calculated the center of the Nile Delta in 2000 and 2020. Measured in the direction of 207.5° from the center, the distances from the center to the edge of the oasis were 51 km and 120.54 km, and the oasis penetrated a total of 69.54 km into the desert, mainly through encroachment on cultivated land into the sand. The extension of the Nile Delta, mainly in the southwest direction, is evident because the southwest direction is topographically located in a low-lying area with abundant water resources, which makes it more suitable for human activities and exchanges. Impervious surfaces expanded over 1903.70 km^2 of arable land, accounting for 66.67% of the expansion area, and it was most significant near Cairo (Figure 8).

3.3.2. Dynamic Mechanisms of Oasis–Desert–Impervious Surface Interaction Evolution

The analysis reveals that human activities were the key driving force that changed Egypt's arable land, sand, and impervious surfaces through land use changes during the study period. The process of interactive evolution between oasis, desert, and impenetrable surface results from a spatial game between the three. The power factor of the development of things includes internal power and external power; internal power is inherent in things, whereas external power is the external conditions for the development of things, and internal and external power interact to form a power mechanism and jointly promote the development of things. Therefore, a result layer was created with the interactive development of oases, deserts, and impervious surfaces, and a response layer was created with the transfer flow between oases, deserts, impervious surfaces, and other land uses. A power layer was proposed with economic development, population size, food demand, and scientific and technological progress considered external drivers, and water scarcity and national policies considered the internal drivers, to form the power–response–outcome driving mechanism (Figure 9). The drivers are interdependent and limited. First, rapid economic development triggers urbanization, expanding impervious areas and resulting in population growth. Second, population growth accelerates the demand for food, encouraging the development of oasis agriculture. Technological progress in oasis agriculture results in the transformation of a large area of sand, inevitably leading to water shortages and forcing the state to take appropriate measures to promote economic development. Therefore, the changes that occur in the dynamic factors are correlated in space and time.

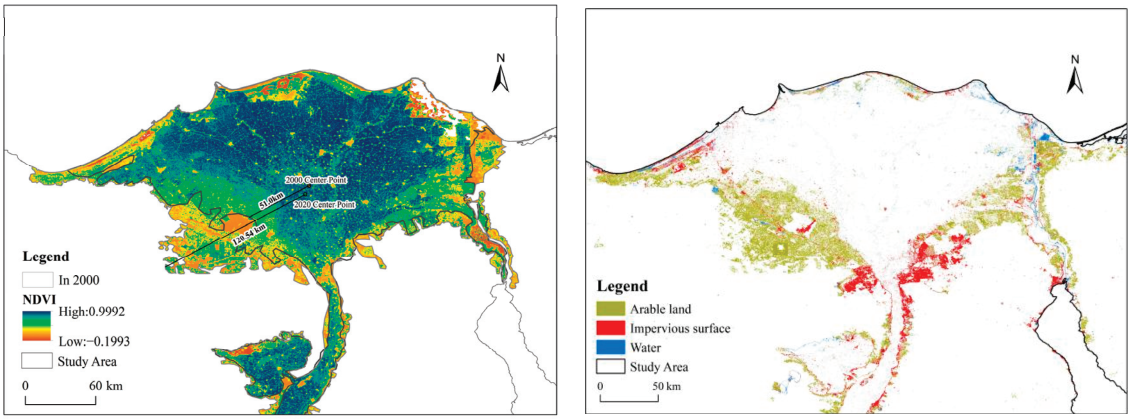

Figure 8. Map of NDVI change lines and land use change lines in the northern region of Egypt from 2000 to 2020.

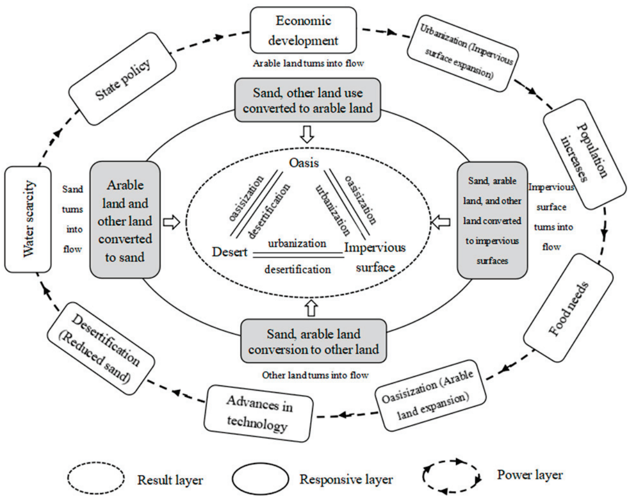

Figure 9. Schematic diagram of the dynamic mechanism of oasis–desert–impervious surface interaction evolution (image by the authors).

4. Discussion and Conclusions

4.1. Discussion

The harmonious development of oases and deserts, oases and impervious surfaces is a global problem. Land use interactions occur in the northern part of Egypt, where improvement in environmental quality is accompanied by degradation [31]. The rapid spread of impervious surfaces influenced by human activities has led to a dramatic process of ossification and desertification. With the construction of the Aswan Dam in 1970, a large amount of arable land was reclaimed, totaling more than 10 million hectares of reclaimed land. During the same period, Egypt lost almost as much agricultural land to industrial and urban development [32]. Recognizing the need to protect and increase the area of arable land, the Egyptian government began to encourage the establishment of new settlements in desert areas and the cultivation of large areas of sand. This has led to a continuous advance of the oasis line in the delta area towards the desert, which is more pronounced in the southwest and southeast directions of the oasis. The oasis extends nearly 69.54 km to the southwest, and the land use type is dominated by agricultural land, which has the apparent characteristic of oasis advance and sand retreat. This significantly reduces the risk of exposure of oasis ecosystems to wind and sand, prevents the country's desertification, and protects the development of agricultural oasis areas [33].

At the same time, Egypt's population growth led to a massive expansion of impervious surfaces. Spatially, the expansion was most pronounced to the west and northeast, showing a clear pattern of population growth driving the decline of the oases. This reflects the contradiction between human–land relationships and the laws of natural evolution. The northern region of Egypt is in the oasis development phase, and by revealing the oasis–desert impervious surface interactions over two decades, it has been found that oases and impervious surfaces in the northern region of Egypt have expanded significantly, and deserts have shrunk, a finding consistent with the global trend of land use change [34]. The expansion of oases in the northern region of Egypt needs to be improved in two ways: Firstly, the proximity of the northern region of Egypt to the Mediterranean Sea and the lack of natural drainage for wastewater treatment in remote areas for long periods, coupled with the excessive use of irrigation water and inadequate drainage systems, have led to the shallow evaporation of groundwater and gradual salinization of soils [35], which in turn affects the sustainable development of agriculture and the stability of the ecosystem as a whole. Subsequently, soil properties can be restored through rice cultivation, underground drainage system installation, and land improvement programs to promote oasis development. Second, the expansion of impervious surfaces affects oases and forces them to expand, requiring large amounts of water recharge. Due to the scarcity of water resources in the northern region of Egypt, it is crucial to rationalize the use of these oases. Water resources provided by the Nile in Egypt should be exploited to promote the development of oases in the northern region of Egypt. In contrast, China has achieved some success in conserving and intensively using water resources [36]. The protective measures taken include regulating the balance between the supply and demand of water resources through market mechanisms and actively promoting advanced water-saving irrigation technologies (sprinklers, micro-irrigation, and drip irrigation), the rational adjustment of planting structure, promoting the use of treated water, etc. China's water conservation measures can be used as a reference for the northern region of Egypt to improve the use of water resources and promote the development of oases.

4.2. Conclusions

This article analyzes the interaction characteristics between oases, deserts, and impervious surfaces in northern Egypt based on gridded data such as land use and NDVI and examines their dynamics using modeling and geographic information mapping methods. The main conclusions are as follows:

1. Considering the interaction between deserts and oases, the primary manifestation is the expansion of oases and the reduction of deserts. During the study period, the oases in the Nile Delta and Fayoum District increased significantly, with the area of oases in 2020 being 1.19 times the area in 2000, which shows a clear trend of advance of people and retreat of sand.
2. The interaction between oases and impervious surfaces was mainly observed in the form of the spread of impervious surfaces on arable land into oases. During the study period, the area of impervious surfaces increased 2.32 times. The impervious

surface expanded over 1903.70 km^2 of arable land, accounting for 66.67% of the expanded area.

3. Regarding the interaction between the impervious surface and the desert, the central phenomenon is the encroachment of the covered area of the impervious surface into the desert, especially around the city of Cairo.
4. The need for increased food production due to population growth has forced oases to move deeper into the desert, and the occupation of arable land due to urbanization has led to increasing pressure on arable land, creating a pressure-conducting dynamic mechanism. It is recommended that the intensification of impervious surfaces in land use be mitigated to reduce pressure on arable land.

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Data Availability Statement: The data used to support the findings of this study can be made available by the first author upon request. The data are not publicly available due to privacy restrictions.

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

References

1. Jiao, Y.; Yan, F.; Lu, Q.; Wang, Y.J. Spatiotemporal variation and driving factors of oases in the arid region of Northwest China. *Chin. J. Appl. Ecol.* **2024**, *35*, 2206–2216.
2. Yang, H.Q.; Wang, H.B.; Zuo, H.J.; Qiao, S.; Li, S.Q. Change pattern and stability of oasisization land in Mu Us Sandy land. *Chin. J. Appl. Ecol.* **2024**, *35*, 687–694.
3. Zou, Y.; Meng, J.J. Evaluation of an oasis-urban-desert landscape and the related ecoenvironmental effects in an arid area. *Arid Zone Res.* **2023**, *40*, 988–1001.
4. Qiao, P.; Sun, C.J.; Li, Y.X.; Zhou, S.J.; Chen, Y.N. Analysis on temporal and spatial changes of vegetation net primary productivity in typical "Alpine-Oasis-Desert" ecological region. *Spectrosc. Spectr. Anal.* **2022**, *42*, 2595–2602.
5. Chen, S.; Wang, Z.R.; Zhao, G.X. Analysis of the evolution characteristics and driving force of land use and landscape pattern in 2000-2020 in arid and Semi-arid areas in China. *J. Shandong Agric.* **2023**, *54*, 620–627.
6. Sun, X.W.; Li, S.; Wang, Y.H.; Tang, X.; Zhao, H.Y. Spatiotemporal change of oasis in Shule River Basin during 1975–2020. *Acta Ecol. Sin.* **2022**, *42*, 9111–9120.
7. Sun, M.T.; Jiang, H.N.; Xu, J.H.; Zhou, P.; Li, X.; Xie, M.Y.; Hao, D.D. The Relationship between the Carbon Fixation Capacity of Vegetation and Cultivated Land Expansion and Its Driving Factors in an Oasis in the Arid Region of Xinjiang, China. *Forests* **2024**, *15*, 262. [CrossRef]
8. Liu, J.M.; Pei, X.T.; Zhu, W.Y.; Jiao, J.Z. Simulation of the Ecological Service Value and Ecological Compensation in Arid Area: A Case Study of Ecologically Vulnerable Oasis. *Remote Sens.* **2023**, *15*, 3927. [CrossRef]
9. Zhang, L.; Bo, Y.M.; Li, X.C.; Wang, L.J.; Yu, H.X.; Zhang, L.J. Study on Land Use Change and Driving Mechanism of Typical Basin inSemi-arid Area of Loess Plateau. *J. Gansu For. Sci. Technol.* **2024**, *49*, 1–8.
10. Li, W.X.; Ma, Y.X.; Liu, Y.Q.; Zhang, Y.F. Study on the Correlation between Ecological Service Value and Ecological Risk of Typical Mountain-Oasis-Desert Ecosystems: A Case Study of Aksu City in Northwest China. *Sustainability* **2024**, *16*, 3915. [CrossRef]
11. Zhang, J.Z.; Zhang, P.; Gu, X.C.; Deng, M.J.; Lai, X.Y.; Long, A.H.; Deng, X.Y. Analysis of Spatio-Temporal Pattern Changes and Driving Forces of Xinjiang Plain Oases Based on Geodetector. *Land* **2023**, *12*, 1508. [CrossRef]
12. Cheng, W.H.; Ma, C.H.; Li, T.S.; Liu, Y.Y. Construction of Ecological Security Patterns and Evaluation of Ecological Network Stability under Multi-Scenario Simulation: A Case Study in Desert–Oasis Area of the Yellow River Basin, China. *Land* **2024**, *13*, 1037. [CrossRef]
13. Yin, H.H.; Wu, Z.P. Spatiotemporal changes of urban construction land expansion in oasis in arid region. *Ecol. Sci.* **2023**, *42*, 231–240.
14. Zhang, F.; Wang, Y.S.; Jim, C.Y.; Chan, N.W.; Tan, M.L.; Kung, H.T.; Shi, J.C.; Li, X.Y.; He, X. Analysis of Urban Expansion and Human–Land Coordination of Oasis Town Groups in the Core Area of Silk Road Economic Belt, China. *Land* **2023**, *12*, 224. [CrossRef]
15. Pariha, H.L.L.; Zan, M. Spatio-temporal changes and influencing factors of ecologicaenvironments in oasis cities of arid regions. *Remote Sens. Nat. Resour.* **2023**, *35*, 201–211.

16. Liu, Y.B.; Liu, B.Y.; Cheng, C.; Zhang, J.Q.; Lu, S.J. Spatio-temporal changes and influencing factors of vegetation coverage in Yulin city during the past 20 years since the implementation of the "Grain for Green" program. *J. Soil Water Conserv.* **2022**, *36*, 197–208+218.
17. Jiang, S.; Chen, X.; Smettern, K.; Wang, T.J. Climate and land use influences on changing spatiotemporal patterns of mountain vegetation cover in Southwest China. *Ecol. Indic.* **2021**, *121*, 107193. [CrossRef]
18. Han, H.Q.; Su, Z.H. Research progress and prospects of karst ecosystem services. *Carsplogica Sin.* **2017**, *36*, 352–358.
19. Zhang, Y. Issues of land exploring in Egypt. *J. Inn. Mong. Univ. Natl. (Soc. Sci.)* **2011**, *37*, 66–68.
20. Bratley, K.; Ghoneim, E. Modeling Urban Encroachment on the Agricultural Land of the Eastern Nile Delta Using Remote Sensing and a GIS-Based Markov Chain Model. *Land* **2018**, *7*, 114. [CrossRef]
21. Zhang, B.T.; Li, Z.S.; Feng, Q.; Lu, Z.X.; Zhang, B.J.; Cheng, W.J. Evolution of ecosystem services values in Qilian Mountains based on land-use change from 1990 to 2020. *Acta Ecol. Sin.* **2024**, *44*, 4187–4202.
22. Qiu, H.H.; Hu, B.O.; Zhang, Z. lmpacts of land use change on ecosystem service value based on SDGs report-Taking Guangxi as an example. *Ecol. Indic.* **2021**, *133*, 108366. [CrossRef]
23. Schild, J.E.M.; Vermaat, J.E.; Van Bodegom, P.M. Differential effects of valuation method and ecosystem type on the monetary valuation of dryland ecosystem services: A quantitative analysis. *J. Arid Environ.* **2018**, *159*, 11–21. [CrossRef]
24. Yang, A.M.; Zhu, L.; Chen, S.H.; Jin, H.; Xia, X.X. Geo-informatic spectrum analysis of land use change in the manas reiver basin, China during 1975–2015. *Chin. J. Appl. Ecol.* **2019**, *30*, 3863–3874.
25. Yang, H.; Ma, C.H.; Hua, Y.Q.; Li, C.H.; Liu, Y.Y. Spatiotemporal Variation Atlas of Grassland Greenness in Ningxia and ltsDriving Factors. *Res. Soil Water Conserv.* **2024**, *31*, 228–239.
26. Du, G.M.; Zhang, R.; Yu, F.R. Analysis of cropping pattern in black soil region of Northeast China basedon geo-information Tupu. *Chin. J. Appl. Ecol.* **2022**, *33*, 694–702.
27. Zhang, X.; Zhao, T.T.; Xu, H.; Liu, W.D.; Wang, J.Q.; Chen, X.D.; Liu, L.Y. GLC_FCS30D: The first global 30 m land-cover dynamics monitoring product with a fine classification system for the period from 1985 to 2022 generated using dense-time-series Landsat imagery and the continuous change-detection method. *Earth Syst. Sci. Data* **2024**, *16*, 1353–1381. [CrossRef]
28. Ma, C.H.; Ren, Z.Y.; Li, X.Y. Land use change flow and its spatial agglomeration in the loess platform region. *Acta Geogr. Sin.* **2013**, *68*, 257–267.
29. Ma, C.H.; An, S.W.; Wen, Q.; Hua, Y.Q.; Li, C.H. Evolution of territorial spatial pattern and its driving mechanism based on land use transfer flow: A case of Yuanzhou district in Ningxia. *Arid Land Geogr.* **2022**, *45*, 925–934.
30. He, L.; Li, W.F.; Tian, S.F.; Zheng, H. Analysis of the impact of repid urbanization on farmland protection in the Yangtze river economic belt. *Acta Ecol. Sin.* **2018**, *38*, 7782–7789.
31. Cao, X.M.; Cui, M.C.; Xi, L.; Feng, Y.M. Spatial-Temporal Process of Land Use/Land Cover and Desertification in the Circum-Tarim Basin during 1990–2020. *Land* **2024**, *13*, 735. [CrossRef]
32. AbdelRahman, M.A.E. An overview of land degradation, desertification and sustainable land management using GIS and remote sensing applications. *Rend. Fis. Acc. Lincei* **2023**, *34*, 767–808. [CrossRef]
33. Youssef, Y.M.; Gemail, K.S.; Atia, H.M.; Mahdy, M. Insight into land cover dynamics and water challenges under anthropogenic and climatic changes in the eastern Nile Delta: Inference from remote sensing and GIS data. *Sci. Total Environ.* **2024**, *913*, 169690. [CrossRef] [PubMed]
34. Masood, M.; He, C.G.; Shah, S.A.; Rehman, S.A.U. Land Use Change Impacts over the Indus Delta: A Case Study of Sindh Province, Pakistan. *Land* **2024**, *13*, 1080. [CrossRef]
35. Kotb, T.H.S.; Watanabe, T.; Ogino, Y.; Tanji, K.K. Soil salinization in the Nile Delta and related policy issues in Egypt. *Agric. Water Manag.* **2000**, *43*, 239–261. [CrossRef]
36. Gan, R.Q.; Zeng, L.W.; Chen, Y.; Sun, D.Z. Water resources conservation and intensive utilization capability of cities in the middle and lower reaches of the Yellow river basin. *Environ. Sci.* **2024**, 1–17. [CrossRef]

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Article

Incorporation of Spatially Heterogeneous Area Partitioning into Vector-Based Cellular Automata for Simulating Urban Land-Use Changes

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Abstract: In cellular automata (CA) modeling, spatial heterogeneity can be delineated by geographical area partitioning. The dual constrained space clustering method is a prevalent approach for providing an objective and effective representation of differences within urban regions. However, previous studies faced issues by ignoring spatial heterogeneity, which could lead to an over- or under-estimation of the simulation results. Accordingly, this study attempts to incorporate spatially heterogeneous area partitioning into vector-based cellular automata (VCA), producing more accurate and reliable simulations of urban land-use change. First, an area partition strategy with DSC algorithm was employed to generate multiple relatively homogeneous sub-regions, which can effectively capture the spatial heterogeneity in the distribution of land-use change factors. Second, UrbanVCA, a brand-new VCA-based framework, was utilized for simulating land-use changes in distinct urban partitions. Finally, the constructed partitioned VCA model was applied to simulate rapid urban development in Jiangyin city from 2012 to 2017. The results indicated that the combination of DSC clustering and UrbanVCA model could obtain satisfying results as the average FoM values for the partitions and the entire study area exceeded 0.22. Furthermore, a comparative analysis of results from traditional area-partitioned CA models revealed that the proposed area partitioning approach had the potential to yield more accurate simulation outcomes as the FoM values were higher and SHDI and LSI metrics were closer to real-world observations, indicating its good performance in simulating fragmented urban landscapes.

Keywords: urban land-use change simulation; area partitioning; spatial heterogeneity; vector-based cellular automata (VCA); Jiangyin city

1. Introduction

Urban growth is a complex and dynamic process, which is influenced by various factors, including natural, social, and economic factors [1]. "Spatial heterogeneity" refers to the non-uniform and complex distribution of land-use patterns. Rapid urban growth, in turn, leads to increasingly fragmented landscapes characterized by heightened spatial heterogeneity [2]. Cellular automata (CA) have emerged as effective tools for describing historical land-use transformations and forecasting prospective land scenarios, thus enhancing our comprehension of land-use dynamics [3,4]. Accordingly, it is crucial to integrate spatial heterogeneity into the CA model to yield accurate land-use simulation and prediction results.

According to the difference in the cells' design, CA can be generally divided into two groups: raster cellular automaton and vector cellular automaton. In a raster urban CA model, geographic space can be described with regular units (often square) in a raster structure, which can facilitate subsequent computations by harnessing the extensive raster analysis functions available in GIS [5,6]. The unavoidable loss of detail induced by the raster data format motivated researchers to employ some irregular-shaped frameworks (e.g., land parcels) as the minimum space description modules, hereafter referred to as vector-based CA (VCA) [7,8]. Due to the inherent morphological advantage of vector cells, available VCA models have illustrated their considerable potential in simulating fine-scale urban growth, helping produce the model output more realistically [9,10].

Early VCA models were built using graph theory, which included Voronoi polygons [11] and Delaunay triangulation [12]. Nevertheless, VCA models rooted in graph theory may not entirely encompass real-world geographical objects due to their automated generation. As an enhancement to this spatial representation, the urban area was subdivided into various spatial units, such as land-use parcels, census blocks, and planning zones, which enhanced the model's realism by establishing connections between land use and socioeconomic information. Among the different VCA models, those built upon land or cadastral parcels play a vital role in urban planning and provide a more realistic representation of ground objects. In brief, VCA models exhibit a substantial advantage in modeling land-use changes at a very fine scale [13]. Nevertheless, several issues in VCA models remain to be addressed. Firstly, the complexity increases due to the diversity of polygon shapes, leading to varying connections between neighboring cells. The neighborhood definitions in VCA models can be roughly classified into two categories: topology-based neighborhood and buffer-based neighborhood [10]. Dahal and Chow [14] defined 30 neighborhood configurations to evaluate parameter sensitivity in simulation results, revealing that VCA models with center-buffer neighborhoods can achieved the highest simulation accuracy. Additionally, urban land-use change is frequently characterized as an incremental and fragmented process, rather than an abrupt conversion of an entire land parcel from one land-use type to another within a short period [15]. Yao [8] introduced the dynamic land parcel subdivision-based vector cellular automaton (DLPS-VCA) framework. This framework efficiently simulates urban expansion, land parcel fragmentation, and land-use type transitions during urban development. Despite its advantages in urban simulation, the complex vector subdivision mechanism has limited the widespread use of DLPS-VCA.

In CA modeling, the concept of spatial heterogeneity can be captured by locally varying transition rules, spatially heterogeneous neighborhoods, and geographical area partitioning. To account for the spatially heterogeneous impacts of drivers on land-use change, researchers have employed local spatial statistical models, such as the spatial autoregressive (SAR) model and geographically weighted regression (GWR) [16], to derive the transition rules of the CA model by assigning weights to regression coefficients based on local proximity. Other studies adopted a hybrid modeling approach, such as GWANN [17] and ART-P-MAP [18], to describe a comprehensive exploration of the spatially heterogeneous driving forces influencing urban sprawl by coupling the spatial statistical model with the intelligent model. The neighborhood, as a critical internal component of the CA model, is notably influenced by spatial heterogeneity [19,20]. The most common types of neighborhood definitions are typically referred to as Von Neumann, Moore neighborhoods, and topology-based, buffer-based neighborhoods, where the size and shape of neighborhood is equivalent. This assumption obviously violates the spatial heterogeneity in reality, even with a well analysis of size sensitivity in related studies [21,22]. Recently, there have been some studies taking the distance–decay, multi-layer, and orientation weighted into account to investigate the influence of heterogeneous neighborhoods on individual cells [23,24]. These studies on heterogeneous neighborhoods have significantly contributed to the expansion of our knowledge regarding spatially varying interactions among adjacent cells.

Area partitioning in geographic space is another common strategy to address spatial heterogeneity in CA modelling [25,26]. By adopting a partitioning-based approach to acquire cell transition rules, the model's ability to capture the similar patterns of land-use change evolution within each partition is notably improved, thereby leading to more precise and realistic representations of land-use dynamics. Area partitioning can be achieved through two primary methods: the administrative-based approach and the dual spatial clustering method. The former usually refers to administrative division such as administrative districts [27], planning zones [28], urban spatial structure [29], and other custom-defined units [30]. Although the administrative-based approach was simple and practical, these partitioning strategies mainly relied on empirical evidence, resulting in subjective outcomes and growing complexity with an increasing number of driving factors [31]. Furthermore, they may face challenges in capturing the inherent similarity characteristics of land-use changes, as they tend to overlook the spatial variations at micro scales [32]. Using the dual spatial clustering method, the entire cell space was segmented into several homogeneous regions considering both spatial proximity and attribute similarity, and then transformation rules were obtained for each partition individually. This process entails partitioning the cellular space based on the spatial heterogeneity characteristics of land-use change. They aimed to comprehensively account for the similarity in both spatial and attribute relations of land-use change. Therefore, they employed a clustering method to achieve the partitioning of the cellular space. As such, the conversion rules for each partition can effectively express the driving mechanism behind land-use changes. The existing dual spatial clustering algorithms, such as MK-means [33], SOM (self-organizing map) [26], and KDE (kernel density function) [29], were utilized for partitioning, providing an objective and effective representation of urban area differences with minimal human interference. Incorporating the non-uniform distribution of driving factors during the partitioning process, several limitations of these algorithms can be highlighted. First, land parcels are nonuniformly distributed with varying concentrations or dispersion [8]; the existing partitioning algorithms have difficulties in detecting clusters of irregular shapes and varying densities. Additionally, the results of these algorithms' clustering can often be sensitive to noise. Second, attribute similarity measurements in these algorithms primarily relies on a binary predicate that utilizes Euclidean distance as the fundamental metric. However, in the face of uneven distributions in the attribute space, their inherent transitivity could lead to the continuous propagation and accumulation of differences between attribute values during the clustering process. As a result, the clustering results may fail to accurately reflect the transitional nature of geographical features in spatial distributions, eventually leading to over- or under-simulation results [34,35]. One dual spatial clustering algorithm, denoted as DSC, can handle both spatial proximity and attribute similarity in the presence of heterogeneity and noise [36]. The detection of these clusters is valuable for gaining insights into the localized patterns of geographical phenomena, and it has been successfully used for urban element identification and urban spatial structure analysis [37,38].

In view of the problems described above, this study attempts to incorporate spatially heterogeneous area partitioning into vector-based cellular automata (VCA), facilitating more accurate modeling of urban dynamics. First, an area partition strategy with DSC algorithm was employed to generate multiple relatively homogeneous sub-regions, which could effectively capture the geographic heterogeneity in the distribution of land-use change factors. Second, UrbanVCA, a brand-new vector CA-based framework to simulate the urban land-use change at the land parcel level, was adopted for the study [8,39]. By employing a set of pre-defined rules driving urban land-use changes, the UrbanVCA model can not only simulate the process of land fragmentation but also support a variety of machine learning algorithms to mine the probability of urban land-use changes. Finally, the constructed partitioned VCA model was applied to simulate rapid urban development in Jiangyin city, China, from 2012 to 2017. In addition, a comparison and analysis of traditional partitioned CA models were performed to validate the effectiveness of the proposed partitioned CA model using accuracy statistics and vector-based landscape indexes.

2. Study Area and Datasets

Jiangyin is located in the Jiangsu Province of China, situated at the northern end of the Yangtze River Delta (Figure 1). It is comprised of five districts: Central, Chengdong, Chengxi, Chengnan, and Chengdongnan, with a nearly 1.775 million residential population and a total area of 987.5 km^2. In 2020, Jiangyin achieved a notable GDP of 411.375 billion yuan, affirming its standing as the second-ranked county-level city on the Chinese mainland (http://www.jiangyin.gov.cn/, accessed on 31 December 2020). Jiangyin city has experienced fast urbanization in the last two decades because the city has attracted significant direct foreign investment since the 1990s, leading to industrial development and an enhanced foundation. It is appropriate for a detailed analysis of neighborhood features due to its complex, fragmented land-use parcels, as well as its ongoing urban expansion and its size.

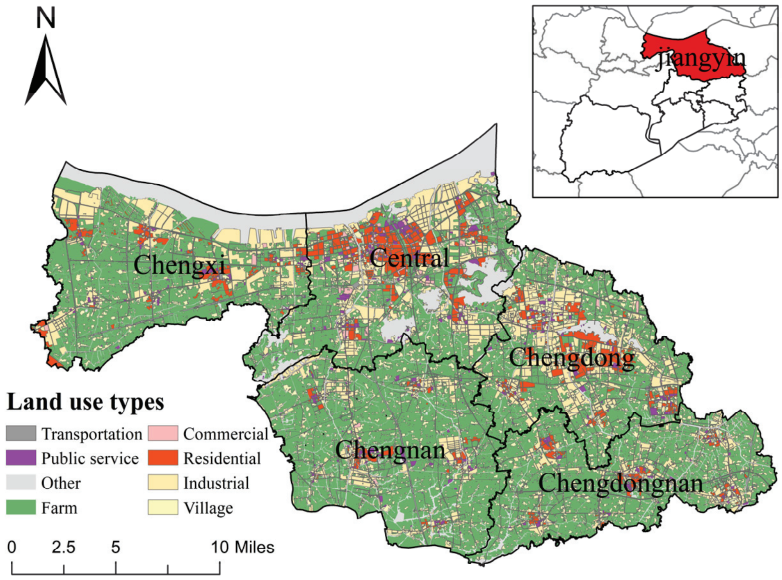

Figure 1. Location of the study area.

The cadastral parcel data of Jiangyin was acquired from planning bureaus between the years 2012 and 2017. Each land-use pattern map was further recategorized into eight groups based on the land-use/cover features in Jiangyin, including commercial (C), residential (R), industrial (I), public service (P), transportation (T), farm (F), village construction (V), and other lands (O). During the period from 2012 to 2017, there was a rapid occurrence of land-use changes in Jiangyin, with the number of land parcels increasing by 31.5% from 18,327 to 24,101. This observation suggests a noticeable fragmentation trend in the landscape.

In the wake of the early studies in CA modeling [27,29,40], several driving factors were introduced to provide a quantitative measure of the suitability for the occurrence of different land types, including topographical and geographical conditions, transportation factors, location factors, economic and population factors, some POI information, and government planning policy. Specially, the distance variables indicate accessibility to transportation and location factors using the "Euclidean Distance" tool within ARCGIS. The density of POI information was computed through the kernel density estimation (KDE) method. The primary data sets employed in this study were derived from Jiangyin urban master plan (2011–2030) (http://www.jiangyin.gov.cn/, accessed on 24 October 2012), Open Street Map (https://www.openstreetmap.org), Geospatial Data Cloud (http://www.gscloud.cn), and Resource and Environment Data Cloud Platform (http://www.resdc. cn, accessed on 25 December 2012) (see Supplementary Table S1). A stratified random sampling approach was employed to acquire 20% of the samples from the spatial variables for the determination of transition rules. As part of the data processing, all datasets underwent normalization, which standardized them within a common range from 0 to 1. Moreover, to ensure spatial consistency, all data were resampled to a uniform spatial resolution of 30 m (Figure 2).

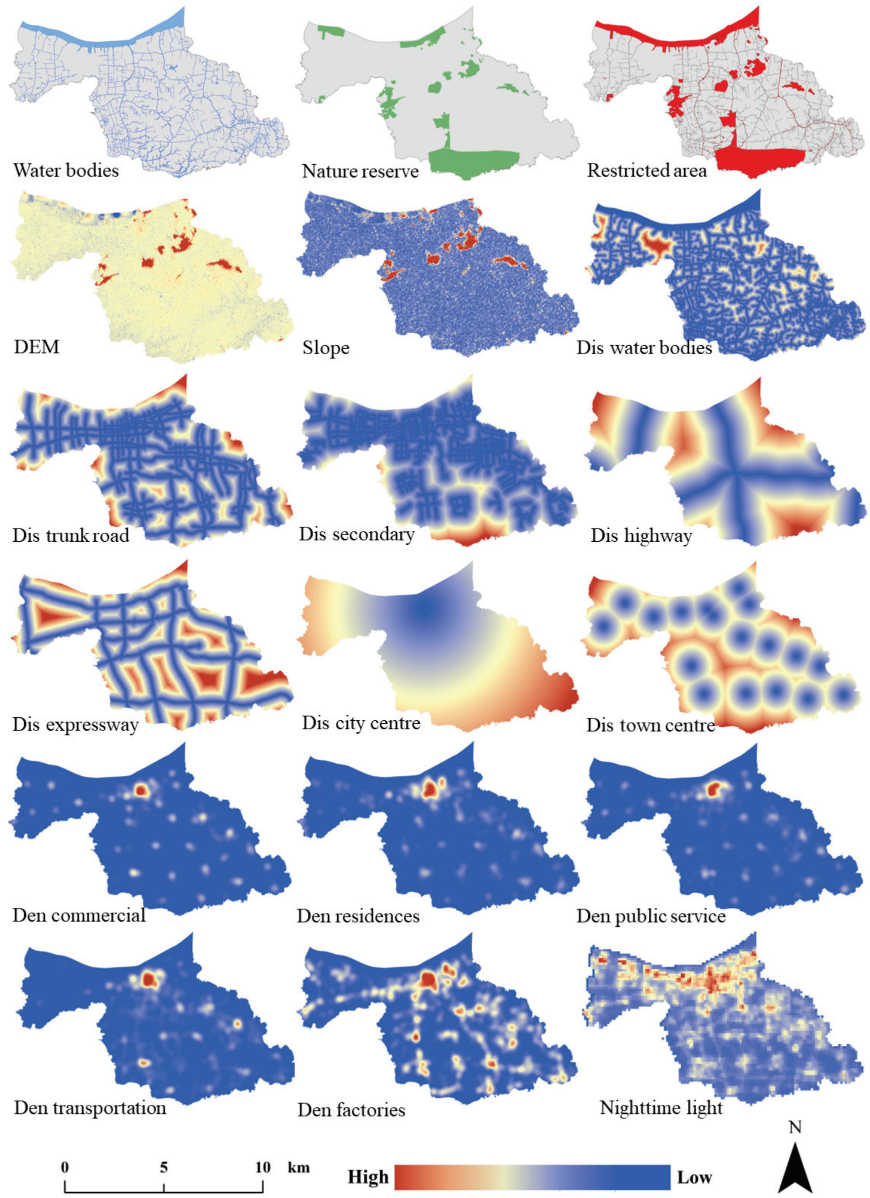

Figure 2. Maps of driving factors in this study.

3. Methodology

The proposed model contains three main parts (Figure 3): (1) input data; (2) area partitioning by DSC method; (3) UrbanVCA simulation. Firstly, the land parcels used for the DSC runs were abstracted into a Delaunay triangulation (*DT*) representation, where each parcel was represented by a node (i.e., centroid), and their neighboring relationships were defined through edges, establishing connections between pairs of centroids. *DT* containing two-level edge-length restrictions considering irregular distributions was adopted to establish spatial proximity relationships among land parcels. On this basis, an iterative clustering strategy utilizing information entropy (IE) was then employed. This strategy employed breadth-first search (BFS) to sequentially traverse kth-order neighbors for each land parcel, enabling the precise identification of clusters with similar attributes (i.e., driving factors of land-use change listed in Figure 2), while accounting for heterogeneity and noise. Secondly, a collection of urban development factors was gathered to train the transition potential map through UrbanVCA for each partitioned zone to simulate the urban land-use changes of Jiangyin, and various assessment metrics were employed to evaluate and compare the performance of different area partitioning models.

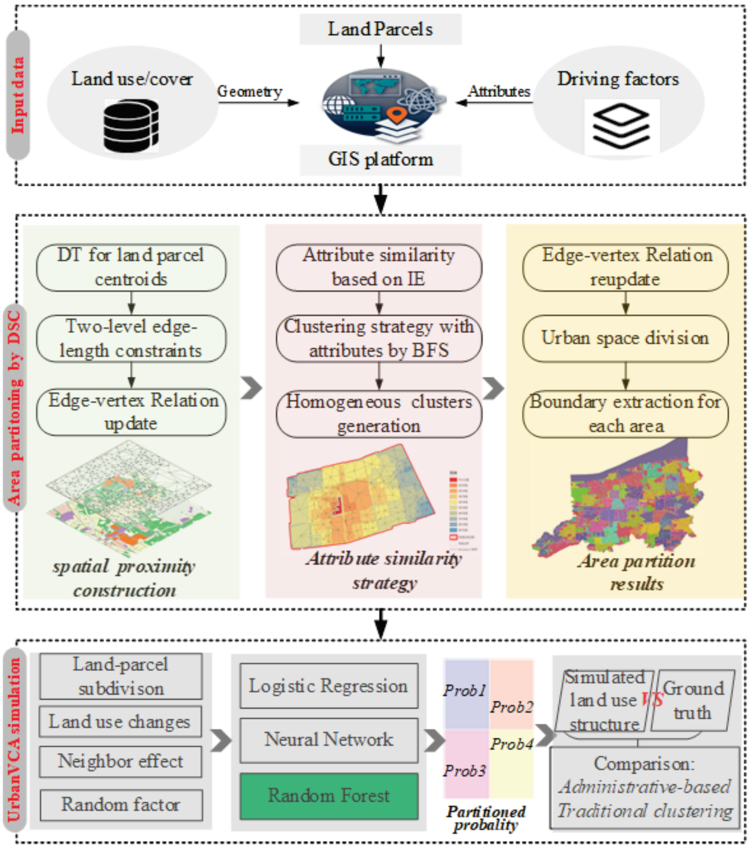

Figure 3. Flowchart of the partitioned VCA model for simulating urban land-use changes.

3.1. *Spatially Heterogeneous Area Partitioning by DSC Method*

DSC aims to address the challenges of heterogeneity and noise by incorporating both spatial proximity and attribute similarity [36]. In real-world scenarios, spatially adjacent clusters usually exist in a spatial dataset where the difference of observations in attribute distribution is homogeneous within each cluster but inhomogeneous between clusters. However, in the face of uneven distributions in the attribute space, attribute similarity measurements in these algorithms primarily relied on a binary predicate that utilizes Euclidean distance as the fundamental metric; their inherent transitivity could lead to the continuous propagation and accumulation of differences between attribute values during the clustering process. As a result, the clustering results may fail to accurately reflect the transitional nature of geographical features in spatial distributions, eventually leading to over- or under-simulation results (the validation of this point was demonstrated using both simulated and real-world data in [36]). The DSC algorithm primarily addresses the challenge of discovering homogeneous spatially adjacent clusters while dealing with between-cluster inhomogeneity and noise where those spatial points are described in the attribute domain. The detection of these clusters is valuable for gaining insights into the localized patterns of geographical phenomena. DSC methodology is initiated through the application of *DT* with edge-length constraints. This approach considers diverse geometric shapes, varying land parcel densities, and spatial noise to effectively establish spatial proximity relationships among the land parcels. Subsequently, an IE clustering strategy is devised to identify clusters that exhibit similar attributes. This approach enables adaptive and precise cluster detection while taking into account the existence of heterogeneity and noise.

3.1.1. Clustering Constrained by Spatial Proximity

Following the construction of the *DT* of the points (parcel centroids), the DSC algorithm proceeded to utilize global and local proximity criteria to partition the points into multiple spatial clusters. Through the application of global criteria, the long edges will be removed at the global level. This process can be expressed as follows:

$$Global\_LongEdges(p) = \{e_i|e_i\rangle GlobalMean + GlobalSD * \frac{GlobalMean}{PartialMean(p)}\} \quad (1)$$

where *Global_LongEdges*(*p*) represents the set of long edges that need to be deleted at point *p*. *GlobalMean* refers to the average length of all edges in *DT*, *PartialMean*(*p*) denotes the average length of the edges directly connected to point *p*, and *GlobalSD* denotes the standard deviation of edge lengths in *DT*.

Subsequently, the local proximity constraint is applied to eliminate any remaining lengthy edges. The local process follows the following criteria:

$$\begin{cases} F(p) = Local\_SD(p)/Local\_Mean\_Length(p) \\ Local\_Mean\_Length(p) = \frac{1}{d(p)} \sum\limits_{i=1}^{d(p)} |e_i| \\ Local\_SD(p) = \sqrt{\frac{\sum\limits_{i=1}^{d(p)} (Local\_Mean\_Length(p) - |e_i|)^2}{d(p)}} \end{cases} \quad (2)$$

where *Local_Mean_Length*(*p*) represents the mean length of edges in $N(p)$, and $Local\_SD(p)$ is the standard deviation of the lengths of edges in $N(p)$. $d(p)$ denotes the number of edges incident to *p*, and $|e_i|$ is the length of edges in $N(p)$. The final spatial proximity comprises all connected mutation points for which $F(p) \leq \gamma$.

3.1.2. Clustering Constrained by Attribute Similarity

DSC utilizes an attribute clustering method that relies on IE to classify the clustering results according to the attributes of the points (i.e., driving factors of land-use change listed in Figure 2). The attribute entropy represents the degree of similarity between the central point and the neighboring points within the first-order neighborhood. It can be computed using the following formula, where a higher value indicates a smaller difference between the central point and the connected points:

$$\begin{cases} DAE_{nei}(O) = \frac{E_{oc}}{n+1} \\ E_{oc} = -\sum\limits_{i=1}^{n+1} p_i \ln p_i \\ p_i = \frac{v_i}{\sum_{j=1}^{n+1} v_j} \end{cases} \quad (3)$$

where $DAE_{nei}(O)$ represents the attribute entropy of point *O*, and E_{oc} represents the attribute similarity between point *O* and clustering cluster *C*. The clustering cluster *C* consists of n points $\{C_1, C_2, C_3, \ldots, C_n\}$, where point *O* represents the central point and cluster *C* is the set of points within the first-order neighborhood of point *O*. The driving factor values of each point in the cluster are denoted as $\{v_1, v_2, v_3, \ldots, v_n\}$, and the driving factor values of the central mutation point *O* is represented as v_{n+1}.

After calculating the attribute entropy for each point, the point with the highest attribute entropy is selected as the starting point. Using Equation (3), the starting point is considered as the central point *O*, and each neighboring point is treated as a separate clustering cluster *C*. The attribute similarity E_{oc} between the central point and each surrounding point is computed. The initial clustering cluster is formed by combining the mutation point *O* with the highest attribute entropy and the point with the maximum attribute similarity E_{oc} among its surroundings. The candidate points are determined as the points within the first-order neighborhood of the initial clustering cluster. Equation (4) is employed to compute the E_{oc} between each candidate point and the initial cluster:

$$\begin{cases} \theta = \frac{E_{oc}}{E_{oc_{max}}} \\ E_{oc_{max}} = \ln(n+1) \end{cases} \tag{4}$$

where θ is the standardized variable; the maximum information entropy between mutation point O and the temporal cluster C, denoted as $E_{oc_{max}}$, is obtained by the hypothesis that the attribute values of the mutation points within temporal cluster C are equal. When θ is greater than the threshold, the mutation point O will be added into cluster C. If this exceeded the threshold, we allowed the mutation point O to be added to temporal cluster C. By choosing an appropriate value for θ, the PBM index is employed to achieve favorable outcomes. Achieving a high score for the PBM index confirms the acceptability of the result in terms of the attribute entropy measurement [41].

The cluster was iteratively expanded by repeating the steps of candidate selection until the first-order neighborhood of the cluster no longer contained similar points. Subsequently, the remaining points in the initial cluster were evaluated based on their $DAE_{nei}(O)$ values, and the point with the highest $DAE_{nei}(O)$ value was selected as the starting point for the second cluster. The aforementioned steps were repeated to group all points into different sub-clusters.

3.2. Urban Land-Use Change Simulation by UrbanVCA Model

UrbanVCA starts by utilizing a subdivision approach to establish the fundamental cellular unit as the minimum vector land parcel. In the context of this model, the segmented land-use parcels were characterized by the averages of spatial variables, denoted as X. These spatial variables served as the basis for defining probabilities of transformed land-use types, represented as Y. Subsequently, a model denoted as $Y = f(X)$ is formulated. Ultimately, the probability of the segmented parcel transitioning into the specific land-use type in the initial year, denoted as Y_i, served as the comprehensive suitability measure for land-use transformation when utilizing a VCA model (Figure 4).

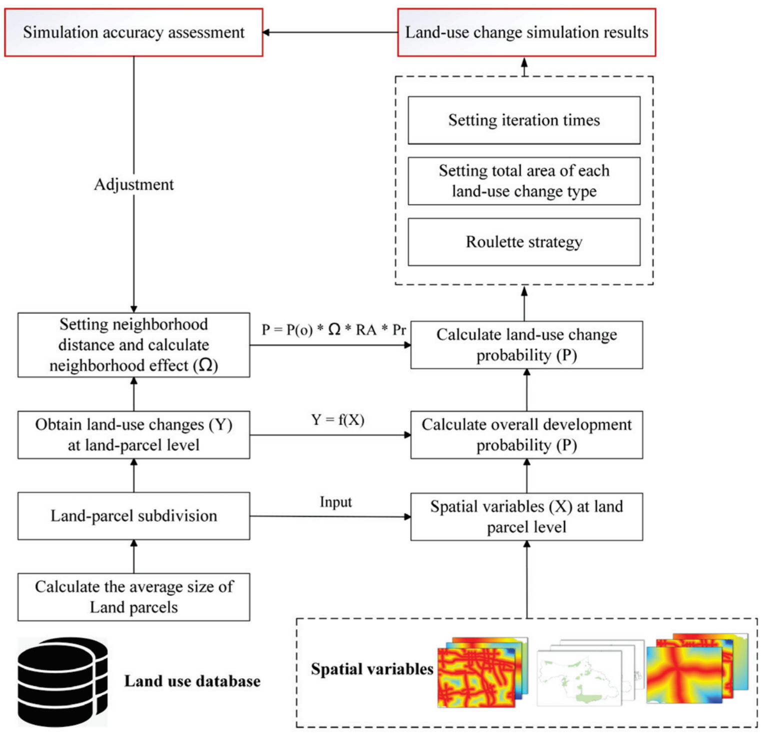

Figure 4. The UrbanVCA framework.

3.2.1. Deriving the Minimum Vector Land Parcels

The use of raw land parcels as the primary simulation units poses a challenge due to their coarse granularity, which ultimately results in a significant reduction in simulation precision [39]. Thus, an appropriate land subdivision tool must be employed. The DLPS tool, which was developed by Yao [8], can divide land parcels into finer layouts according to the initial plots' shape, size, and direction. The iterative and subdivision process continues until the area of each plot becomes smaller than the average area of the initial input plots (For more detailed information about data processing and execution, please refer to: https://www.urbancomp.net/archives/urbanvca-v2, accessed on 26 May 2022).

3.2.2. Mining the Urban Development Probability

After the subdivision of parcels through the DLPS module, the parcels were treated as fundamental units for simulation based on a VCA model. The urban developmental probability (P) of each cell was mainly determined by four factors: the land-use suitability (Pg), constraint factor (Pc), neighborhood effect (Ω), and random factor (RA). The probability of the i-th land parcel transitioning into the k-th type of land use at time t can be determined through the following calculation:

$$P_i^{k,t} = Pg_i^{k,t} \times \Omega_{i,j}^t \times Pc_i^t \times RA \tag{5}$$

The calibration of land-use suitability (Pg) as defined in Equation (5) was carried out by employing a selection of geospatial variables outlined in Figure 2. The UrbanVCA provided a selection of three machine learning algorithms to obtain the overall suitability: logistic regression (LR), neural network (NN), and random forest (RF). Here, we employed the RF-based model to perform the calibration and estimation of land-use suitability. Compared with LR, it proves highly effective in addressing the issue of multicollinearity among spatial variables, rendering it highly efficient when dealing with tasks that involve fitting in high-dimensional spaces. In addition, the RF-based model is better suited for extracting a variety of transformation rules in different regions compared with NN. Therefore, the land-use suitability of the i-th land parcel transitioning into the k-th land-use type at time t can be expressed as follows:

$$Pg_i^{k,t} = \frac{\sum_{n-1}^{M} I(h_n(x) == Y_k)}{M} \tag{6}$$

where i serves as an indicator for the ensemble of decision trees, with M representing the total number of decision trees. The vector x encompasses auxiliary spatial variables that are linked to the specific land parcel, and $h_n(x)$ indicates the predicted type of the n-th decision tree for vector x. The determination of the optimal number of decision trees involved iterative parameter adjustments, with comparison of the corresponding simulation accuracy results.

The fundamental units of VCA are irregular parcels, making it impossible to obtain the homogeneous neighborhoods commonly found in patch-based or raster-based CAs. Consequently, defining rules for VCA neighborhoods is both intricate and sensitive. In UrbanVCA, a centroid-based buffering rule was employed, which considered parcel area as a weight, facilitating the capture of actual parcel neighborhood effects (Ω), and thereby enhancing the accuracy of simulating diverse land-use types. Assuming that the j-th parcel is located within a buffer zone centered on the i-th parcel with a buffer range of d, and there are no physical barriers between the i-th and j-th parcels, the formula for the neighborhood effect of the j-th parcel on the i-th parcel at time t is as follows:

$$\Omega_{i,j}^t = e^{-d_{i,j}/d} * \frac{S_j/S_i}{S_{max}/S_{min}} \tag{7}$$

where e represents an exponential constant, while $d_{i,j}$ indicates the central distance between the i-th and j-th parcels. The variables S_i and S_j, respectively, represent the areas of the i-th and j-th parcels. Additionally, S_{max} and S_{min} denote the maximum and minimum parcel areas within the study area. Consequently, the formula expressing the neighborhood effect of the k-th land-use type on the i-th parcel at time t is as follows:

$$\Omega_i^{k,t} = \sum_j \Omega_{i,j}^{k,t} \left(if\ dis_{i,j} \leq buffer\_d\ and\ No\ River\ between\ i\ and\ j\right) \tag{8}$$

Constraint factor (Pc) refers to a specific land-use type that remains unchanged during the simulation process and does not transition into other land-use types. In this study, water area factor and ecological redline zones were considered as development-restricted areas. The constraint factor for the i-th parcel can be computed based on the following formula, where S_i represents the suitability status of the parcel for development:

$$Pc_i^t = \begin{cases} 0\{\ S_i = \text{restriction development area}\} \\ 1\ \{S_i = \text{suitable development area}\} \end{cases} \tag{9}$$

Taking into account the uncertainty inherent in the land-use change process, the random factor $RA = 1 + (-\ln y)^{\alpha}$ was introduced, where α is a parameter ranging within (1, 10), and y represents a stochastic variable with values that falls within the range of 0 to 1.

By calculating the probabilities for the conversion of each land parcel into different land-use types, the conversions that exceeded the development thresholds and had the highest probabilities were chosen for execution. For specific land-use classes in this study, the development thresholds were determined by computing the average probabilities of transition from all non-built-up land parcels to these particular land-use classes.

3.3. Model Performance Assessment

In this study, the figure-of-merit (FoM) method was employed to assess the accuracy of the simulation results [42]. FoM serves as a valuable indicator used to gauge the consistency between the actual transition pattern and the simulated transition pattern, calculated as the ratio between the intersection and union of the actual change and simulated change as follows:

$$\text{FoM} = \text{B}/(\text{A} + \text{B} + \text{C} + \text{D}) \tag{10}$$

where A denotes the area undergoing change, which remains constant during the simulations. B represents the common area of change shared between the actual and the simulation results. C corresponds to the area where changes are observed in both the actual and simulated maps, even though the specific land-use change types may differ between them. D represents the area that remains constant in the actual map but experiences changes throughout the simulations.

According to previous studies [26,43,44], several landscape indices, including PD (patch density), LPI (largest patch index), LSI (landscape shape index), and SHDI (Shannon's diversity index), were employed to assess how closely the patterns of the simulated results matched those of the actual scenario. PD plays a crucial role in describing landscape fragmentation. The higher the PD value, the more pronounced the landscape fragmentation becomes. LPI is determined by calculating the ratio between the area of the largest patch and the total landscape area, which quantifies the level of aggregation within the simulated landscape. A higher LPI value indicates a higher degree of aggregation within the simulated urban landscape. LSI provides a measure of the shape complexity of the landscape by quantifying the extent to which the shape of the simulated landscape deviates from that of a square with an equivalent area. The complexity of the shape of simulated urban patches increases with a higher LSI value. The SHDI is a metric that gauges the complexity and heterogeneity of various types of patches within a landscape. As SHDI increases, it tends to be a more uniform distribution of different patch types throughout the landscape. The landscape indices calculation process was performed using VecLI v3.0.0 software: https://www.urbancomp.net/archives/vecliv300, accessed on 18 September 2022.

4. Results and Discussions

4.1. Area Partitioning Implementation

To partition the research area, we employed the DSC algorithm. The land parcels are represented using DT, revealing an uneven dispersion of points that densely cover the entire city (Figure 5a). In such instances where spatial datasets are irregularly distributed, the natural neighbors distinguished through DT are imperfect with varying densities. The constrained DT is firstly employed to model the spatially heterogeneous adjacency relationships among these points (Figure 5b). It entails the use of varying search radii, with larger radii applied to low-density regions and smaller radii to high-density regions. As a result, every node and edge can retain the essential data required for model execution, such as parcel land-use type, neighboring parcels, and parcel development factors. On this basis, high-order extension strategy is iteratively implemented to traverse *k*th-order neighbors for each parcel based on IE-based attribute similarity, enhancing the capability of DSC to handling multidimensional data into a number of clusters. In Figure 5c, the points of the same color indicate that they belong to the same clusters. Finally, a Delaunay-based shape reconstruction method, as outlined by Peethambaran and Muthuganapathy [45], was utilized to accurately identify the boundaries of 17 different zones (Figure 5d).

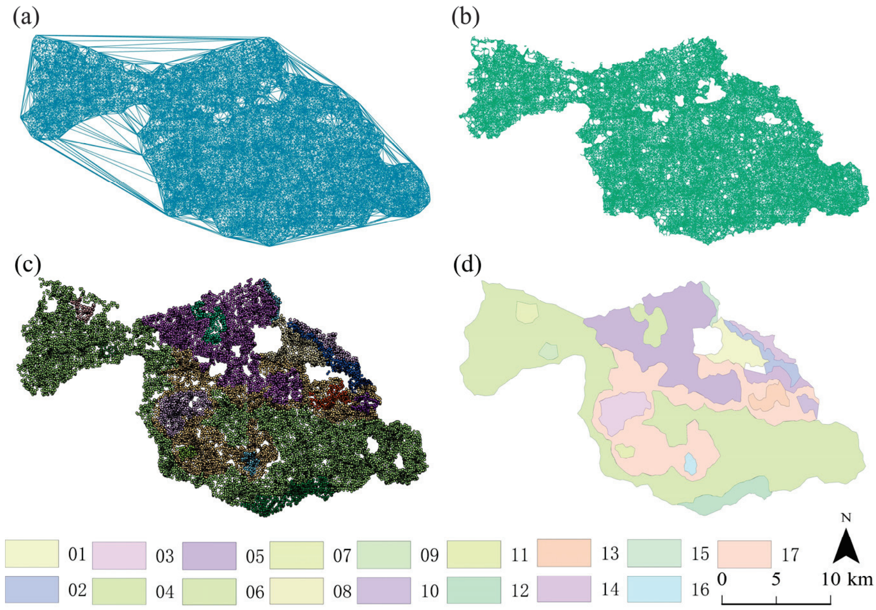

Figure 5. The area partitioning by DSC: (**a**) DT of land parcel centroids; (**b**) spatial proximity construction by DSC; (**c**) attribute similarity clustering by DSC; (**d**) 17 sub-regions.

4.2. Spatial Stratified Heterogeneity Measurement

In this study, we employed Geodetector [46] to quantify the degree of spatial stratified heterogeneity using various area partitioning strategies. Spatial stratified heterogeneity (SH) is represented by the q value: a higher q value indicates greater SH, signifying the need to divide the entire sample into stratified samples for modeling. The q value falls within the range of (0, 1), where 0 indicates insignificant spatial stratification of heterogeneity, and 1 signifies a perfect spatial stratification of heterogeneity. Under different area partitioning strategies in this study, Mk-means-based zoning indicates a q value of 0.327 and administrative-based zoning indicates a q value of 0.241. DSC-based zoning has the largest q value of 0.748. This means that DSC-based zoning helps to divide the whole urban space into more homogeneous sub-region areas (Figure 6).

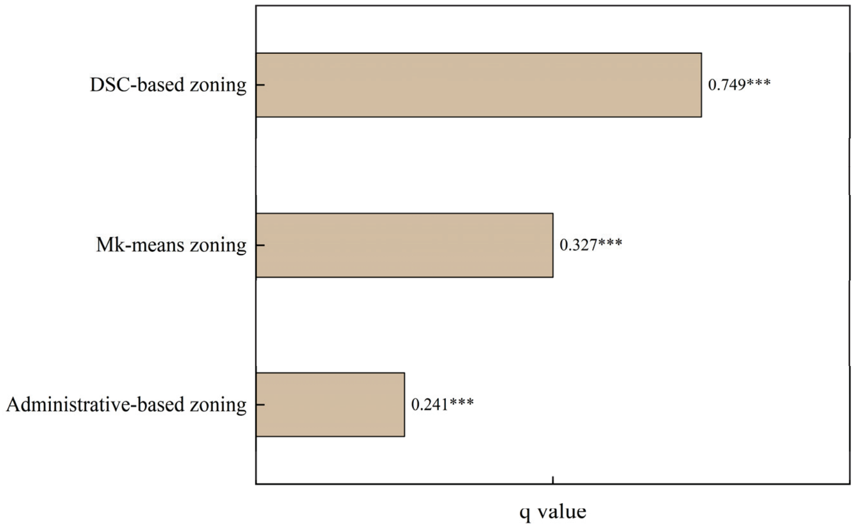

Figure 6. SH in three area partitioning strategies, ***: $p < 0.01$.

4.3. Urban Land-Use Changes Simulation

As described in the previous section, the transition rules were independently calculated with UrbanVCA in each partition. By using the DLPS tool, the initial 18,327 and 24,101 parcels from 2012 and 2017 have been respectively subdivided into 23,204 and 27,839 individual parcels. In the training of the RF model, we conducted a random selection of 60% of the data for training the model, reserving the remaining portion for cross-validation, to evaluate the model's accuracy. Specially, we established 90 decision trees with a 30% utilization of OOB data. Cross-validation was carried out through boosted random sampling over 100 epochs to calculate the average accuracy, thereby ensuring the utmost reliability of the outcome. Through the configuration of the RF, we can derive the land-use transition probability for each parcel by integrating the spatial variables listed in Table 1 within the partitioned study area. Additionally, the optimal value of Ω was determined by the best simulation result according to the FoM metric. For the purpose of determining the optimal radius value, we established the search step as 100 m in the range (200, 900) to conduct simulation. In this study, the neighborhood distance was adjusted to 700 m, resulting in the highest simulation accuracy being achieved (Figure 7).

Table 1. The FoM of different sub-regions and whole study area by administrative-based zoning.

Comparison Method	Sub-Region	FoM
Administrative-based zoning	Chengdong	0.192221
	Chengxi	0.239187
	Chengnan	0.215116
	Chengdongnan	0.192636
	Central	0.256496
	Jiangyin	0.221000

Transition rules for the partitioned CA model were determined by incorporating constraint factors, neighborhood effects, random factors, and land-use transition probabilities. Subsequently, the partitioned CA model was executed to simulate the evolution of urban land use in Jiangyin from 2012 to 2017, where the urban growth pattern in Jiangyin in 2017 was simulated. Figure 8 displays the FoM values of the simulation results in different partitions. The accuracy of each area was relatively high and the FoM of the whole study area was significantly larger than 0.22. Especially, the average FoM values for the partitions exceeded 0.22, except for partitions 11 and 16. The main reason for this is the significantly small number of land parcels in these two subzones, coupled with the absence of comprehensive land-use types. Among the numerous subzones, they constituted only a tiny fraction, leading to their notable low accuracy (0.098 and 0.039, respectively). These results indicated two key points: (1) The partition VCA model, which relies on DSC clustering and RF-based rule mining, is capable of achieving a high degree of accuracy in simulating land-use patterns for both individual subzones and the entire study area; (2) The DSC algorithm is well-suited for identifying clusters within datasets characterized by an uneven distribution of non-spatial attributes. Nevertheless, it has the potential to lead to an over-segmentation of urban space into numerous smaller areas, thereby affecting the accuracy of partition simulation.

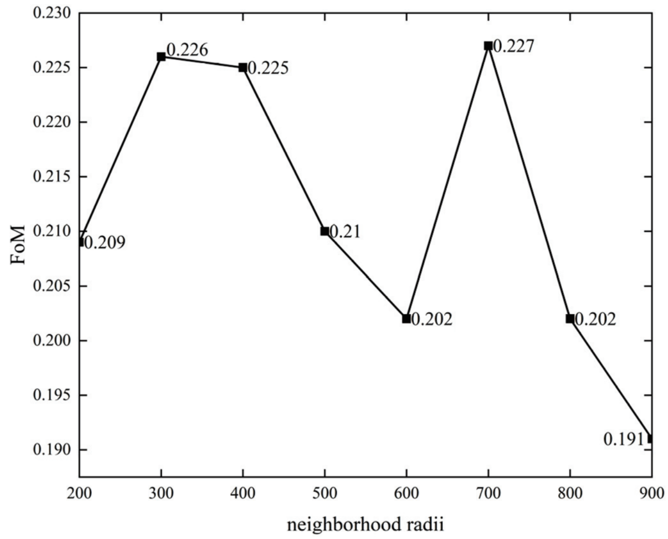

Figure 7. The FoM of different neighborhood radii (unit: meters) via RF model.

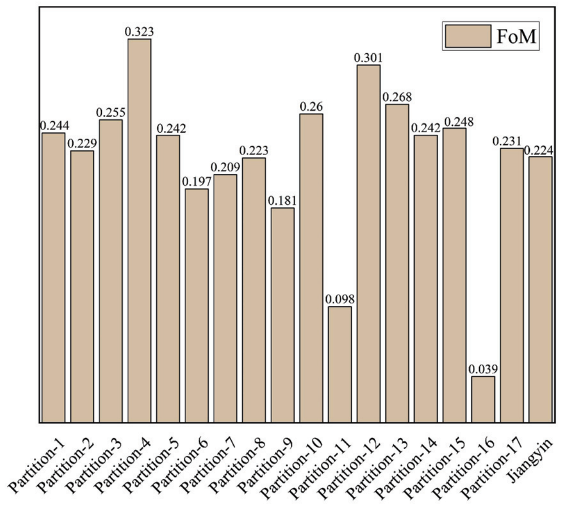

Figure 8. The FoM of different sub-regions and whole study area by proposed model.

Additionally, we conducted a comparison between the simulated results and the actual urban land use, as illustrated in Figure 9. This comparison specifically focuses on landscape indices within the study area. It can be observed in Figure 10 that the proposed framework can obtain acceptable results as the PD, LPI, LSI, and SHDI metrics are similar to the actual case. In a more detailed analysis, the PD values obtained in simulation results were typically higher than the actual values, leading to a significantly greater degree of land fragmentation, coupled with lower LPI values. This could be due to the increased landscape fragmentation caused by parcel subdivision, as well as an over-segmentation of the zoning scheme. Notably, the SHDI obtained from DSC clustering is higher than the actual land-use situation. This observation suggests that, when applying DSC, there is a tendency for different patch types to exhibit a balanced distribution within the landscape. This capability effectively illustrates landscape heterogeneity, particularly in capturing the non-uniform distribution of various patch types within the landscape.

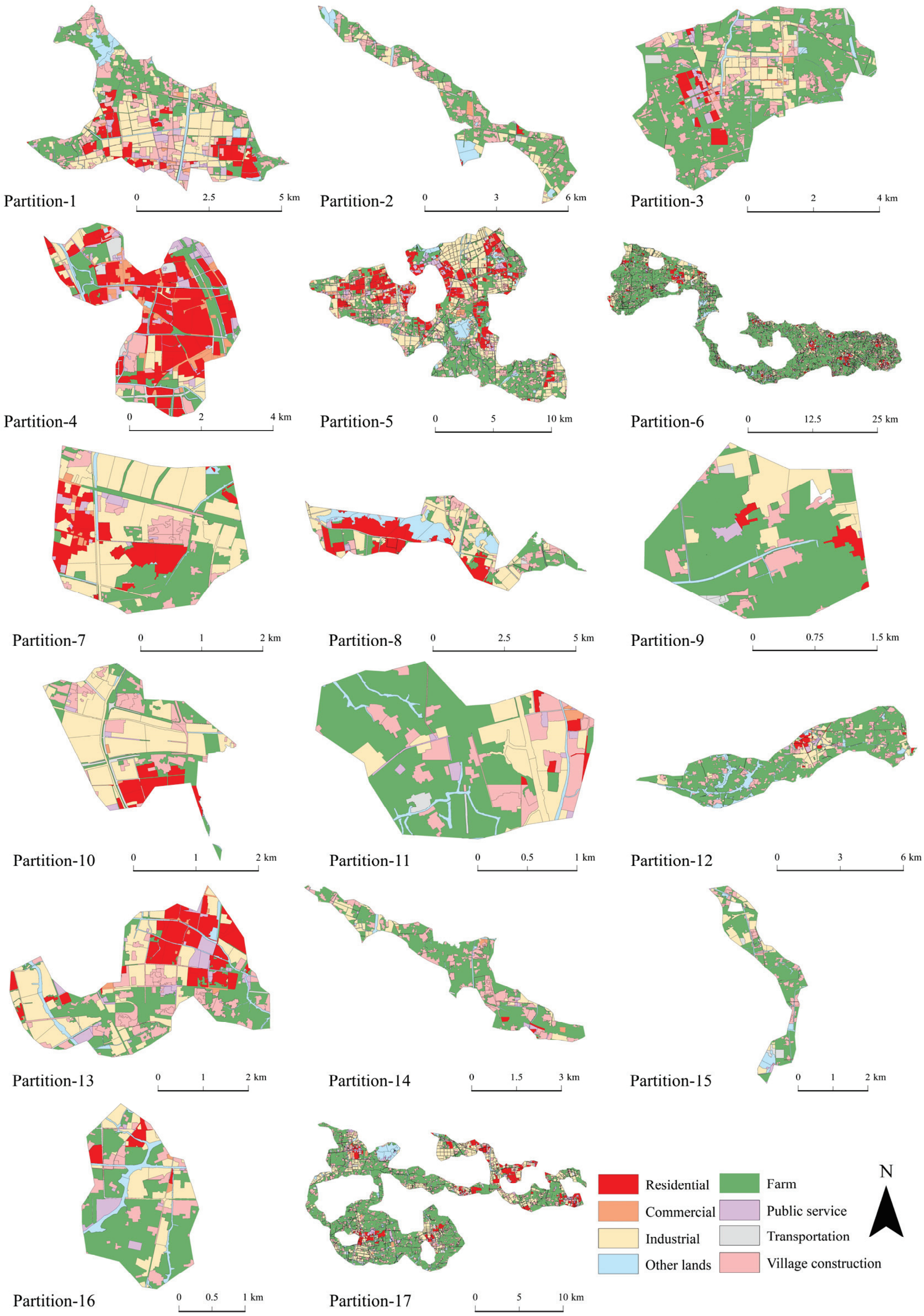

Figure 9. The simulation results of different sub-regions by the proposed framework.

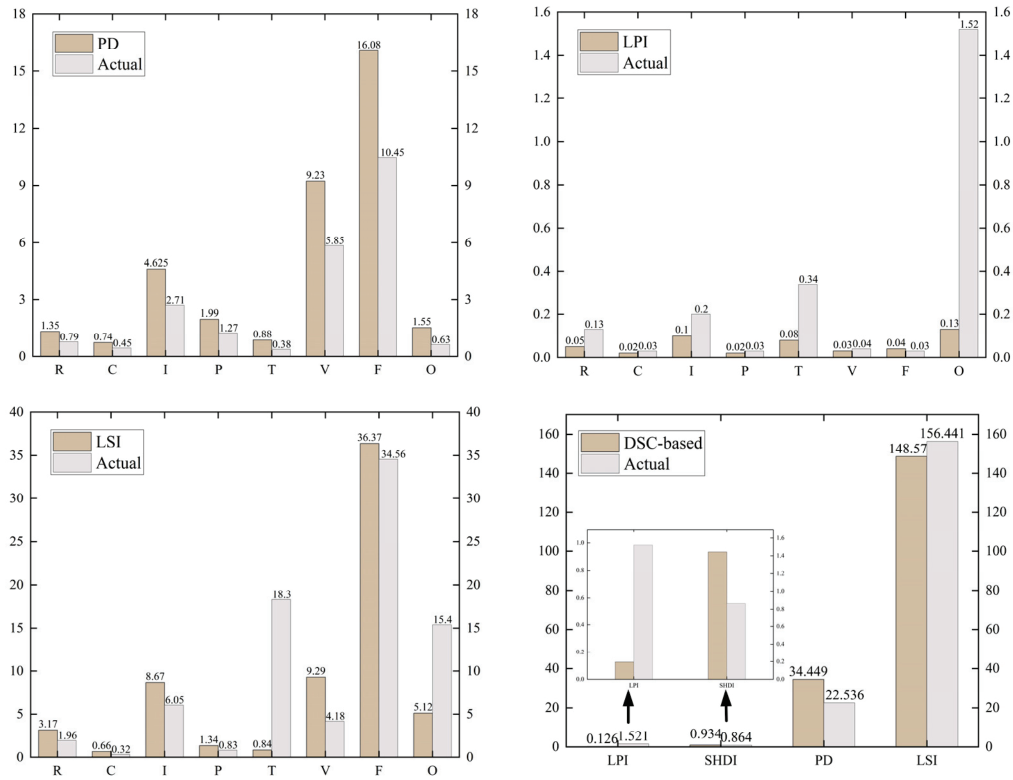

Figure 10. Landscape indices of the simulated results via the proposed model in the study area.

4.4. Model Comparison and Assessment

4.4.1. Comparison of Simulation Using Administrative-Based Zoning

As described in the previous section, Jiangyin city was divided into five administrative districts: Chengdong, Chengxi, Chengnan, Chengdongnan, and the Central Zones. The UrbanVCA model was then employed to simulate each partition, and the simulation accuracy is presented in Table 1. Overall, the administrative-based approach demonstrated acceptable simulation performance. There remain differences between the proposed approach and the two models. As Figure 11 demonstrates, the results of the proposed area partitioning approach tend to be more fragmented than that achieved through administrative-based zoning, as characterized by both the PD and LPI metrics showing a great difference from the actual scenario. Nevertheless, the proposed area partitioning approach, taking spatial heterogeneity into account, has the potential to generate more accurate simulation results, as FoM values are higher and SHDI and LSI metrics are closer to real-world observations. Through details in Part 1, Part 2, and Part 3 (Figure 12), it is evident that the administrative-based zoning scheme displays cases of misclassifying agricultural land as residential land and rural construction land. In comparison, the simulation results obtained using DSC clustering came closest to representing the actual land-use situation. Furthermore, when considering the shapes of individual land parcels, they also closely resemble the real land use. These findings suggest that the administrative-based zoning scheme results in a higher degree of urban landscape aggregation and lower shape complexity, highlighting its effectiveness in simulating regular urban landscapes [47,48].

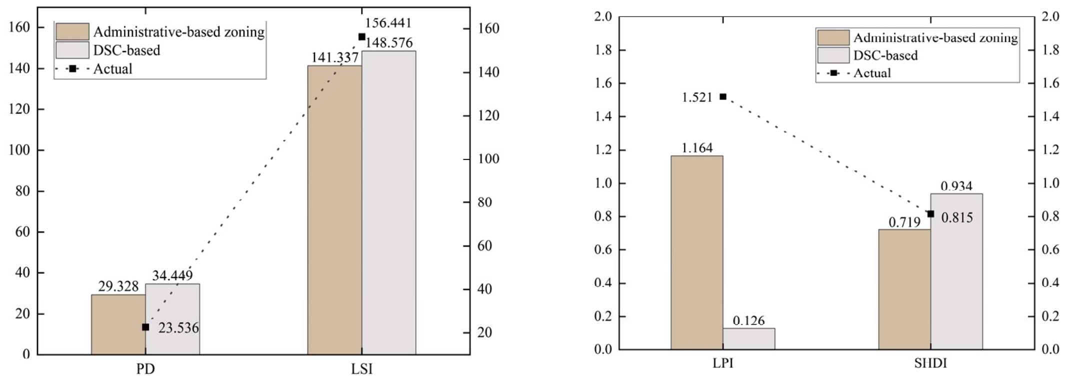

Figure 11. Comparison of the simulated results by the DSC-based vs. administrative-based zoning.

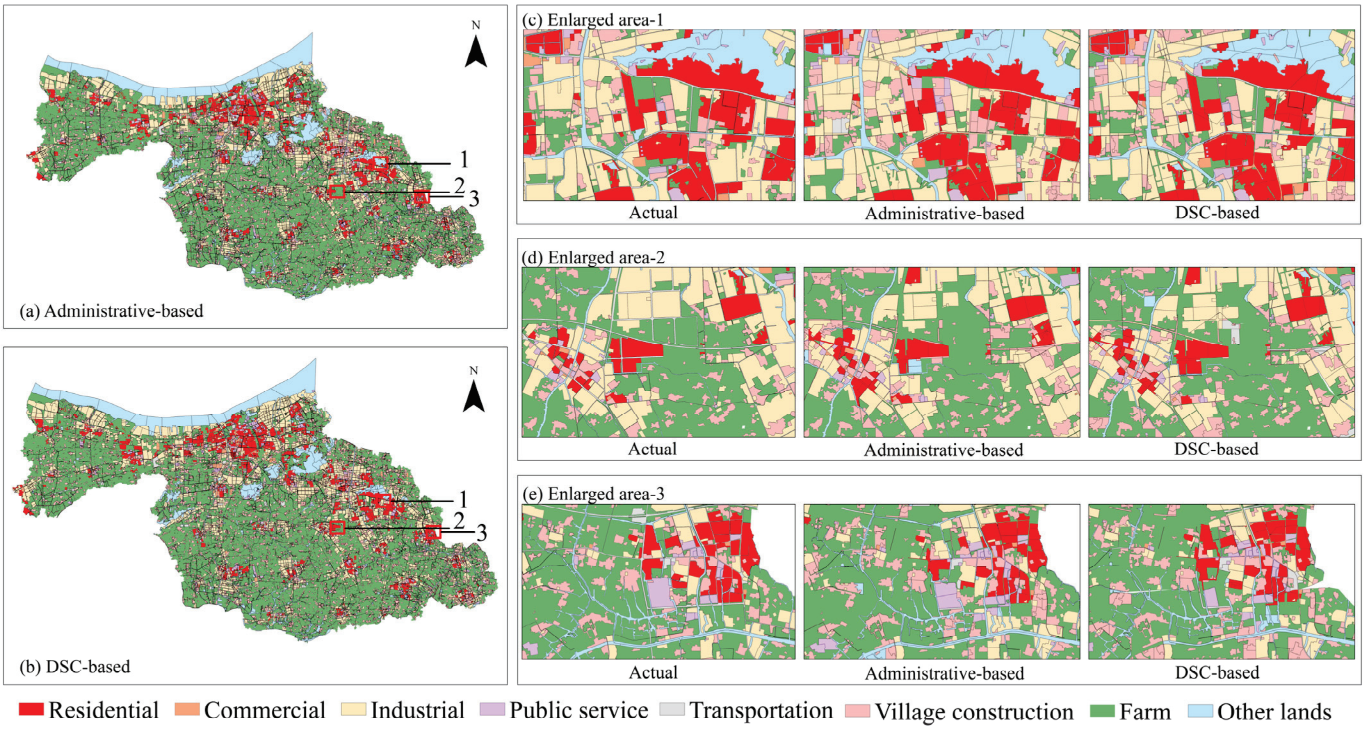

Figure 12. Details of actual and simulated (DSC-based and administrative-based zoning) land-use changes.

4.4.2. Comparison of Simulation Using Traditional Dual Spatial Clustering Zoning

For comparative purposes, we also introduced two typical dual spatial strategies: modified k-means (MK-means) [49] and DBSC [50]. The K-means method calculates the spatial distance of the clustering targets, while the MK-means algorithm not only focuses on the spatial clustering of the targets but also takes into account their attribute distance. Therefore, the MK-means algorithm uses a generalized Euclidean distance as the clustering metric, replacing the spatial distance used in the K-means method. The generalized Euclidean distance is defined as follows:

$$D(p_i, p_j) = \sqrt{w_1 D_S(p_i, p_j) + w_2 D_A(p_i, p_j)} \tag{11}$$

In this equation, $D(p_i,p_j)$ between p_i and p_j is calculated as the weighted sum of the normalized spatial distance $D_S(p_i,p_j)$ and non-spatial distance $D_A(p_i,p_j)$. The default values for the weights, w_1 and w_2, are both set to 0.5 [51].

The DBSC algorithm is a clustering method that identifies spatial clusters by modelling the spatial proximity and attribute similarity relationships among spatial objects with the help of constrained Delaunay triangulation (for more details, refer to [50]). The DBSC algorithm has proven to be efficient and applicable in detecting clusters characterized by irregular shapes and varying densities.

For the first experiment, the optimal value of K was also determined by the best simulation result according to the FoM metric. We conducted the clustering for five different values of k: 3, 4, 5, 6, and 7, and the k value was adjusted to 4, resulting in the highest simulation accuracy being achieved (i.e., FoM = 0.223). Figure 13 visually represents the partitioning results obtained through Mk-means, dividing the area into four sub-regions. Interestingly, these sub-regions exhibit a resemblance to the administrative divisions. This is primarily due to the challenge of the MK-means method in detecting clusters of arbitrary shapes and different densities. Moreover, the sensitive to noise parcels in the partition results could lead to systematic bias of simulated results [29]. Similar to the outcomes observed with the administrative zoning scheme, the MK-means method also presented instances of misclassification. It is detailed in Part 1, Part 2, and Part 3 (Figure 14) that while the MK-means zoning scheme effectively simulates the agricultural and public service land within the specified area, it still encounters instances of misclassifying certain agricultural land as other land-use types. Figure 15 displays the landscape metrics of the urban landscape, which were simulated using the three zoning schemes. The landscape metrics of the simulation results of MK-means are all positioned at a moderate level in comparison with that of the other two models. This suggests that the simulation accuracy of spatially heterogeneous area partitioning by different methods is DSC-based > Mk-means-based > administrative-based zoning.

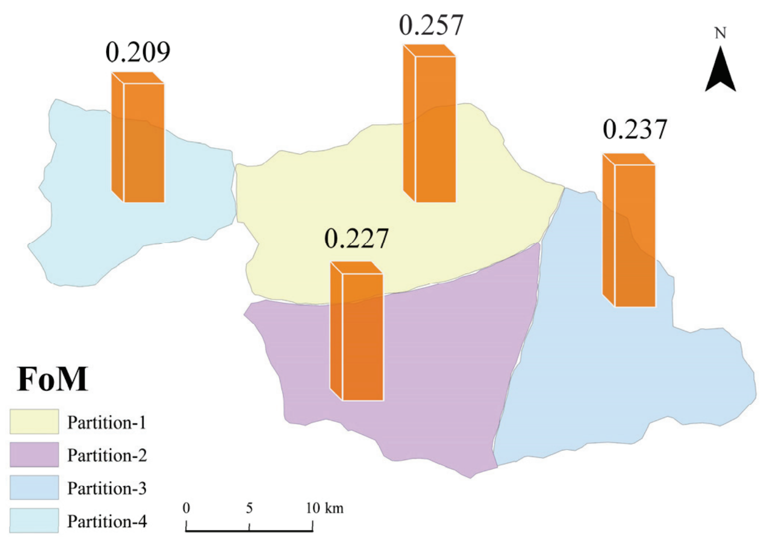

Figure 13. The area partitioning result by Mk-means.

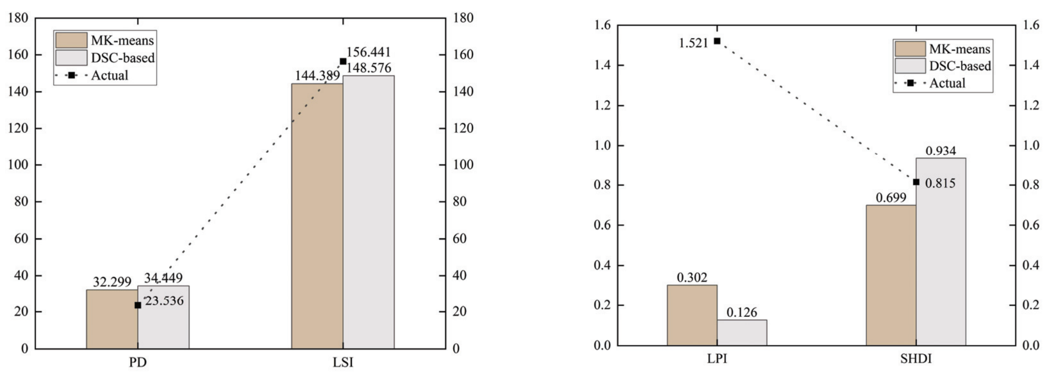

Figure 14. Comparison of the simulated results by the DSC-based vs. Mk-means-based zoning.

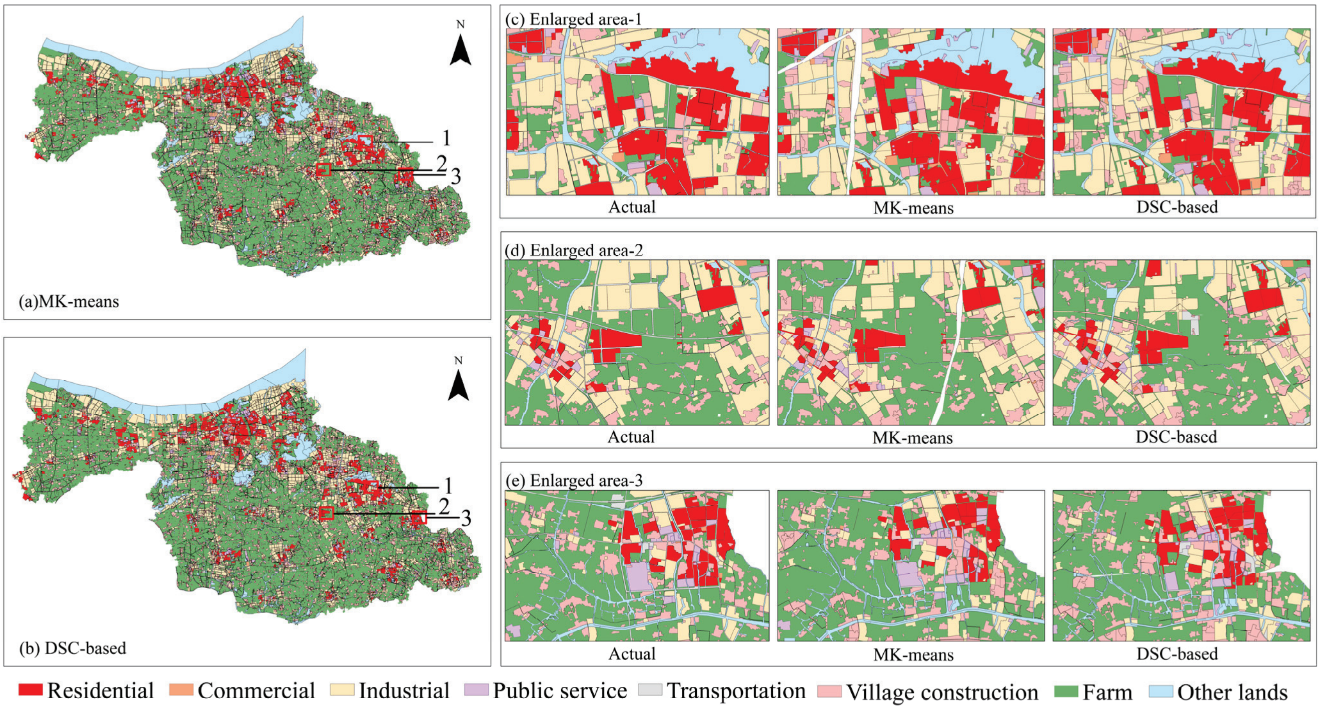

Figure 15. Details of actual and simulated (DSC-based and Mk-means-based zoning) land-use change.

For the second experiment, DBSC algorithm had difficulties in obtaining satisfactory results, where urban space was over-segmented into 2750 clusters (see Supplementary Figure S1). This is mainly attributed to the fact that the attribute similarity measurements in DBSC is treated as the Euclidean distance. Existing research has indicated that clustering methods developed for Euclidean scenarios can introduce systematic bias, leading to either an overestimation or underestimation of the clustering tendency [35]. Through the utilization of the information entropy clustering strategy, the DSC algorithm is able to identify appropriate indivisible clusters and mitigate the challenges associated with both over- and under-segmentation phenomena. The outcome demonstrates that the DBSC algorithm is unsuitable for datasets characterized by uneven attribute distributions.

5. Conclusions

Spatial planning in China not only encompasses individual regions but also requires the consideration of synergistic effects among different regions, resulting in distinctive interactive characteristics during the land evolution process [52]. Spatially heterogeneous area partitioning refers to the distribution and variations in various geographical features, conditions, and resources. These differences serve as the medium for interactions between different regions, influencing land-use decisions. By effectively utilizing information from spatial heterogeneity, planners can gain a more profound understanding of the structured development patterns in different regions. This aids in making spatial planning adjustments more effectively to promote balanced development across various regions, preventing excessive concentration or unreasonable dispersion of land use. These considerations hold significant practical importance for optimizing spatial planning at the urban level.

In CA modeling, spatial heterogeneity can be effectively characterized through geographical area partitioning. DSC is regarded as a suitable method to enhance the partition VCA model, as it can efficiently capture the spatial heterogeneity in the distribution of land-use change factors. We adopted the DSC clustering to produce multiple relatively homogeneous sub-regions, thereby strengthening the transition rules of the UrbanVCA model and accurately simulating the urban growth of Jiangyin city. Three comparisons of traditional partitioned models (i.e., administrative-based, Mk-means-based, and DBSC-based zoning) were conducted to validate the effectiveness and merits of the proposed partitioned CA model using FoM accuracy metric and several vector-based landscape indexes. The primary conclusions can be summarized as follows:

For spatial stratified heterogeneity assessment: In order to demonstrate the effectiveness and superiority of the DSC algorithm, we assessed this spatial heterogeneity by applying the q-statistic to the distribution of land-use change factors of the DSC zones.

Under different division strategies in this study, Mk-means-based zoning indicates a q value of 0.327 and administrative-based zoning indicates a q value of 0.241. DSC-based zoning has the largest q value of 0.748. This means that DSC-based zoning helps to divide the whole urban space into more homogeneous sub-region areas.

For accuracy assessment: The proposed DSC-based area partitioning approach can obtain satisfying results as the average FoM values for the partitions exceed 0.22. Despite the fact that the DSC method may result in an excessive subdivision of the study area into several small areas, the tiny size of these areas does not compromise the model's ability to achieve the highest simulation accuracy. The administrative-based and MK-means-based zoning models demonstrated acceptable simulation performance. The MK-means algorithm faces challenges in accurately identifying the clusters of non-convex shapes and varying densities, resulting in partitioning results that visually resemble the administrative divisions. While both the DSC and DBSC methods tend to lead to an over-segmentation of urban space, the DBSC method, as opposed to DSC, utilizes a binary relation strategy for attribute clustering. This leads to an excessive over-segmentation of urban space, generating a considerable number of clusters and consequently causing systematic bias in simulation outcomes.

For landscape assessment: The fragmentation (i.e., PD index), aggregation (i.e., LPI index), shape complexity (i.e., LSI), and land heterogeneity (i.e., SHDI) of simulated urban landscape were conducted for the study region to evaluate the performance of different models. The results of the DSC-based area partitioning approach tend to be more fragmented compared with other models. The administrative-based zoning scheme results in the highest degree of urban landscape aggregation and lowest shape complexity, indicating its good performance in simulating regular urban landscapes. Meanwhile, the landscape metrics derived from the simulation results obtained using the MK-means approach are situated at a moderate level. Notably, the SHDI obtained from DSC clustering is closer to the actual land-use situation. This suggests that the DSC-based model can effectively portray landscape heterogeneity, particularly in capturing the non-uniform distribution of various patch types within the landscape.

In general, the simulation performance of spatially heterogeneous area partitioning by different methods is DSC-based > Mk-means-based > administrative-based zoning. DSC-based zoning indicates the largest q value, highlighting its effectiveness in capturing the spatial heterogeneity in the distribution of land-use change factors. MK-means-based and administrative-based zoning have advantages in capturing regular urban landscapes of urban growth. However, when considering the degree of spatial stratified heterogeneity, they fall short in comparison with DSC with lower q-values.

There remain certain limitations that require further attention and resolution. First, the DSC algorithm was utilized for partitioning, and the outcome indicated that the combination of DSC clustering and RF-based rule mining was appropriate. Future research concerning partitioned vector CA models should focus on their capacity to recognize and effectively model land-use patterns, dynamics, and sensitivity to spatial heterogeneity. For example, how to measure the landscape heterogeneity from different aspects to improve the performance of partitioned transition rules. Second, the state-of-the-art convolutional neural network (CNN)-VCA model has achieved remarkable simulation performance at the land parcel level, representing a substantial advancement within the domain of VCA models [40]. Future research can apply the combination of DSC and CNN-VCA to the urban growth modeling to further validate its advantages and potential benefits. Finally, it is crucial to note that our study focused on testing the applicability within a specific city. Currently, our recommendation is for researchers to utilize the GeoDetector tool (http://www.geodetector.cn/, accessed on 3 October 2023) to measure the degree of spatial stratified heterogeneity (SH) by different division strategies. This approach has already gained recognition among scholars from diverse fields as a quantitative foundation for partitioning decisions. Future research could expand the proposed model to other cities to further validate the findings of this study.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land12101893/s1, Figure S1: DBSC clustering; Table S1: Spatial driving factors of land use change.

Author Contributions: J.Z. and J.Y. conceived and designed the experiments; M.Z. and J.N. performed the experiments and wrote the paper; Z.L. and Y.L. contributed to discussions and validation. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study can be obtained upon request from the corresponding author. Please be aware that the data are not publicly available, as they require approval from the Jiangyin Urban and Rural Planning and Design Institute.

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

References

1. Wang, H.; Guo, J.; Zhang, B.; Zeng, H. Simulating urban land growth by incorporating historical information into a cellular automata model. *Landsc. Urban Plan.* **2018**, *214*, 104168.
2. Gao, C.; Feng, Y.; Tong, X.; Lei, Z.; Chen, S.; Zhai, S. Modeling urban growth using spatially heterogeneous cellular automata models: Comparison of spatial lag, spatial error and GWR. *Comput. Environ. Urban Syst.* **2020**, *81*, 101459.
3. Li, X.; Liu, X. An extended cellular automaton using case-based reasoning for simulating urban development in a large complex region. *Int. J. Geogr. Inf. Sci.* **2006**, *20*, 1109–1136. [CrossRef]
4. Liu, X.; Liang, X.; Li, X.; Xu, X.; Ou, J.; Chen, Y.; Li, S.; Wang, S.; Pei, F. 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.
5. Li, X.; Yeh, G. Neural-network-based cellular automata for simulating multiple land use changes using GIS. *Int. J. Geogr. Inf. Sci.* **2002**, *16*, 323–343. [CrossRef]
6. Moreno, N.; Ménard, A.; Marceau, D.J. VecGCA: A vector-based geographic cellular automata model allowing geometric transformations of objects. *Environ. Plan. B* **2008**, *35*, 647–665. [CrossRef]
7. Pinto, N.; Antunes, A.P.; Roca, J. Applicability and calibration of an irregular cellular automata model for land use change. *Comput. Environ. Urban Syst.* **2017**, *65*, 93–102.
8. Yao, Y.; Liu, X.; Li, X.; Liu, P.; Hong, Y.; Zhang, Y.; Mai, K. Simulating urban land-use changes at a large scale by integrating dynamic land parcel subdivision and vector-based cellular automata. *Int. J. Geogr. Inf. Sci.* **2017**, *31*, 2452–2479.
9. Zhu, J.; Sun, Y.; Song, S.; Yang, J.; Ding, H. Cellular automata for simulating land-use change with a constrained irregular space representation: A case study in Nanjing city, China. *Environ. Plan. B* **2020**, *48*, 1841–1859. [CrossRef]
10. Guan, X.; Xing, W.; Li, J.; Wu, H. HGAT-VCA: Integrating high-order graph attention network with vector cellular automata for urban growth simulation. *Comput. Environ. Urban Syst.* **2023**, *99*, 101900.
11. Shi, W.; Pang, M.Y.C. Development of voronoi-based cellular automata -an integrated dynamic model for geographical information systems. *Int. J. Geogr. Inf. Sci.* **2000**, *14*, 455–474. [CrossRef]
12. Semboloni, F. The growth of an urban cluster into a dynamic self-modifying spatial pattern. *Environ. Plan. B* **2000**, *27*, 549–564. [CrossRef]
13. Gonzále, P.; Gómez-Delgado, M.; Benavente, F. Vector-based cellular automata: Exploring new methods of urban growth simulation with cadastral parcels and graph theory. In Proceedings of the International Conference on Computer in Urban Planning and Urban Management (CUPUM), Cambridge, MA, USA, 7–10 July 2015.

14. Dahal, K.; Chow, T. Characterization of neighborhood sensitivity of an irregular cellular automata model of urban growth. *Int. J. Geogr. Inf. Sci.* **2015**, *29*, 475–497. [CrossRef]
15. Dahal, K.; Chow, T. A GIS toolset for automated partitioning of urban lands. *Environ. Model. Softw.* **2014**, *55*, 222–234. [CrossRef]
16. Feng, Y.; Tong, X. Dynamic land use change simulation using cellular automata with spatially nonstationary transition rules. *GISci. Remote Sens.* **2018**, *55*, 678–698. [CrossRef]
17. Zeng, H.; Zhang, B.; Wang, H. A hybrid modeling approach considering spatial heterogeneity and nonlinearity to discover the transition rules of urban cellular automata models. *Environ. Plan. B* **2023**, *50*, 1898–1915. [CrossRef]
18. Gong, Z.; Thill, J.-C.; Liu, W. ART-P-MAP neural networks modeling of land-use change: Accounting for spatial heterogeneity and uncertainty. *Geogr. Anal.* **2015**, *47*, 376–409.
19. Feng, Y.; Tong, X. Incorporation of spatial heterogeneity-weighted neighborhood into cellular automata for dynamic urban growth simulation. *GISci. Remote Sens.* **2019**, *56*, 1024–1045. [CrossRef]
20. Zhang, B.; Hu, S.; Wang, H.; Zeng, H. A size-adaptive strategy to characterize spatially heterogeneous neighborhood effects in cellular automata simulation of urban growth. *Landsc. Urban Plan.* **2023**, *229*, 104604.
21. Wu, H.; Li, Z.; Clarke, K.C.; Shi, W.; Fang, L.; Lin, A.; Zhou, J. Examining the sensitivity of spatial scale in cellular automata Markov chain simulation of land use change. *Int. J. Geogr. Inf. Sci.* **2019**, *33*, 1040–1061. [CrossRef]
22. Ménard, A.; Marceau, D. Exploration of spatial scale sensitivity in geographic cellular automata. *Environ. Plan. B* **2005**, *32*, 693–714.
23. Liao, J.; Tang, L.; Shao, G.; Su, X.; Chen, D.; Xu, T. Incorporation of extended neighborhood mechanisms and its impact on urban land-use cellular automata simulations. *Environ. Model. Softw.* **2016**, *75*, 163–175.
24. Roodposhti, M.S.; Hewitt, R.J.; Bryan, B.A. Towards automatic calibration of neighbourhood influence in cellular automata land-use models. *Comput. Environ. Urban Syst.* **2020**, *79*, 101416.
25. Ke, X.; Qi, L.; Zeng, C. A partitioned and asynchronous cellular automata model for urban growth simulation. *Int. J. Geogr. Inf. Sci.* **2016**, *30*, 637–659. [CrossRef]
26. Qian, Y.; Xing, W.; Guan, X.; Yang, T.; Wu, H. Coupling cellular automata with area partitioning and spatiotemporal con-volution for dynamic land use change simulation. *Sci. Total. Environ.* **2020**, *722*, 137738.
27. Xia, C.; Zhang, B. Exploring the effects of partitioned transition rules upon urban growth simulation in a megacity region: A comparative study of cellular automata-based models in the Greater Wuhan Area. *GISci. Remote Sens.* **2021**, *58*, 693–716.
28. Lu, Y.; Laffan, S.; Pettit, C. A geographically partitioned cellular automata model for the expansion of residential areas. *Trans. GIS* **2022**, *26*, 1548–1571. [CrossRef]
29. Yang, J.; Zhu, X.; Chen, W.; Sun, Y.; Zhu, J. Modeling land-use change using partitioned vector cellular automata while considering urban spatial structure. *Environ. Plan. B* **2023**, 23998083231152887.
30. Xu, Q.; Zhu, A.-X.; Liu, J. Land-use change modeling with cellular automata using land natural evolution unit. *Catena* **2023**, *224*, 106998.
31. Kazemzadeh-Zow, A.; Zanganeh Shahraki, S.; Salvati, L.; Samani, N. A spatial zoning approach to calibrate and validate urban growth models. *Int. J. Geogr. Sci.* **2017**, *31*, 763–782. [CrossRef]
32. Xu, Q.; Wang, Q.; Liu, J.; Liang, H. Simulation of Land-Use Changes Using the Partitioned ANN-CA Model and Considering the Influence of Land-Use Change Frequency. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 346.
33. Ke, X.; Deng, X.; Liu, C. Interregional Farmland Layout Optimization Model Based on the Partition Asynchronous Cellular Automata: A Case Study of the Wuhan City Circle. *Prog. Geogr.* **2010**, *29*, 1442–1450, (In Chinese with English Abstract).
34. Liu, Q.; Wu, Z.; Deng, M.; Liu, W.; Liu, Y. Network-constrained bivariate clustering method for detecting urban black holes and volcanoes. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 1903–1929.
35. Zhu, J.; Sun, Y.; Chen, L.; Zhou, W.; Meng, Y. A spatial clustering method based on uneven distribution of non-spatial at-tributes—Identifying city commercial center. *Geomat. Inf. Sci. Wuhan Univ.* **2017**, *42*, 1697–1701. (In Chinese with English Abstract).
36. Zhu, J.; Zheng, J.; Di, S.; Wang, S.; Yang, J. A dual spatial clustering method in the presence of heterogeneity and noise. *Trans. GIS* **2020**, *24*, 1799–1826.
37. Yang, J.; Dong, J.; Sun, Y.; Zhu, J.; Huang, Y.; Yang, S. A constraint-based approach for identifying the urban–rural fringe of polycentric cities using multi-sourced data. *Int. J. Geogr. Inf. Sci.* **2021**, *36*, 114–136.
38. Zhu, J.; Lang, Z.; Yang, J.; Wang, M.; Zheng, J.; Na, J. Integrating Spatial Heterogeneity to Identify the Urban Fringe Area Based on NPP/VIIRS Nighttime Light Data and Dual Spatial Clustering. *Remote Sens.* **2022**, *14*, 6126.
39. Yao, Y.; Li, L.; Liang, Z.; Cheng, T.; Sun, Z.; Luo, P.; Ye, X. UrbanVCA: A vector-based cellular automata framework to simulate the urban land-use change at the land-parcel level. *arXiv* **2021**, arXiv:2103.08538.
40. Zhai, Y.; Yao, Y.; Guan, Q.; Liang, X.; Li, X.; Pan, Y.; Yue, H.; Yuan, Z.; Zhou, J. Simulating urban land use change by integrating a convolutional neural network with vector-based cellular automata. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 1475–1499.
41. Pakhira, M.K.; Bandyopadhyay, S.; Maulik, U. Validity index for crisp and fuzzy clusters. *Pattern Recognit.* **2004**, *37*, 487–501.
42. Pontius, R.; Boersma, W.; Castella, J.; Clarke, K.; de Nijs, T.; Dietzel, C.; Verburg, P. Comparing the input, output, and vali-dation maps for several models of land change. *Ann. Reg. Sci.* **2008**, *42*, 11–37. [CrossRef]
43. Yin, H.; Kong, F.; Yang, X.; James, P.; Dronova, I. Exploring zoning scenario impacts upon urban growth simulations using a dynamic spatial model. *Cities* **2018**, *81*, 214–229.
44. Tong, X.; Feng, Y. A Review of Assessment Methods for Cellular Automata Models of Land-Use Change and Urban Growth. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 866–898.

45. Peethambaran, J.; Muthuganapathy, R. A non-parametric approach to shape reconstruction from planar point sets through Delaunay filtering. *Comput.-Aided Des.* **2015**, *62*, 164–175.
46. Wang, J.-F.; Zhang, T.-L.; Fu, B.-J. A measure of spatial stratified heterogeneity. *Ecol. Indic.* **2016**, *67*, 250–256.
47. Zhang, B.; Wang, H. Exploring the advantages of the maximum entropy model in calibrating cellular automata for urban growth simulation: A comparative study of four methods. *GISci. Remote Sens.* **2022**, *59*, 71–95.
48. Zhang, Y.; Liu, X.; Chen, G.; Hu, G. Simulation of urban expansion based on cellular automata and maximum entropy model. *Sci. China Earth Sci.* **2020**, *63*, 701–712.
49. Lin, C.-R.; Liu, K.-H.; Chen, M.-S. Dual clustering: Integrating data clustering over optimization and constraint domains. *IEEE Trans. Knowl. Data Eng.* **2005**, *17*, 628–637.
50. Liu, Q.L.; Deng, M.; Shi, Y.; Wang, J.Q. A density-based spatial clustering algorithm considering both spatial proximity and attribute similarity. *Comput. Geosci.* **2012**, *46*, 296–309. [CrossRef]
51. Liu, Y.; Wang, X.; Liu, D.; Liu, L. An adaptive dual clustering algorithm based on hierarchical structure: A case study of settlement zoning. *Trans. GIS* **2017**, *21*, 916–933.
52. Guo, R.; Chen, D.; Fan, J. Territory spatial planning system and the convergence between different levels. *Geogr. Res.* **2019**, *38*, 2518–2526. (In Chinese with English Abstract).

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Article

Spatial–Temporal Characteristics and Influencing Factors of Land-Use Carbon Emissions: An Empirical Analysis Based on the GTWR Model

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Abstract: An in-depth comprehension of the spatial–temporal characteristics of land-use carbon emissions (LUCE), along with their potential influencing factors, is of high scientific significance for the realization of low-carbon land use and sustainable urban development. Academic investigations pertaining to LUCE predominantly encompass three key dimensions: assessment, optimization, and characterization research. This study aimed to investigate the spatial and temporal variations in LUCE within Zhejiang Province by analyzing data from 11 cities and identifying the key factors influencing these emissions. This research work employed the geographically and temporally weighted regression (GTWR) model to explore the patterns of variation in these factors across each city. The results reveal that (1) the temporal changes in LUCE display two predominant trends, while the spatial distribution exhibits a distinct "high in the northeast and low in the southwest" divergence; (2) the average intensity of each factor follows the order of economic level > government intervention > urban compactness > public facilities level > urban greening level > industrial structure > population density; (3) and the influencing factors exhibit significant spatial and temporal heterogeneity, with varying direction and intensity of effects for different cities at different stages of development. This study integrated the dimensions of time and space, systematically examining the evolutionary trends of influencing factors on LUCE within each region. Consequently, it contributes to the comprehension of the spatiotemporal effects associated with the driving mechanisms of LUCE. Moreover, it offers a foundation for formulating customized patterns and strategies to mitigate such emissions, taking into account specific local contexts.

Keywords: land-use carbon emissions; spatial–temporal characteristics; influencing factors; geographically and temporally weighted regression; Zhejiang Province

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1. Introduction

China's land financial model has yielded expeditious economic growth; however, it has concurrently fostered incautious land utilization and extensive urban sprawl, culminating in a discernible upsurge in carbon emissions. This, in turn, has instigated grave climate issues and the occurrence of extreme weather events, which substantively encroach upon the productivity and well-being of the population [1,2]. Global climate change poses new requirements and challenges for energy efficiency and low-carbon sustainable development in cities. Land-use changes and their associated land cover modifications represent the second most prominent factor contributing to the escalation of environmental issues, particularly the surge in carbon emissions, behind the combustion of fossil fuels [3]. Land-use changes exert influences not only on the urbanization process [4] and energy consumption [5,6] but also assume a crucial role within the complex interplay between carbon emissions and carbon sequestration. Furthermore, they directly or indirectly impact the mechanisms of carbon emission and sequestration at the interface of the terrestrial ecosystem and the atmosphere [7]. These influences are primarily manifested through modifications in land-use type, function, and structure [8–10]. Currently, due to inefficient land urbanization in China, leading to urban sprawl and generating large amount of carbon emissions [11,12], establishing how to coordinate the relationship between urban land and carbon emissions is a major issue to be solved [13]. Studying the spatial and temporal characteristics of land-use carbon emissions (LUCE), as well as the underlying influencing factors, holds paramount practical significance in achieving low-carbon land utilization and fostering a sustainable economy with a reduced carbon footprint.

The investigation of LUCE has garnered significant attention in recent academic research endeavors. In terms of the research scope, scholars have extensively investigated LUCE across various scales, encompassing national [10,14], regional [2,15], provincial [16], municipal [17], and county levels [18]. Furthermore, considering diverse research objectives, scholars commonly adopt a comprehensive approach by integrating spatial research scales and land-use types into a research matrix. For instance, some scholars focus on examining the spatial and temporal characteristics of carbon emissions within the same land type but across different regions, such as analyzing carbon emissions from industrial land in various cities [19]. Conversely, others concentrate on analyzing different land types within a specific region [20] or conducting detailed studies on a singular land type within the same region [21]. Additionally, comprehensive research and analysis encompassing various land types across different regions have been conducted to align with distinct emission reduction objectives aimed at fostering differentiation and coordination [22].

In terms of research content, the current scholarly investigations pertaining to LUCE can be broadly categorized into three primary aspects.

Firstly, there is a focus on assessing the effectiveness, efficiency, and carbon emission intensity of different land uses. LUCE should be considered in a comprehensive manner for economic and social benefits as well as ecological benefits [23]. Furthermore, certain scholars have developed an evaluation index system to assess the level of land-intensive use [24], focusing on land-use efficiency as a key perspective. This evolution is evident in the transition from single-index measurements to the adoption of multi-index measurement systems [25]. The research scope encompasses individual cities and urban agglomerations, enabling a more comprehensive analysis [26]. The evaluation methodologies employed have advanced from descriptive models to encompass regression models, data envelopment models, and panel data models [27].

The second aspect of current research on LUCE involves investigating the optimization of land-use structures and patterns. Human activities can significantly influence regional carbon emissions by altering land-use patterns [28], subsequently impacting energy consumption patterns and ultimately influencing the quantity of carbon emissions. Given that the configuration and distribution of land use profoundly shape the spatial arrangement of the built environment and associated human activities, particular emphasis is placed on the spatial layout of urban land use as a pivotal factor with a significant impact on carbon emissions [29]. It is essential to explore the relationship between land-use patterns and overall carbon emissions, analyze the carbon emission effects resulting from land-use changes, and propose viable and effective approaches for land managers and policymakers to consider for reducing carbon emissions [28]. Notably, optimization studies employ optimization models where varying constraints represent the values associated with adopting different optimization strategies. When optimizing the spatial distribution of land use with the constraint of minimizing carbon emissions, scholars incorporate additional factors such as population carrying capacity [30], economic development [31], and the ecological environment [32] to account for various considerations.

The third aspect encompasses the examination and analysis of LUCE mechanisms from the perspective of mixed land use and compact cities. Achieving effective mixed land use in urban areas necessitates moving beyond the traditional approach of functional zoning in urban planning [33]. Instead, it requires the rational integration of work, living, and recreational spaces at the community level. Mixed land use exerts both direct and indirect effects on carbon dioxide emissions. The direct effect involves the carbon source and carbon sink dynamics of the land, while the indirect effect primarily stems from enhanced production efficiency, increased public transport utilization, and reduced traffic congestion. Existing research indicates a positive U-shaped correlation between mixed land use and carbon dioxide emissions [34], suggesting that a certain degree of mixed land use can contribute to carbon dioxide reduction. The term "compact" embodies three key aspects: functional compactness, scale compactness, and morphological compactness [35]. The realization of spatially compact cities can substantially alleviate road traffic, particularly the reliance on private vehicles, thereby mitigating traffic congestion, reducing oil consumption, preserving resources, and curbing air pollution [33]. Emphasis is placed on optimizing the internal structure of urban areas, renewing inefficient land use within built-up areas, and fostering polycentric urban configurations within the framework of compact development.

The academic research on LUCE and their influencing factors has experienced continuous improvement and expansion and yielded fruitful outcomes. These studies have utilized various models selected at appropriate scales to investigate significant issues. For instance, researchers have employed the Future Land Use Simulation (FLUS) model to predict optimal spatial land-use configurations [32,36], utilized Cellular Automaton (CA) to simulate natural processes of land-use changes [37], and more recently, adopted machine learning methods like the Back Propagation Neural Network (BPNN) to forecast urban LUCE [18]. Nevertheless, these studies are not without limitations. Primarily, geographic models predominantly focus on investigating the spatial distribution characteristics of carbon sources and sinks, as well as the spatial correlation of LUCE from a spatial geography perspective. However, only a few studies have effectively integrated both time series and spatial geographic dimensions to analyze LUCE comprehensively. Furthermore, previous studies have often utilized factor decomposition methods such as the Logarithmic Mean Divisia Index (LMDI) model to rank influencing factors and generalize the factors contributing to LUCE [38,39], neglecting the diverse development stages of cities and failing to provide policy recommendations tailored to specific developmental phases. The geographically and temporally weighted regression (GTWR) model has been extensively employed in carbon emissions research [40–42] and is applicable to the realm of LUCE. Therefore, the primary aim of this study is to conduct a comprehensive analysis of the spatial and temporal differentiation characteristics of LUCE, utilizing an extended time series in conjunction with the GTWR model. Additionally, it seeks to investigate the patterns and trends of crucial influencing factors associated with LUCE across various stages of urban development.

2. Overview of the Study Area and Data Source

2.1. Study Area

Zhejiang Province is situated on the southeast coast of China and represents the southernmost part of the Yangtze River Delta (118°01′~123°10′ E, 27°02′~31°11′ N). It is bordered by the East China Sea to the east, Fujian Province to the south, Shanghai and Jiangsu Province to the north, and Anhui Province and Jiangxi Province to the west. The province spans approximately 450 km in both the north–south and east–west directions (Figure 1). Since the implementation of China's reform and opening-up policy, Zhejiang Province has strategically capitalized on its coastal location, yielding notable advancements in economic development. Concurrently, this progress has engendered substantial modifications in land-use patterns and carbon emissions [43]. Additionally, as the birthplace of the "Two Mountains Theory", an innovative framework for ecological civilization construction, Zhejiang Province demonstrates commendable ingenuity in the realm of low-carbon sustainable development practices. Analyzing the LUCE can provide a distinctive standpoint for comprehensively understanding the developmental trajectory of the province from diverse perspectives.

This study focused on the correlation between land-use change and carbon emissions at the city scale within Zhejiang Province. The research encompassed 11 prefecture-level cities that fall under the administrative division of the province, namely, Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou, and Lishui. The inclusion of diverse cities within the same province as the research subjects served to mitigate the impact of macro policies on carbon emissions across different provinces. Moreover, it facilitated a comparative analysis across cities in distinct stages of urbanization and varying levels of development.

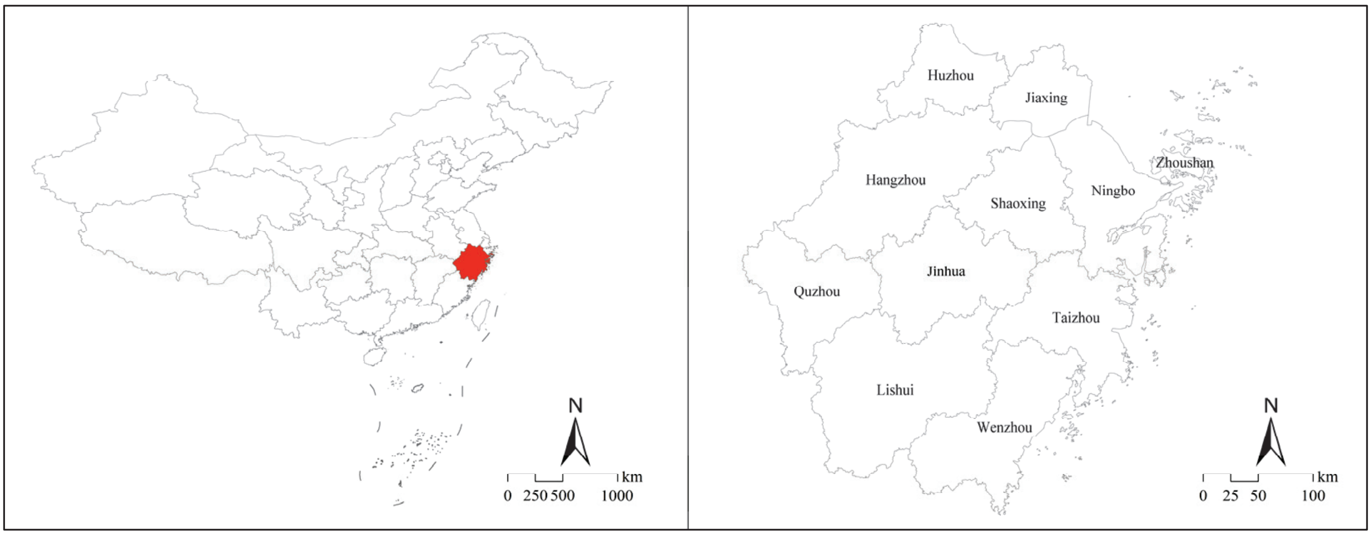


Figure 1. Location of the study area.

2.2. Data Sources

The present study utilized a comprehensive database to conduct a case study on preprocessing and further analysis. The database included the following components:

(1) Land-use data obtained for the interval of one year (10 years in total) from 2001 to 2019 were acquired. The relevant data were obtained from a widely utilized dataset [44] (https://zenodo.org/record/5816591, accessed on 10 May 2023), which has been widely used as the basic data for LUCE research [45,46]. The dataset was subjected to preprocessing, and ArcGIS 10.8 software was employed to extract information on construction land. Subsequently, the construction land patches within each city of Zhejiang Province were obtained through mask extraction operations. Patches with an area smaller than 0.01 km^2 and those exhibiting scattered distribution were excluded and manually corrected, resulting in the acquisition of construction land patches for the 11 cities in Zhejiang Province for each year;

(2) Socioeconomic data, including population, GDP, industrial structure, government revenue, general public budget expenditure, fixed asset investment, and livestock population, were retrieved from the *Zhejiang Statistical Yearbook*. Additionally, data on the completed area's green-covered area were obtained from the *China Urban Statistical Yearbook*. The accuracy and consistency of all of the aforementioned data were cross-referenced and verified against the statistical yearbooks of each city;

(3) Carbon emission data for the 11 cities in Zhejiang Province from 2001 to 2019 were obtained. These data represent estimated carbon emissions resulting from the primary energy consumption in each city. These data serve as a partial estimation of carbon emissions from construction land in the present article. The data were sourced from the Carbon Emission Accounts and Datasets (https://www.ceads.net.cn/, accessed on 10 May 2023), which comprise carbon emission inventories for 290 Chinese cities over the years under investigation. Previous studies have confirmed the comprehensiveness and effectiveness of these datasets [47,48].

It is worth noting that this study covered a substantial time period, and as a result, data for certain cities may have been missing for specific years. To address this issue, a limited number of missing data were supplemented using data from adjacent years or compensated for using the linear interpolation method. Moreover, all data were normalized before calculation.

3. Methodology

3.1. Calculation of LUCE

The present study classified land types into seven distinct categories, namely, cropland, forestland, shrubland, grassland, water bodies, construction land, and other lands. These land-use categories within Zhejiang Province can be further classified into two overarching types: "carbon sources" and "carbon sinks". In order to estimate carbon sinks and carbon emissions, calculations were performed based on established research findings and guidelines outlined by the Intergovernmental Panel on Climate Change (IPCC).

3.1.1. Accounting for Total Carbon Sinks

Carbon sinks primarily arise from the sequestration of carbon within terrestrial ecosystems, including forestland, shrubland, grasslands, water bodies, and other land categories. These specific land types can be directly quantified. Table 1 presents the carbon emission coefficients for different land-use types, which were derived from previous research findings. The total volume of carbon sinks (CS) in a natural ecosystem is calculated using the following formula:

$$CS = \sum CS_i = \sum (A_i \times \theta_i) \tag{1}$$

where CS_i is the carbon sink amount of each land type; A_i is the area of each carbon sink land type; and θ_i is the carbon sink coefficient per unit area of each carbon sink land type.

Table 1. Carbon emissions and sink coefficients.

Notation	Carbon Emission Component	Coefficient	Units	Source
θ_1	Forestland	−0.586	t/(hm^2·yr)	[15]
θ_2	Shrubland	−0.161	t/(hm^2·yr)	[49,50]
θ_3	Grassland	−0.021	t/(hm^2·yr)	[15,51]
θ_4	Water bodies	−0.253	t/(hm^2·yr)	[22,51]
θ_5	Other lands	−0.005	t/(hm^2·yr)	[15]
θ_c	Cropland	0.497	t/(hm^2·yr)	[15]
δ_1	Human respiration	0.079	t C/(person·yr)	[50,52]
δ_2	Pig respiration	0.082	t C/(head·yr)	[50,53]
δ_3	Cattle respiration	0.374	t C/(head·yr)	[50,53]

3.1.2. Accounting for Total Carbon Emissions

Construction land and cropland function as significant sources of carbon emissions, with construction land facilitating various economic and social activities encompassing human habitation and production. Notably, the primary factors under consideration pertain to energy consumption and respiratory emissions originating from both human activities and livestock. Specifically, the main livestock species taken into account are pigs and cattle. The following formula is utilized:

$$CE = C_u + C_c = C_e + C_p + C_c = C_e + \sum (p_i \times \delta_i) + A_c \times \theta_c \tag{2}$$

where C_u and C_c represent the emissions from construction land and cropland, respectively; C_e represents the carbon emissions of apparent energy consumption; C_p represents the carbon emissions of human and livestock respiration; P_i is the number of humans and livestock in a city; δ_i indicates the annual carbon emissions per person (head); A_c is the area of cropland; and θ_c is the carbon emission coefficient of cropland.

3.2. Net Land-Use Carbon Emissions

Net land-use carbon emissions (NLUCE) are the sum of carbon sources and sinks in a region and are calculated as follows:

$$C = CS + CE \tag{3}$$

where C is the NLUCE; CS is the total volume of carbon sinks; and CE is the total carbon emissions.

3.3. Influencing Factors

Drawing on relevant studies, this study focuses on the following influencing factors based on three aspects—socioeconomic aspects, urban form aspects, and urban environment aspects:

- Socioeconomic aspects

(1) Population density, represented by the number of people per unit area;
(2) Economic level, represented by GDP per capita to measure economic level;
(3) Industrial structure, represented by the ratio of secondary industry to GDP;
(4) Government intervention, represented by the ratio of general budget expenditure to total financial revenue;
(5) Public facilities level, represented by the ratio of investment in fixed assets to GDP.

- Urban form aspects

(6) The compactness of the peripheral profile form in urban areas holds significant importance as an indicator of urban spatial structure. In general, during the phase of rapid urban expansion, the compactness tends to decrease, whereas it tends to increase when cities transition toward internal filling and transformative development stages. The cyclical expansion of cities is intricately linked to the cyclical nature of urban economic development, and investigating the changes in the compactness of urban form allows for the identification of such cyclic patterns in urban expansion.

Enhancing the urban compactness index contributes to reducing the distance between various parts within the city, thereby improving the efficiency of urban infrastructure and optimizing the utilization of developed land. The compactness index CI is calculated by means of the following formula [54]:

$$CI = \frac{2\sqrt{\pi A}}{P} \tag{4}$$

where A is the area of the built-up area, and P is the perimeter of the built-up area of the city. A higher value of the compactness index indicates a more compact shape of the city;

- Urban environment aspects

(7) Urban greening level, represented by the proportion of green covered area to the built-up area.

3.4. GTWR Models

Compared with previous research models, this study incorporates the GTWR model into the investigation of LUCE. It focuses on comprehensively examining the dynamic evolution of influential factors contributing to LUCE during various stages of development within each city. Consequently, this approach enhances the ability to elucidate the spatiotemporal effects of the driving mechanisms behind LUCE in a scientifically robust manner. The conventional geographically weighted regression (GWR) model is subject to certain limitations when applied in specific contexts, primarily due to the restricted sample size of cross-sectional data. One prominent drawback is that the explanatory stability is constrained by the sample size, thereby impeding the accurate estimation of model parameters. In an effort to address this issue, researchers [55] introduced the temporal dimension to the GWR model, thereby incorporating the combined influence of spatiotemporal factors.

This advancement has led to the proposal of the geographically and temporally weighted regression model, known as GTWR. The GTWR model effectively extends the GWR framework by integrating temporal and spatial information, thus enhancing the weighting matrix and resolving the challenge of spatial and temporal nonsmoothness. Consequently, the estimation process is significantly improved. The specific equation for the GTWR model can be represented as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \tag{5}$$

where Y and X represent the dependent and explanatory variables, respectively. The variable i represents the sample region, while u and v represent the geographical coordinates of the sample region. Additionally, the variable t represents time. The term $\beta_0(u_i, v_i, t_i)$ corresponds to the intercept term, and $\beta_k(u_i, v_i, t_i)$ signifies the estimated coefficient for the explanatory variables. A positive value of β indicates a positive correlation between the explanatory and dependent variables, while a negative value indicates a negative correlation. The term ε_i represents the random disturbance term.

4. Results and Discussion

4.1. Land-Use Changes

As urbanization progresses, cities in Zhejiang Province require the ongoing expansion of construction land to facilitate their developmental needs. Consequently, urban construction land areas have expanded outward, resulting in substantial alterations to land-use patterns. The observed increase in construction land area across each city between 2001 and 2019 was approximately twice the original area. Notably, Hangzhou and Ningbo exhibited the most significant increments in construction land expansion, measuring 831.92 km^2 and 879.01 km^2, respectively. Furthermore, Jiaxing experienced substantial growth in construction land from 248.03 km^2 to 778.33 km^2, exceeding three times its initial size. Table 2 reveals that the augmentation of construction land predominantly occurred through the conversion of three land-use types: cropland, forestland, and water bodies. Five distinct land-use transformation patterns can be identified: first, the primary conversion involved cropland transforming into construction land, exemplified by Jiaxing. Second, there were instances of forestland being converted into both construction land and cropland, as observed in Wenzhou, Quzhou, and Lishui. Third, the most prevalent land-use change pattern entailed the conversion of cropland and forestland into urban construction land, evident in Hangzhou, Huzhou, Shaoxing, Jinhua, and Taizhou. Fourth, the conversion of cropland and water bodies into construction land was evident in the island city of Zhoushan. Finally, the city of Ningbo demonstrated the conversion of cropland, forestland, and water bodies into construction land. Irrespective of the specific conversion mode, whether involving a single land type such as cropland or forestland, or the combined conversion of cropland, forestland, and water bodies to facilitate construction, all these processes result in diminished carbon sinks and increased carbon sources. Therefore, it is imperative to conduct further investigations to explore the spatial and temporal differentiation of LUCE and their underlying influencing factors.

Table 2. Major land-use changes in Zhejiang's cities from 2001 to 2019.

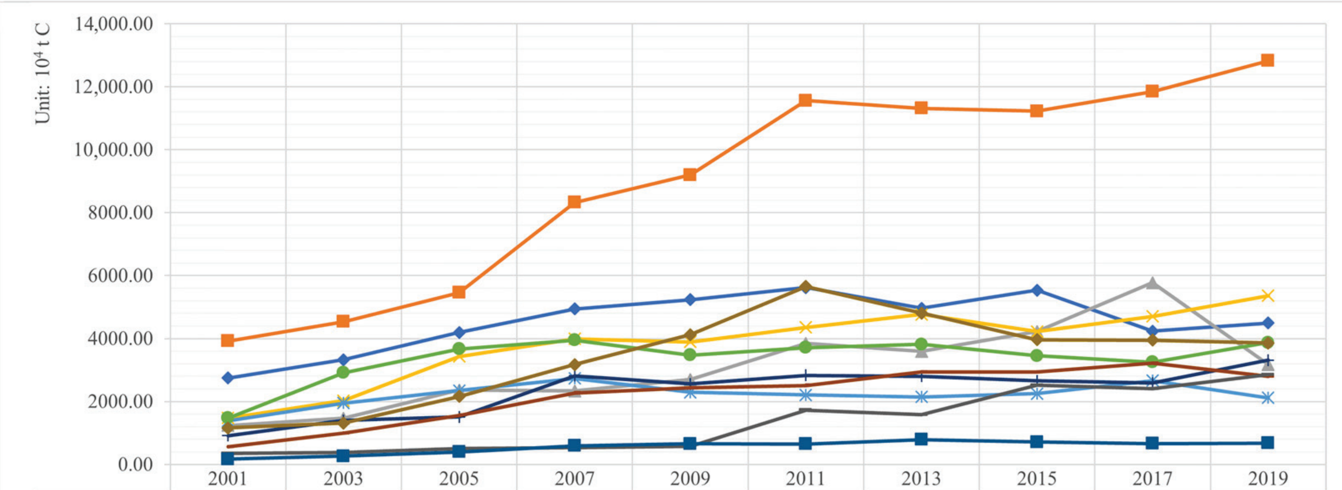
Cities	Land-Use Types	2001 (km^2)	2011 (km^2)	2019 (km^2)	2001–2019 (km^2)
Hangzhou	Cropland	3205.45	2553.36	2686.83	−518.63
	Construction land	636.69	1167.11	1468.61	831.92
	Forestland	12,201.59	12,280.22	11,930.67	−270.92
	Water bodies	836.67	879.03	794.27	−42.40
Ningbo	Cropland	3253.42	2901.97	2850.59	−402.84
	Construction land	698.29	1303.45	1577.30	879.01
	Forestland	4521.21	4348.68	4266.27	−254.94
	Water bodies	755.51	674.04	534.61	−221.10
Wenzhou	Cropland	2047.19	1801.55	2109.13	61.94
	Construction land	441.43	680.23	814.82	373.39
	Forestland	8698.51	8716.95	8313.80	−384.70
	Water bodies	242.19	232.49	194.81	−47.38
Jiaxing	Cropland	3591.53	3321.43	3117.16	−474.38
	Construction land	248.03	550.66	778.33	530.30
	Forestland	25.39	22.80	23.68	−1.71
	Water bodies	1049.84	1019.25	995.61	−54.23
Huzhou	Cropland	2849.06	2646.92	2589.38	−259.68
	Construction land	210.68	424.66	603.73	393.05
	Forestland	2523.62	2389.94	2284.23	−239.39
	Water bodies	240.64	361.76	346.64	106.00
Shaoxing	Cropland	2557.55	2265.12	2363.91	−193.64
	Construction land	423.85	710.55	867.12	443.27
	Forestland	4925.04	4911.33	4715.85	−209.19
	Water bodies	372.05	391.05	331.94	−40.11
Jinhua	Cropland	3118.94	2651.72	2817.73	−301.21
	Construction land	426.40	790.21	983.04	556.65
	Forestland	7276.66	7326.01	6993.81	−282.84
	Water bodies	138.41	191.90	166.06	27.65
Quzhou	Cropland	2046.61	1944.41	2079.32	32.72
	Construction land	218.11	322.73	409.76	191.64
	Forestland	6519.36	6479.76	6262.37	−256.99
	Water bodies	90.66	127.88	123.64	32.97
Zhoushan	Cropland	420.34	403.46	360.30	−60.04
	Construction land	95.48	168.92	214.31	118.83
	Forestland	568.12	531.55	559.48	−8.64
	Water bodies	95.01	74.96	44.89	−50.12
Taizhou	Cropland	2508.14	2280.38	2300.04	−208.10
	Construction land	416.91	714.22	860.08	443.18
	Forestland	6258.94	6182.98	6050.61	−208.33
	Water bodies	257.26	263.93	231.44	−25.82
Lishui	Cropland	870.00	731.62	1075.23	205.23
	Construction land	123.89	188.09	257.07	133.18
	Forestland	16,234.14	16,278.26	15,866.92	−367.82
	Water bodies	75.97	107.25	107.05	31.08

4.2. Spatial and Temporal Variation Characteristics of LUCE

4.2.1. Temporal Evolution Characteristics

Between 2001 and 2019, the total LUCE in Zhejiang Province exhibited a pattern of rapid growth followed by a period of stability. The emissions increased from 153.90 million tons in 2001 to 446.56 million tons in 2011, representing a substantial increase of 292.66 million tons. By 2019, LUCE reached 453.43 million tons, signifying an additional increase of 6.87 million tons compared to 2011. These data indicate a significant slowdown in the growth rate of carbon emissions, suggesting that Zhejiang Province is gradually exploring a sustainable development path characterized by a green economy, resulting in more effective carbon reduction outcomes.

Specifically, when examining LUCE at the city level, two distinct trends emerge (Figure 2). The first trend is exemplified by Ningbo, Wenzhou, Jiaxing, Quzhou, Zhoushan, and Lishui, where carbon emissions have consistently risen over the past two decades. Among these cities, Ningbo exhibits the highest annual average LUCE of 90.21 million tons, making it the city with the greatest annual emissions in Zhejiang Province. The second trend entails a phased rise and subsequent stabilization of LUCE. Hangzhou, Huzhou, Shaoxing, Jinhua, and Taizhou exemplify this pattern. Notably, Taizhou achieved the largest reduction in carbon emissions between 2011 and 2019, with a decrease of 17.92 million tons in LUCE compared to 2011. Overall, the cities in Zhejiang Province possess significant potential for carbon emission reduction. Whether following a trend of continuous growth or a phased rise followed by stabilization, the carbon emission increment index displays a general slowdown, indicating a shift away from the initial stage of crude carbon emission control and management. Instead, cities in Zhejiang Province are gradually embracing strategies and initiatives for green and low-carbon urban development.



	2001	2003	2005	2007	2009	2011	2013	2015	2017	2019
Hangzhou	2747.68	3327.29	4191.84	4938.31	5230.94	5618.24	4962.24	5535.80	4232.32	4493.95
Ningbo	3919.27	4537.89	5454.71	8323.78	9199.99	11,562.77	11,317.07	11,223.59	11,847.97	12,823.24
Wenzhou	1239.68	1466.80	2362.79	2329.66	2698.58	3840.80	3592.34	4223.06	5769.78	3170.04
Jiaxing	1474.31	2024.01	3432.98	3990.75	3893.56	4353.82	4764.27	4219.82	4703.60	5361.25
Huzhou	1384.83	1950.58	2347.52	2728.52	2295.06	2208.81	2142.65	2252.84	2659.15	2118.70
Shaoxing	1472.68	2915.19	3668.79	3950.67	3469.93	3707.86	3816.43	3454.28	3247.50	3874.41
Jinhua	916.30	1398.53	1508.15	2816.95	2558.11	2827.07	2799.29	2656.03	2581.24	3315.15
Quzhou	556.44	992.47	1555.97	2271.05	2434.10	2510.89	2935.00	2937.98	3213.14	2795.66
Zhoushan	349.85	379.36	500.32	533.27	572.45	1728.36	1575.75	2513.80	2402.83	2853.53
Taizhou	1161.28	1310.52	2155.95	3171.17	4125.57	5650.37	4807.12	3964.21	3946.90	3858.22
Lishui	167.70	260.66	399.29	592.59	653.75	647.25	788.62	713.14	660.15	679.32

Figure 2. Trends in the evolution of LUCE of cities in Zhejiang Province.

4.2.2. Spatial Distribution Characteristics

The spatial distribution of carbon emissions resulting from land-use activities in Zhejiang Province exhibits a distinct "high in the northeast and low in the southwest" pattern (Figure 3). Examining regional agglomeration, in 2001, the areas with elevated LUCE were primarily concentrated in the northern part of Zhejiang Province, with Hangzhou and Ningbo, the two central cities of the metropolitan area, accounting for the highest emissions. Huzhou, Jiaxing, and Shaoxing followed closely in the second gradient. Between 2001 and 2007, the northern region of Zhejiang Province maintained consistently high carbon emissions, while Hangzhou and Huzhou gradually decelerated their emission rates. From 2007 to 2017, there was a shift in the spatial distribution of the dual-center cities, with Ningbo emerging as the sole city with the highest carbon emissions. This shift in spatial dynamics indicated a transition in the center of carbon emission aggregation from the northern part of Zhejiang Province to the eastern coastal region. Moreover, a trend of carbon emission concentration and a circular spatial distribution pattern emerged. In 2019, Ningbo remained the largest urban area in terms of carbon emissions, with most cities experiencing a reduction in emissions compared to the previous period. The center of carbon emissions shifted from the east to the northeast, and the spatial distribution transformed from a scattered pattern to a more concentrated circular configuration. At the city level, Ningbo in the northeast consistently ranked highest regarding carbon emissions, exerting significant influence on the overall spatial distribution of carbon emissions in Zhejiang Province. Conversely, Lishui and Wenzhou in the southern part of the province maintained a relatively steady state in terms of total carbon emissions.

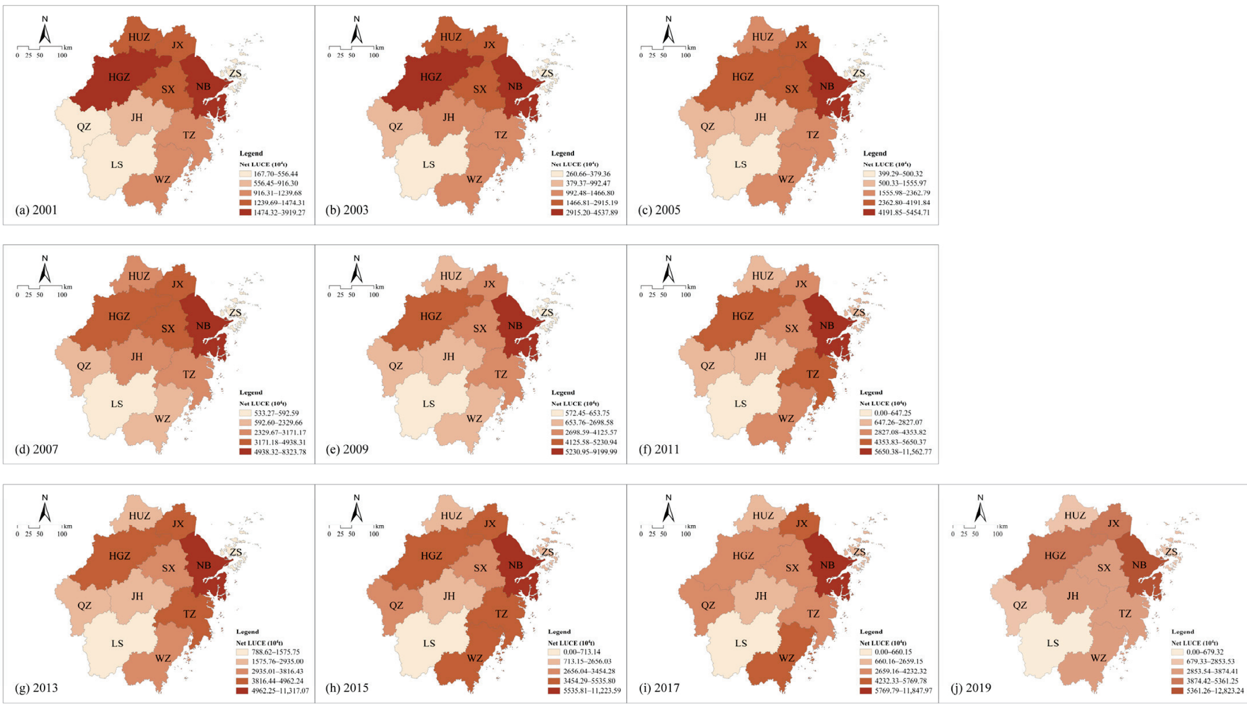


Figure 3. Spatial distribution of LUCE by cities in Zhejiang Province. Note: HGZ, Hangzhou City; NB, Ningbo City; WZ, Wenzhou City; JX, Jiaxing City; HUZ, Huzhou City; SX, Shaoxing City; JH, Jinhua City; QZ, Quzhou City; ZS, Zhoushan City; TZ, Taizhou City; LS, Lishui City. The same abbreviations are used for the following figures.

4.3. Spatial and Temporal Variation Characteristics of LUCE Influencing Factors

4.3.1. GTWR Empirical Results

Moran's I was employed to examine the global autocorrelation of the seven influencing factors, and the corresponding results are presented in Table 3. It was observed that each influencing factor demonstrated a positive Moran's index, with all global spatial autocorrelation coefficients being significantly greater than 0 at the 1% significance level. These findings indicate the presence of positive spatial correlation among the factors, implying a spatial clustering characteristic.

To investigate the localized correlation between different factors and LUCE, the GTWR model was used to analyze the spatial heterogeneity considering the influence of the "First Law of Geography". The obtained results are presented in Table 4, where both the R^2 and the adjusted R^2 surpass the threshold of 0.95. This indicates a high level of model fit and suggests that the regression model possesses substantial explanatory power. Consequently, the model outcomes can effectively illuminate the spatial heterogeneity of the influence.

Table 3. Statistical tests of spatial autocorrelation using Moran's I.

Influencing Factors	Moran's Index	Z-Score	*p*-Value	Confidence Interval
Population density (PD)	0.3238	17.1222	<0.01	99%
Economic level (EL)	0.0863	4.8947	<0.01	99%
Industrial structure (IS)	0.2749	14.5810	<0.01	99%
Government intervention (GI)	0.3584	18.9851	<0.01	99%
Public facilities level (PF)	0.1717	9.4052	<0.01	99%
Urban compactness (UC)	0.6188	32.3278	<0.01	99%
Urban greening level (UG)	0.0732	4.2427	<0.01	99%

Note: The contents in parentheses represent the respective abbreviations of the influencing factors.

Table 4. Index of model evaluation.

Bandwidth	Sigma	Residual Squares	AICc	R^2	Adjusted R^2
0.1575	0.0342	0.1288	−208.1290	0.9697	0.9677

4.3.2. Spatial and Temporal Heterogeneity of LUCE Influencing Factors

Through statistical analysis of the regression coefficients (Table 5), it was determined that the average intensity ranking order of each influencing factor is as follows: economic level > government intervention > urban compactness > public facilities level > urban greening level > industrial structure > population density. Among the top three factors, the median regression coefficient of economic level is 0.3417, and the mean value is 0.4171; the median regression coefficient of government intervention is −0.3115, and the mean value is −0.3962; and the median regression coefficient of urban compactness is −0.2977, and the mean value is −0.2850. Their median and mean values exhibit consistent changes in the same direction and are relatively close to each other. Moreover, by examining the range between the minimum and maximum values, it becomes apparent that both positive and negative correlations exist between all seven factors and LUCE. For instance, when considering urban compactness, the minimum compactness value is −0.7052, while the maximum value is 0.4190. The positive and negative effects of urban compactness exhibit variations across different cities, indicating that the general understanding, which posits that higher compactness results in lower carbon emissions from land use and advocates for continuous improvement in compactness in urban development, fails to account for the divergent developmental stages among cities. Therefore, when pursuing low-carbon development, cities need to adopt an adaptive and stratified approach that takes into consideration the specific characteristics of each locality.

Figures 4–10 depict the spatial distribution of the regression coefficients for the seven influencing factors derived from the GTWR model. The figures visually demonstrate the spatial heterogeneity in the impact of various factors on carbon emissions across different time periods.

Table 5. Descriptive statistics of regression coefficients of influencing factors.

Influencing Factors	Mean	S.D.	Min.	Median	Max.
Population density (PD)	−0.0248	0.2895	−1.2100	0.0260	0.4001
Economic level (EL)	0.4171	0.3597	−1.0195	0.3417	1.1011
Industrial structure (IS)	−0.0733	0.2862	−0.7208	−0.0080	0.4078
Government intervention (GI)	−0.3962	0.4375	−1.7426	−0.3115	0.6037
Public facilities level (PF)	−0.1018	0.2595	−1.0618	−0.0122	0.3481
Urban compactness (UC)	−0.2850	0.2438	−0.7052	−0.2977	0.4190
Urban greening level (UG)	−0.0967	0.2556	−1.2192	−0.0201	0.1961

Note: The contents in parentheses represent the respective abbreviations of the influencing factors.

- Socioeconomic Aspects

(1) Spatial and temporal heterogeneity of the influence of the population density factor on LUCE (Figure 4).

In terms of the temporal evolution of influence, population density has the greatest influence on LUCE in Quzhou and Shaoxing. In Quzhou, population density exhibits a negative correlation with LUCE, with the strength of this influence diminishing over time. Conversely, population density in Shaoxing shows a positive correlation with LUCE, and its impact remains relatively stable. In a broader context, the effect of population density on LUCE in each city undergoes a transition from initially negative to ultimately positive. The clustering of the population facilitates the spatial concentration of economic activities and production factors, as well as the sharing of social infrastructure [6,56]. This can result in reduced fixed investment costs, management costs, and improved energy and resource utilization efficiency, thereby lowering carbon emissions. However, excessive population density can lead to heightened energy consumption, hence displaying a positive correlation. The impact of population density on LUCE, while generally modest, should not be disregarded. It is imperative to judiciously manage the influx of migrants, endeavor to enhance demographic conditions, and encourage reasonable growth of the resident population [38].

Concerning the spatial distribution of influence, the impact of population density on LUCE is more significant in inland cities located in western Zhejiang Province compared to their counterparts in the eastern coastal areas.

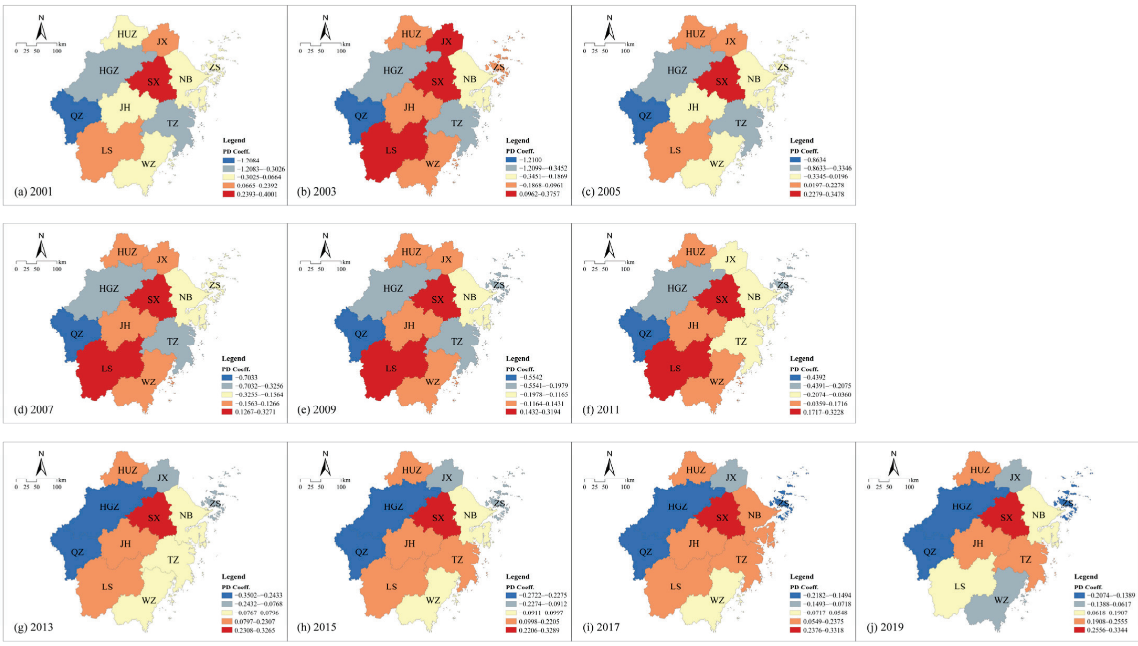


Figure 4. Spatial distribution of population density regression coefficients in Zhejiang's cities from 2001 to 2019.

(2) Spatial and temporal heterogeneity of the influence of the economic level factor on LUCE (Figure 5).

In terms of the temporal evolution of the degree of influence, a positive correlation is observed between the economic level and LUCE in the cities of Zhejiang. Moreover, this influence maintains a consistent stability. These findings align with prior research outcomes [2,39], underscoring the imperative of exploring strategies that foster an optimal equilibrium between economic advancement and LUCE. The economic level exhibits the strongest degree of influence on LUCE in two cities, namely, Ningbo and Taizhou, consistently maintaining a high level of influence. Notably, a negative correlation emerges between the economic level and LUCE in Wenzhou and Lishui after 2015, with the degree of influence steadily increasing. The negative effect of economic development on LUCE is similarly verified within the examination of the Chang–Zhu–Tan urban agglomeration [57]. This trend aligns with the advancement of economic development, optimization of the economic development model, and the implementation of low-carbon economic strategies, including the establishment of carbon emission reduction targets. These measures effectively regulate LUCE resulting from economic development, thereby fostering the emergence of a low-carbon economic development model as a potential catalyst for coordinated economic, social, and environmental development [58].

Regarding the spatial distribution of the degree of influence, the impact of the economic level on LUCE is more pronounced in the eastern coastal cities of Zhejiang Province compared to the western cities. This spatial pattern exhibits a trend characterized by higher influence in the eastern cities and lower influence in the western cities, commonly referred to as a “high in the east and low in the west” distribution. Specifically, Ningbo, Taizhou, Zhoushan, and Jiaxing, situated in the eastern region of Zhejiang Province, consistently experience the significant influence of a high economic level on LUCE. Conversely, Quzhou and Jinhua, located in the western region, demonstrate a lower level of economic influence on their LUCE.

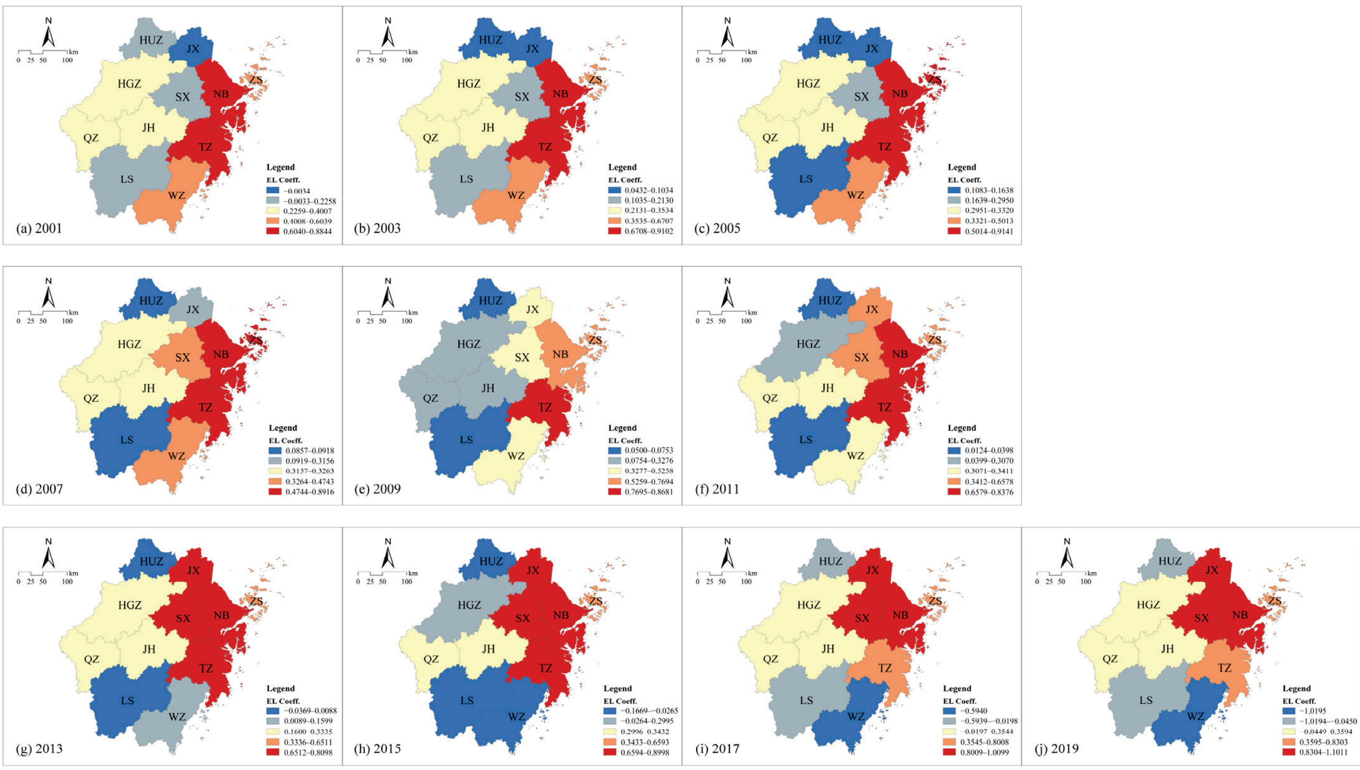


Figure 5. Spatial distribution of economic level regression coefficients in Zhejiang’s cities from 2001 to 2019.

(3) Spatial and temporal heterogeneity of the influence of the industrial structure factor on LUCE (Figure 6).

From a temporal perspective, the relationship between industrial structure and LUCE in Hangzhou and Quzhou consistently exhibits a positive association, with a stable degree of influence. This implies that higher proportions of secondary industry in these cities lead to elevated levels of LUCE. To effectively mitigate total LUCE, cities can appropriately reduce the proportion of secondary industry and prioritize the development of tertiary industry by modifying their industrial structure [2,17]. The impact of the industrial structure on LUCE in most cities shifted from a negative to a positive effect after 2009. A possible explanation is the inadequate transformation and upgrading of industrial structures during the initial stages of urban development. The mismatch between the industrial pattern and the high demand for industries like steel and cement in urban construction results in reduced carbon emissions from the reduced share of secondary industry, which is outweighed by the increased energy consumption associated with urbanization, thereby establishing a negative correlation between the two variables.

The influence of industrial structure on LUCE exhibits significant spatial heterogeneity in Zhejiang Province. Analyzing the dynamic evolution of the influence degree reveals a decreasing influence on cities in northeastern Zhejiang, represented by Ningbo, while cities in southwestern Zhejiang, such as Quzhou and Lishui, experience an increasing influence from the industrial structure.

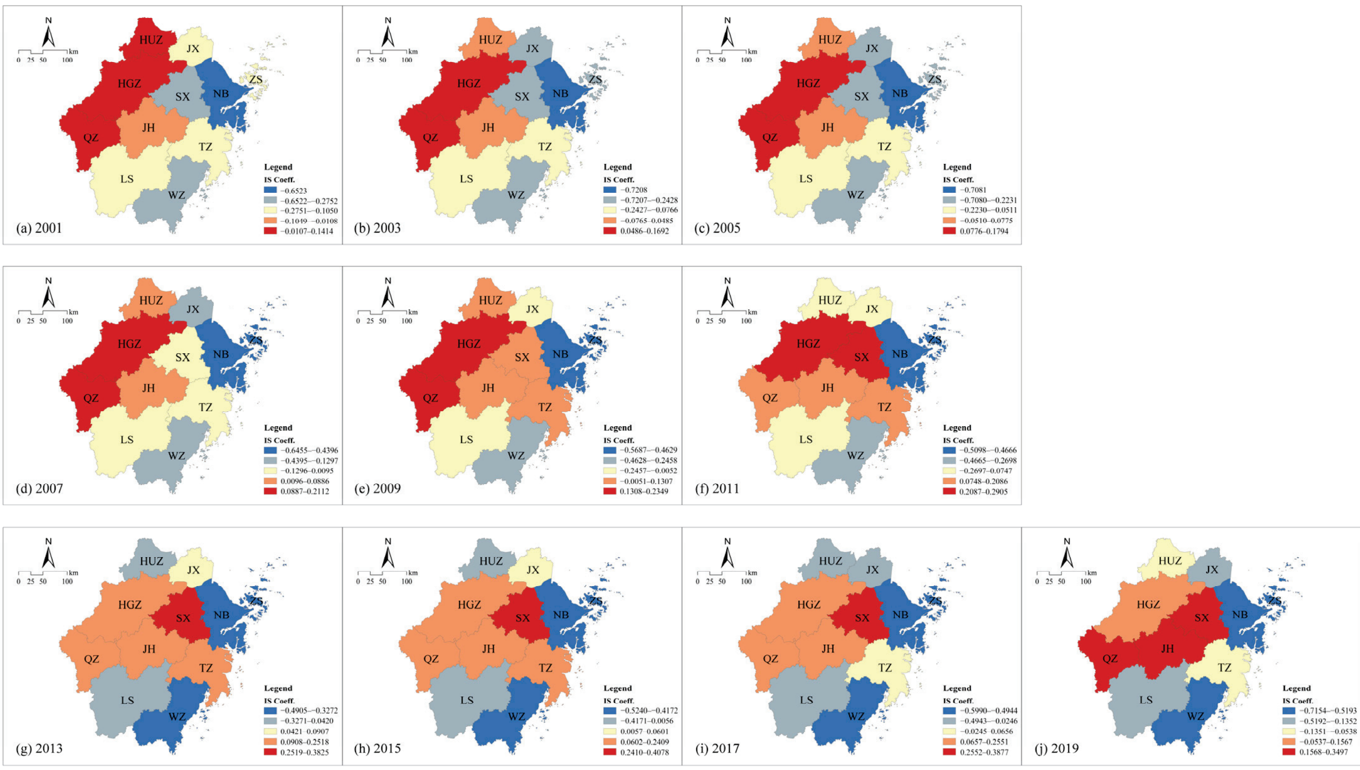


Figure 6. Spatial distribution of industrial structure regression coefficients in Zhejiang's cities from 2001 to 2019.

(4) Spatial and temporal heterogeneity of the influence of the government intervention factor on LUCE (Figure 7).

From a temporal perspective, the relationship between government intervention and LUCE in Zhejiang's cities exhibits a predominantly negative association. Notably, the city of Ningbo experiences the greatest influence; however, the strength of this influence has been gradually diminishing over time. Conversely, the impact of government intervention on LUCE in Jiaxing displays a consistent year-on-year increase. Furthermore, in Shaoxing, there exists a positive correlation between government intervention and LUCE, with the degree of influence showing a progressive rise after 2011. Among the extant studies, the identification of a robust positive relationship between the government intervention factor and LUCE represents an innovative contribution.

In terms of spatial distribution, the influence of government intervention on LUCE in Zhejiang Province shows a spatial heterogeneity of "high in the northeast and low in the southwest". The northeastern region, encompassing cities like Ningbo and Taizhou, experiences the most profound impact of government intervention on LUCE. In particular, the relationship between government intervention and LUCE in Shaoxing shifts from negative to positive, with the degree of influence continuing to grow. Conversely, in the southwestern region of Zhejiang Province, represented by cities such as Quzhou, Jinhua, and Lishui, the influence of government intervention on LUCE is comparatively weaker.

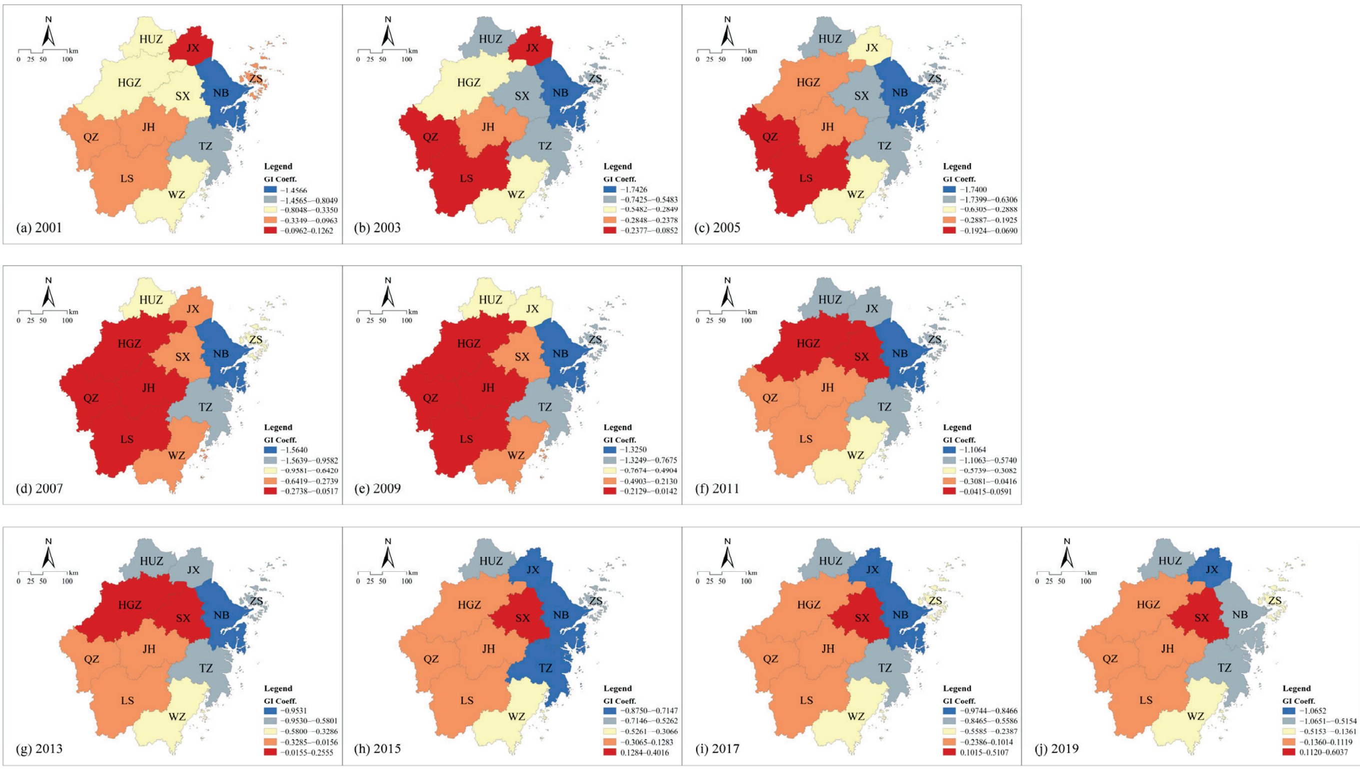


Figure 7. Spatial distribution of government intervention regression coefficients in Zhejiang's cities from 2001 to 2019.

(5) Spatial and temporal heterogeneity of the influence of the public facilities level factor on LUCE (Figure 8).

In terms of the temporal evolution of the influence degree, a positive correlation is observed between the level of public facilities and LUCE in Quzhou and Lishui, with a consistently stable degree of influence. Conversely, a negative relationship persists, albeit with a diminishing degree of influence, on LUCE in Zhoushan. Furthermore, the impact of the public facilities level on LUCE in Ningbo and Shaoxing has transitioned from a negative effect in the initial stages to a positive effect, and the magnitude of this influence has been progressively increasing over the years. Shaoxing, in particular, has consistently exhibited the highest influence degree since 2009. Local governments ought to enhance the criteria for approving high-emission and high-consumption projects, while expediting the implementation of a "carbon assessment" and regulatory framework for fixed-asset investments [56].

Regarding the spatial distribution of the influence degree, the relationship between the public facilities level and carbon emissions in cities across Zhejiang Province displays a three-tiered pattern. The northeast region exhibits the highest level of influence, followed by the southwest region, while the middle belt demonstrates the lowest level. Specifically, the cities in the northeast, such as Ningbo and Shaoxing, experience a significant influence from the public facilities level indicator, which has undergone a dynamic evolution of continuous enhancement. On the other hand, the cities in the southwest, represented by Quzhou and Lishui, as well as the cities in the middle belt, including Huzhou, Hangzhou, and Wenzhou, exhibit a weaker influence degree from the public facilities level indicator.

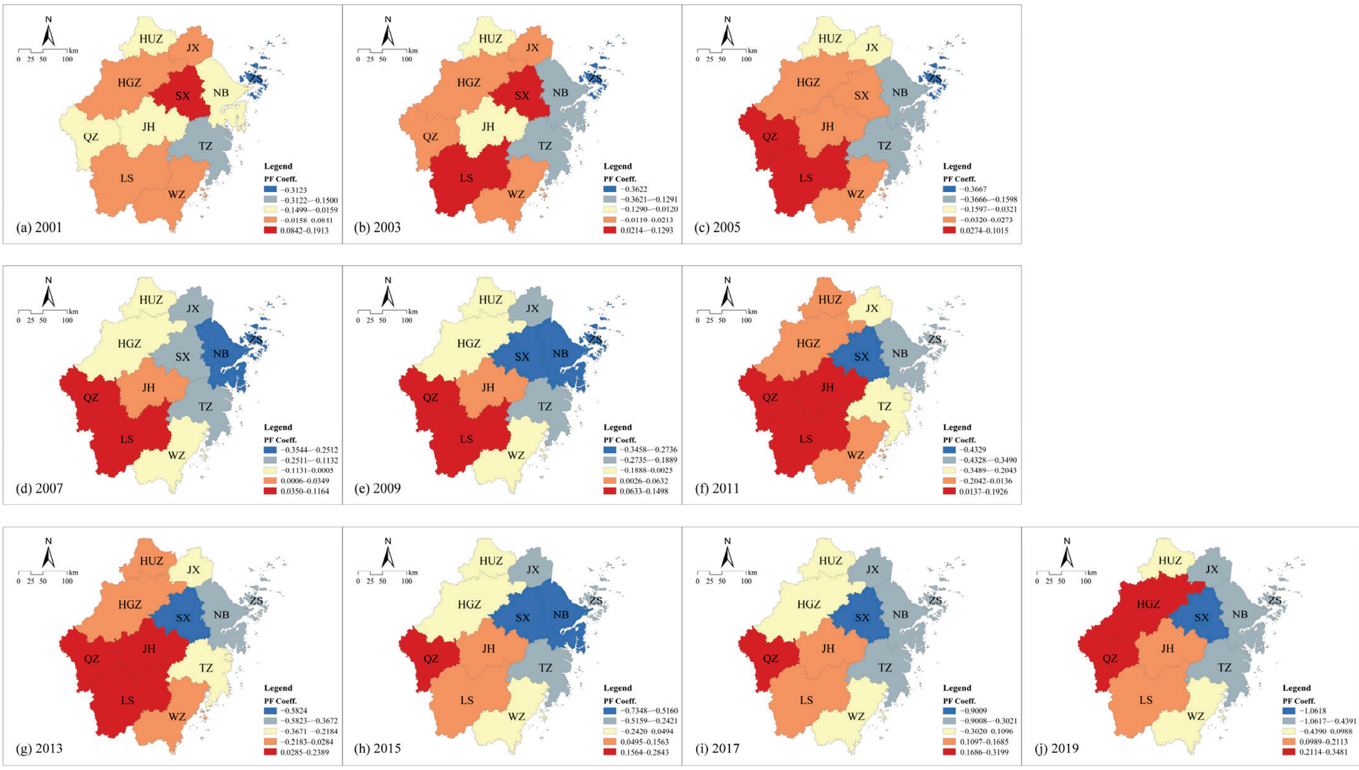


Figure 8. Spatial distribution of public facilities level regression coefficients in Zhejiang's cities from 2001 to 2019.

- Urban Form Aspects

(6) Spatial and temporal heterogeneity of the influence of the urban compactness factor on LUCE (Figure 9).

There exists a predominantly negative correlation between urban compactness and LUCE in cities across Zhejiang Province. This implies that compact urban construction land contributes to the reduction in urban carbon emissions, underscoring the importance for these cities, at their stage of development, to continually optimize and enhance their land-use layout. They should pursue a path of compact and intelligent development while continuously harnessing the effectiveness of urban land use. The impact of urban compactness on LUCE in Quzhou is substantial; however, its influence has been diminishing since 2013. Conversely, in Hangzhou and Huzhou cities, the impact has been deepening over time. Taizhou, on the other hand, consistently maintains a low level of influence. The relationship between urban compactness and LUCE in Jiaxing is particularly unique. Prior to 2013, a negative correlation was observed, with the degree of influence decreasing. Subsequently, a positive correlation emerged, and the degree of influence increased. This suggests that landscape pattern characteristics such as connectivity, complexity, and agglomeration of urban patches need to be taken into account in compact and low-carbon urban development [59]. To achieve this, urban management should exercise control over the peripheral areas of urban growth and redirect development efforts toward optimizing the internal structure of the city and revitalizing underutilized land within built-up areas [60].

Regarding the spatial distribution of the influence degree, the impact of urban compactness on LUCE in cities across Zhejiang Province exhibits a distinct pattern characterized by divergence, with higher levels of influence observed at both ends and lower levels in the middle. The cities that experience a high degree of influence are primarily concentrated in the northern and southern regions of Zhejiang Province, exemplified by Hangzhou, Huzhou, and Wenzhou. Conversely, the cities located in the middle belt, namely, Jinhua and Taizhou, demonstrate a relatively weaker driving force of urban compactness on their LUCE;

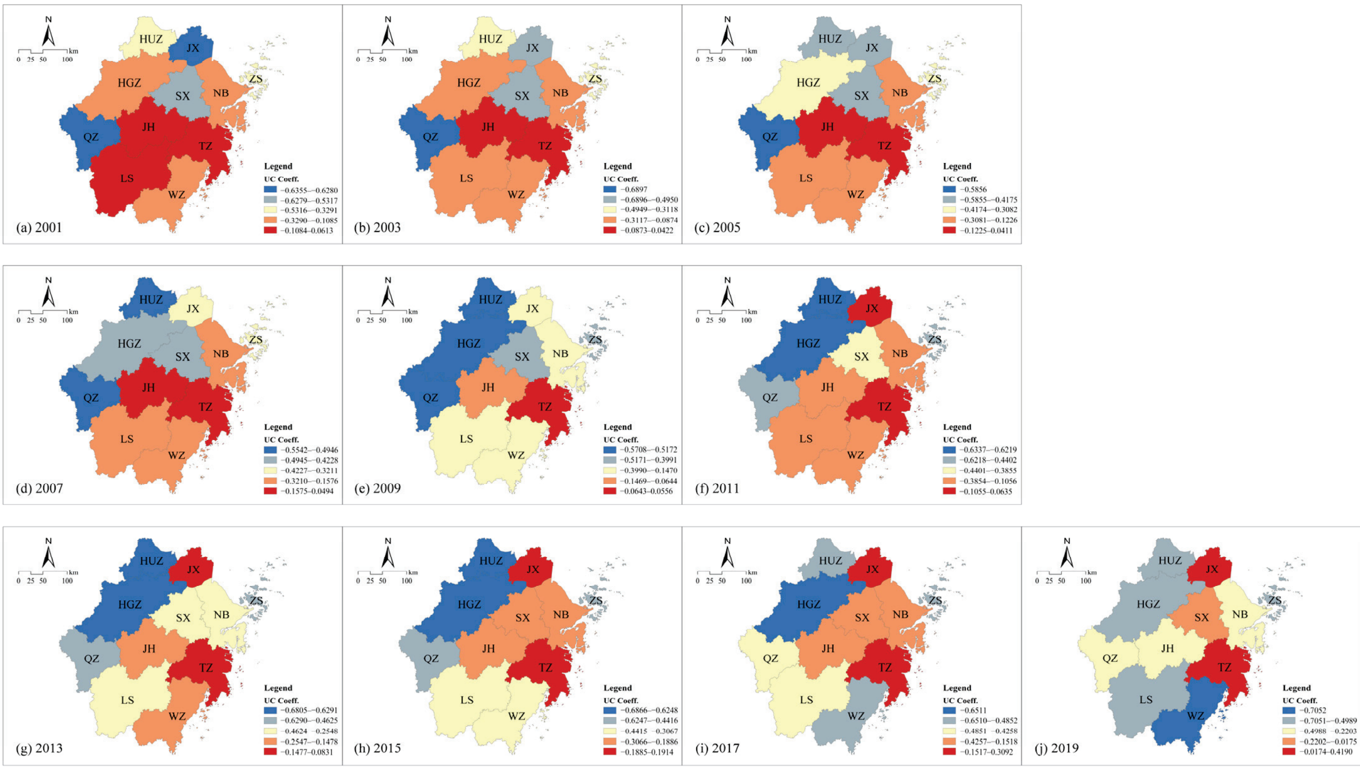


Figure 9. Spatial distribution of urban compactness regression coefficients in Zhejiang's cities from 2001 to 2019.

- Urban Environment Aspects

(7) Spatial and temporal heterogeneity of the influence of the urban greening level factor on LUCE (Figure 10).

From a temporal perspective, the degree of influence of the urban greening level on LUCE in Zhejiang's cities can be classified into three distinct types. Firstly, a consistent positive correlation is observed between urban greening level and the cities of Wenzhou and Lishui. Wenzhou experiences an increasing degree of influence over time, while Lishui demonstrates a fluctuating pattern with an initial decrease followed by an increase in its degree of influence. Secondly, there is a persistent negative correlation between urban greening level and Zhoushan, with the degree of influence continuously increasing. Thirdly, starting in 2007, a notable trend emerged whereby the influence of the urban greening level on LUCE in most cities undergoes a transition from a weakening positive effect in the early stages to a growing negative effect. This effect is most pronounced in Ningbo and Shaoxing, with Ningbo witnessing an increasing degree of influence, while Shaoxing tends to stabilize. This evolutionary trend indicates that promoting the enhancement of green cover facilitates carbon storage and contributes to the reduction in carbon emissions in urban land uses. Furthermore, the implementation of green space construction in built-up areas, coupled with dedicated endeavors to establish robust green infrastructure systems [61], can offer individuals a range of ecological service functions, thereby contributing to the enhancement of the residential living environment [62].

In terms of the spatial distribution of the influence degree, the impact of urban greening level on LUCE in each city of Zhejiang Province exhibits a spatial divergence characteristic, with higher levels of influence observed in the northern regions and lower levels in the southern regions. The northern cities of Ningbo, Shaoxing, and Zhoushan display a consistent increase and stability in the influence of this indicator on LUCE. Conversely, the southern cities of Lishui and Wenzhou exhibit a relatively lower level of influence in this regard.

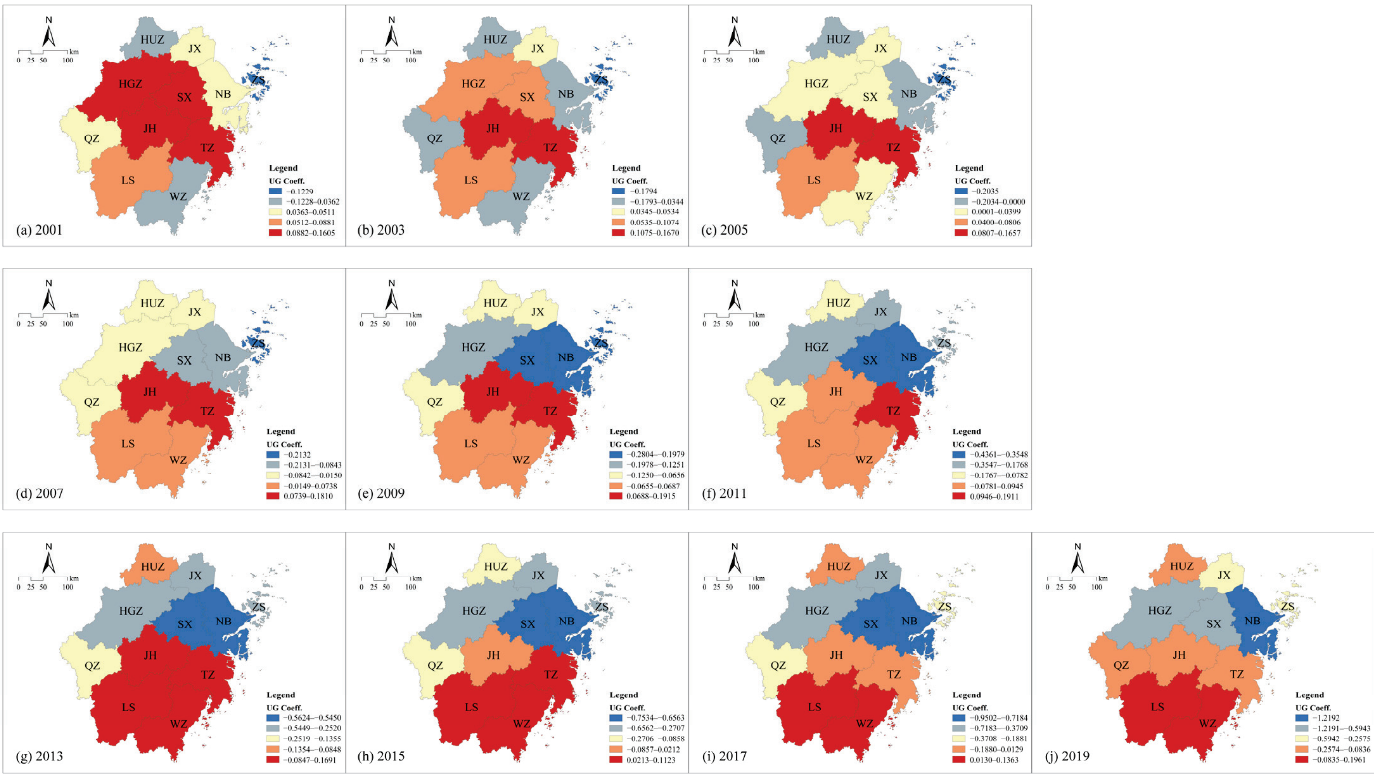


Figure 10. Spatial distribution of urban greening level regression coefficients in Zhejiang's cities from 2001 to 2019.

Based on the spatial and temporal distribution of regression coefficients concerning the influencing factors on LUCE within each city in Zhejiang Province, it is possible to delineate the principal determinants of such emissions in each city. The dominant drivers primarily hinge on the varying degrees of impact exhibited by individual influencing factors on LUCE across different cities (evident through the comparison of the absolute values of regression coefficients during different developmental stages within the same city). Certain cities are predominantly influenced by a single factor, whereas others are subject to the combined effects of multiple factors.

In Hangzhou, LUCE are mainly influenced by both urban compactness and urban greening level. The effect of urban compactness initially increases and then decreases, while urban greening level has exhibited a negative effect since 2007 and continues to increase. In Ningbo, LUCE are influenced by the economic level, government investment interventions, and urban greening level. The influence of the economic level remains stable, that of government investment shows an increasing and then decreasing trend, and the influence of urban greening level continues to increase. Wenzhou is influenced by the economic level, industrial structure, and urban greening level, with the economic level displaying a negative effect since 2013, while the influence of the latter two factors has been increasing since the same year. Jiaxing is primarily influenced by the economic level and government investment interventions, and the driving force of both factors has been increasing year by year. In Huzhou, LUCE are influenced by government investment interventions and urban compactness, with both drivers initially increasing and then stabilizing. In Shaoxing, LUCE are primarily influenced by a combination of the economic level, social infrastructure investment, and urban greening level, with all three drivers showing a continuous increase in influence. In Jinhua, LUCE are mainly influenced by the consistently stable economic level. In Quzhou, population density and urban greening level are the main drivers, with the influence of population density gradually weakening and the influence of urban greening level remaining stable. In Zhoushan, LUCE are influenced by the economic level and government investment interventions, with the former having a consistent and steady impact, while the influence of the latter initially increases and then gradually decreases. Taizhou's LUCE are mainly influenced by the economic level and government intervention, displaying a continuous and steady effect. In Lishui, LUCE are mainly influenced by the economic level and urban compactness, with the former transitioning to a negative effect since 2011, accompanied by an increasing degree of influence, while the influence of urban compactness continues to rise year by year. This analysis and trend assessment of the main driving forces in each city, based on the regression coefficients of the influencing factors, can provide a scientific basis for cities to explore low-carbon economic transition models and achieve differentiated and coordinated emission reduction.

5. Conclusions

This study employed GIS and RS technologies to extract seven types of land-use patches from 11 prefecture-level cities in Zhejiang Province. These patches were used to quantitatively assess the LUCE of each city and examine their spatial and temporal variations. Additionally, a GTWR model was employed to investigate the spatiotemporal characteristics of factors influencing LUCE in each city of Zhejiang Province. The main findings of this study are as follows:

(1) Over a period of nearly 20 years, from 2001 to 2019, the total LUCE in Zhejiang Province exhibited a pattern of rapid growth followed by stability. The change in LUCE in each city demonstrated two primary trends: a continuous increase over time, as observed in Ningbo, and a pattern of stabilization, exemplified by Hangzhou, where emissions initially increased and then decreased in phases. Furthermore, there was a noticeable spatial variation in LUCE among Zhejiang's cities, with higher emissions observed in the northeast region and lower emissions in the southwest;

(2) The influence of the seven indicators on LUCE exhibited significant heterogeneity in both the temporal and spatial dimensions. The statistical analysis of the regression coefficients for the influencing factors revealed that their average intensities were ranked as follows: economic level > government intervention > urban compactness > public facilities level > urban greening level > industrial structure > population density;

(3) The impact of population density on LUCE varied across cities, transitioning from a negative effect in the early stages to a positive effect. Inland cities in western Zhejiang Province exhibited a greater influence on LUCE compared to eastern coastal cities. The relationship between economic level and LUCE in Zhejiang's cities was generally positive and stable, with a spatial distribution characterized by higher levels in the east and lower levels in the west. The association between industrial structure and LUCE remained positive and stable in Hangzhou and Quzhou, while it decreased in northeastern Zhejiang's cities represented by Ningbo and increased in southwestern Zhejiang's cities represented by Quzhou and Lishui. Government intervention exhibited a negative correlation with LUCE in Zhejiang's cities, with a spatial distribution indicating higher levels in the northeast and lower levels in the southwest. The spatial distribution of the influence of public facilities level on carbon emissions in Zhejiang's cities demonstrated a three-tiered hierarchical pattern, with higher levels in the northeast, intermediate levels in the southwest, and lower levels

in the middle. Urban compactness exhibited a negative correlation with LUCE in each city of Zhejiang Province, and its impact displayed a spatial distribution characterized by higher levels at both ends and lower levels in the middle. The influence of urban greening level on LUCE varied among cities and exhibited a spatial divergence, with higher levels in the north and lower levels in the south;

(4) The LUCE in different cities are influenced to varying degrees by cities' respective stages of development. For instance, cities such as Ningbo, Wenzhou, Jiaxing, Shaoxing, Jinhua, Zhoushan, Taizhou, and Lishui are all influenced by their economic levels, albeit with variations in the extent and dynamic evolution of these influences. Therefore, when formulating differentiated low-carbon economic development strategies for different cities, careful consideration should be given to their specific developmental stages and the processes of dynamic evolution they are undergoing.

This study employs the GTWR model to examine the evolving patterns of factors influencing LUCE. This approach offers valuable insights into scientifically characterizing the spatiotemporal effects of the mechanisms driving LUCE. Consequently, it facilitates a more rigorous assessment of the developmental trajectories associated with LUCE. Moreover, the findings serve as a fundamental basis for establishing differentiated models and strategies for land-use carbon reduction, tailored to specific local contexts.

Disparities in urban development stages are not only evident within the 11 cities in Zhejiang Province but also extend to other regions worldwide. This study demonstrates a thorough recognition of the multifaceted nature, systematicity, dynamics, and variability inherent in the driving mechanisms of LUCE. Accordingly, leveraging an extensive time series, this research systematically identified seven pivotal influencing factors derived from the socioeconomic, urban form, and urban environment aspects. These factors were then utilized to investigate the dynamic evolution of the driving mechanism governing LUCE during distinct stages of urban development. The research methodology employed and the resulting findings hold significant potential for generalization and application in studies conducted in diverse regions worldwide.

The current study has certain limitations that need to be acknowledged. Firstly, the classification of land-use types in this study into seven categories may have overlooked the carbon emission variations that could be observed with a more detailed classification. Secondly, this study primarily focused on the city scale due to the availability of basic data. However, counties, being the fundamental administrative units in China, play a crucial role in implementing and enforcing low-carbon policies. Future studies should consider conducting more granular investigations at the county level to analyze the spatial and temporal characteristics of LUCE and their influencing factors.

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References

1. Houghton, R. Magnitude, distribution and causes of terrestrial carbon sinks and some implications for policy. *Clim. Policy* **2002**, *2*, 71–88. [CrossRef]
2. Yan, H.; Guo, X.; Zhao, S.; Yang, H. Variation of net carbon emissions from land use change in the Beijing-Tianjin-Hebei region during 1990–2020. *Land* **2022**, *11*, 997. [CrossRef]
3. Wang, S.; Zeng, J.; Huang, Y.; Shi, C.; Zhan, P. The effects of urbanization on CO_2 emissions in the Pearl River Delta: A comprehensive assessment and panel data analysis. *Appl. Energy* **2018**, *228*, 1693–1706. [CrossRef]
4. 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]

5. Ali, G.; Nitivattananon, V. Exercising multidisciplinary approach to assess interrelationship between energy use, carbon emission and land use change in a metropolitan city of Pakistan. *Renew. Sustain. Energy Rev.* **2012**, *16*, 775–786. [CrossRef]
6. Li, R.; Li, L.; Wang, Q. The impact of energy efficiency on carbon emissions: Evidence from the transportation sector in Chinese 30 provinces. *Sustain. Cities Soc.* **2022**, *82*, 103880. [CrossRef]
7. Li, J.; Guo, X.; Chuai, X.; Xie, F.; Yang, F.; Gao, R.; Ji, X. Reexamine China's terrestrial ecosystem carbon balance under land use-type and climate change. *Land Use Policy* **2021**, *102*, 105275. [CrossRef]
8. Feng, X.; Li, Y.; Zhang, L.; Xia, C.; Yu, E.; Yang, J. Carbon Metabolism in Urban "Production–Living–Ecological" Space Based on Ecological Network Analysis. *Land* **2022**, *11*, 1445. [CrossRef]
9. Xu, Q.; Yang, R.; Dong, Y.-X.; Liu, Y.-X.; Qiu, L.-R. The influence of rapid urbanization and land use changes on terrestrial carbon sources/sinks in Guangzhou, China. *Ecol. Indic.* **2016**, *70*, 304–316. [CrossRef]
10. Lin, Q.; Zhang, L.; Qiu, B.; Zhao, Y.; Wei, C. Spatiotemporal analysis of land use patterns on carbon emissions in China. *Land* **2021**, *10*, 141. [CrossRef]
11. Azevedo, V.G.; Sartori, S.; Campos, L.M. CO_2 emissions: A quantitative analysis among the BRICS nations. *Renew. Sustain. Energy Rev.* **2018**, *81*, 107–115. [CrossRef]
12. 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]
13. Li, C.; Li, Y.; Shi, K.; Yang, Q. A multiscale evaluation of the coupling relationship between urban land and carbon emissions: A case study of Chongqing, China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 3416. [CrossRef] [PubMed]
14. Ke, N.; Lu, X.; Zhang, X.; Kuang, B.; Zhang, Y. Urban land use carbon emission intensity in China under the "double carbon" targets: Spatiotemporal patterns and evolution trend. *Environ. Sci. Pollut. Res.* **2023**, *30*, 18213–18226. [CrossRef] [PubMed]
15. Yu, Z.; Chen, L.; Tong, H.; Chen, L.; Zhang, T.; Li, L.; Yuan, L.; Xiao, J.; Wu, R.; Bai, L. Spatial correlations of land-use carbon emissions in the Yangtze River Delta region: A perspective from social network analysis. *Ecol. Indic.* **2022**, *142*, 109147. [CrossRef]
16. 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]
17. Zhao, R.; Huang, X.; Liu, Y.; Zhong, T.; Ding, M.; Chuai, X. Carbon emission of regional land use and its decomposition analysis: Case study of Nanjing City, China. *Chin. Geogr. Sci.* **2015**, *25*, 198–212. [CrossRef]
18. Xia, C.; Dong, Z.; Wu, P.; Dong, F.; Fang, K.; Li, Q.; Li, X.; Shao, Z.; Yu, Z. How urban land-use intensity affected CO_2 emissions at the county level: Influence and prediction. *Ecol. Indic.* **2022**, *145*, 109601. [CrossRef]
19. Wu, S.; Hu, S.; Frazier, A.E. Spatiotemporal variation and driving factors of carbon emissions in three industrial land spaces in China from 1997 to 2016. *Technol. Forecast. Soc. Change* **2021**, *169*, 120837. [CrossRef]
20. Ke, Y.; Xia, L.; Huang, Y.; Li, S.; Zhang, Y.; Liang, S.; Yang, Z. The carbon emissions related to the land-use changes from 2000 to 2015 in Shenzhen, China: Implication for exploring low-carbon development in megacities. *J. Environ. Manag.* **2022**, *319*, 115660. [CrossRef]
21. Zhang, R.; Matsushima, K.; Kobayashi, K. Can land use planning help mitigate transport-related carbon emissions? A case of Changzhou. *Land Use Pol.* **2018**, *74*, 32–40. [CrossRef]
22. Zhang, C.-y.; Zhao, L.; Zhang, H.; Chen, M.-n.; Fang, R.-y.; Yao, Y.; Zhang, Q.-p.; Wang, Q. Spatial-temporal characteristics of carbon emissions from land use change in Yellow River Delta region, China. *Ecol. Indic.* **2022**, *136*, 108623. [CrossRef]
23. Li, D.; Fan, K.; Lu, J.; Wu, S.; Xie, X. Research on Spatio-Temporal Pattern Evolution and the Coupling Coordination Relationship of Land-Use Benefit from a Low-Carbon Perspective: A Case Study of Fujian Province. *Land* **2022**, *11*, 1498. [CrossRef]
24. 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]
25. Kaur, H.; Garg, P. Urban sustainability assessment tools: A review. *J. Clean. Prod.* **2019**, *210*, 146–158. [CrossRef]
26. Halleux, J.-M.; Marcinczak, S.; van der Krabben, E. The adaptive efficiency of land use planning measured by the control of urban sprawl. The cases of the Netherlands, Belgium and Poland. *Land Use Policy* **2012**, *29*, 887–898. [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]
28. Chuai, X.; Huang, X.; Wang, W.; Zhao, R.; Zhang, M.; Wu, C. Land use, total carbon emissions change and low carbon land management in Coastal Jiangsu, China. *J. Clean. Prod.* **2015**, *103*, 77–86. [CrossRef]
29. Lu, J.; Guldmann, J.-M. Landscape ecology, land-use structure, and population density: Case study of the Columbus Metropolitan Area. *Landsc. Urban Plan.* **2012**, *105*, 74–85. [CrossRef]
30. Wang, G.; Han, Q. The multi-objective spatial optimization of urban land use based on low-carbon city planning. *Ecol. Indic.* **2021**, *125*, 107540. [CrossRef]
31. Li, W.; Chen, Z.; Li, M.; Zhang, H.; Li, M.; Qiu, X.; Zhou, C. Carbon emission and economic development trade-offs for optimizing land-use allocation in the Yangtze River Delta, China. *Ecol. Indic.* **2023**, *147*, 109950. [CrossRef]
32. Liu, J.; Peng, K.; Zuo, C.; Li, Q. Spatiotemporal variation of land-use carbon emissions and its implications for low carbon and ecological civilization strategies: Evidence from Xiamen-Zhangzhou-Quanzhou metropolitan circle, China. *Sustain. Cities Soc.* **2022**, *86*, 104083. [CrossRef]

33. Luo, Y.-l.; Zhang, C.-x. On the Ways to Optimize Land Use Pattern by Basing on the Concept of Low Carbon Eco-city. In Proceedings of the Advances in Education and Management: International Symposium, ISAEBD 2011, Dalian, China, 6–7 August 2011; Proceedings, Part IV. Springer: Berlin/Heidelberg, Germany, 2011; pp. 8–16.
34. Li, Q.; Chen, X.; Jiao, S.; Song, W.; Zong, W.; Niu, Y. Can Mixed Land Use Reduce CO2 Emissions? A Case Study of 268 Chinese Cities. *Sustainability* **2022**, *14*, 15117. [CrossRef]
35. Luo, Y.L.; Zhang, C.X. Research on the Low-Carbon Land Use Pattern. In *Advanced Materials Research*; Trans Tech Publications, Ltd.: Bach, Switzerland, 2012; Volume 598, pp. 241–246.
36. Li, L.; Chen, Z.; Wang, S. Optimization of Spatial Land Use Patterns with Low Carbon Target: A Case Study of Sanmenxia, China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 14178. [CrossRef]
37. Huang, S.; Xi, F.; Chen, Y.; Gao, M.; Pan, X.; Ren, C. Land use optimization and simulation of low-carbon-oriented—A case study of Jinhua, China. *Land* **2021**, *10*, 1020. [CrossRef]
38. Zhao, Y.; Ma, S.; Fan, J.; Cai, Y. Examining the effects of land use on carbon emissions: Evidence from Pearl River Delta. *Int. J. Environ. Res. Public Health* **2021**, *18*, 3623. [CrossRef]
39. Meng, Q.; Zheng, Y.; Liu, Q.; Li, B.; Wei, H. Analysis of Spatiotemporal Variation and Influencing Factors of Land-Use Carbon Emissions in Nine Provinces of the Yellow River Basin Based on the LMDI Model. *Land* **2023**, *12*, 437. [CrossRef]
40. Wang, Y.; Niu, Y.; Li, M.; Yu, Q.; Chen, W. Spatial structure and carbon emission of urban agglomerations: Spatiotemporal characteristics and driving forces. *Sustain. Cities Soc.* **2022**, *78*, 103600. [CrossRef]
41. Liu, J.; Li, S.; Ji, Q. Regional differences and driving factors analysis of carbon emission intensity from transport sector in China. *Energy* **2021**, *224*, 120178. [CrossRef]
42. Chen, Y.; Li, M.; Su, K.; Li, X. Spatial-temporal characteristics of the driving factors of agricultural carbon emissions: Empirical evidence from Fujian, China. *Energies* **2019**, *12*, 3102. [CrossRef]
43. Yang, L.; Xia, H.; Zhang, X.; Yuan, S. What matters for carbon emissions in regional sectors? A China study of extended STIRPAT model. *J. Clean. Prod.* **2018**, *180*, 595–602. [CrossRef]
44. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [CrossRef]
45. Gao, Z.; Li, S.; Cao, X.; Li, Y. Carbon Emission Intensity Characteristics and Spatial Spillover Effects in Counties in Northeast China: Based on a Spatial Econometric Model. *Land* **2022**, *11*, 753. [CrossRef]
46. Huang, X.; Tian, P. How does heterogeneous environmental regulation affect net carbon emissions: Spatial and threshold analysis for China. *J. Environ. Manag.* **2023**, *330*, 117161. [CrossRef]
47. Shan, Y.; Guan, Y.; Hang, Y.; Zheng, H.; Li, Y.; Guan, D.; Li, J.; Zhou, Y.; Li, L.; Hubacek, K. City-level emission peak and drivers in China. *Sci. Bull.* **2022**, *67*, 1910–1920. [CrossRef]
48. Liu, Q.; Song, J.; Dai, T.; Shi, A.; Xu, J.; Wang, E. Spatio-temporal dynamic evolution of carbon emission intensity and the effectiveness of carbon emission reduction at county level based on nighttime light data. *J. Clean. Prod.* **2022**, *362*, 132301. [CrossRef]
49. Piao, S.; Fang, J.; Zhou, L.; Zhu, B.; Tan, K.; Tao, S. Changes in vegetation net primary productivity from 1982 to 1999 in China. *Glob. Biogeochem. Cycles* **2005**, *19*. [CrossRef]
50. Wen, H.; Li, Y.; Li, Z.; Cai, X.; Wang, F. Spatial Differentiation of Carbon Budgets and Carbon Balance Zoning in China Based on the Land Use Perspective. *Sustainability* **2022**, *14*, 12962. [CrossRef]
51. Sun, H.; Liang, H.; Chang, X.; Cui, Q.; Tao, Y. Land use patterns on carbon emission and spatial association in China. *Econ. Geogr* **2015**, *35*, 154–162.
52. Fang, J.Y.; Liu, G.H.; Xu, S.L. Carbon cycle of terrestrial ecosystem in China and its global meaning. In *Monitoring and Relevant Process of Greenhouse Gas Concentration and Emission*; Wang, G.C., Wen, Y.P., Eds.; China Environmental Science Press: Beijing, China, 1996; pp. 129–139.
53. Kuang, Y.; Ouyang, T.; Zou, Y.; Liu, Y.; Li, C.; Wang, D. Present situation of carbon source and sink and potential for increase of carbon sink in Guangdong Province. *China Popul. Resour. Environ.* **2010**, *20*, 56–61.
54. Richardson, H.W. *The Economics of Urban Size*; Saxon House Lexington Books: Farnborough, UK; Lexington, MA, USA, 1973; Volume 26, pp. 66–83.
55. Huang, B.; Wu, B.; Barry, M. Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 383–401. [CrossRef]
56. Lian, W.; Sun, X.; Xing, W.; Gao, T.; Duan, H. Coordinated development and driving factor heterogeneity of different types of urban agglomeration carbon emissions in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 35034–35053. [CrossRef] [PubMed]
57. Yang, X.; Liu, X. Path analysis and mediating effects of influencing factors of land use carbon emissions in Chang-Zhu-Tan urban agglomeration. *Technol. Forecast. Soc. Change* **2023**, *188*, 122268. [CrossRef]
58. Wang, Q.; Wang, X.; Li, R. Does urbanization redefine the environmental Kuznets curve? An empirical analysis of 134 Countries. *Sustain. Cities Soc.* **2022**, *76*, 103382. [CrossRef]
59. Zheng, Y.; Cheng, L.; Wang, Y.; Wang, J. Exploring the impact of explicit and implicit urban form on carbon emissions: Evidence from Beijing, China. *Ecol. Indic.* **2023**, *154*, 110558. [CrossRef]
60. Zhang, H.; Peng, J.; Wang, R.; Zhang, J.; Yu, D. Spatial planning factors that influence CO2 emissions: A systematic literature review. *Urban Clim.* **2021**, *36*, 100809. [CrossRef]

61. Chen, W.; Gu, T.; Fang, C.; Zeng, J. Global urban low-carbon transitions: Multiscale relationship between urban land and carbon emissions. *Environ. Impact Assess. Rev.* **2023**, *100*, 107076. [CrossRef]
62. 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*, 36901. [CrossRef]

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Article

Territorial Spatial Resilience Assessment and Its Optimisation Path: A Case Study of the Yangtze River Economic Belt, China

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Abstract: Along with the rapid development of urbanization and industrialization, the carrying capacity of territorial space has been confronted with a serious crisis. Faced with many uncertain risks and unknown disruptions, it is important to proactively address the uncertainty of future developments in planning and to improve territorial spatial resilience (TSR). Based on the connotation of TSR, we build an assessment framework for TSR containing urban, agricultural and ecological space from three dimensions, including element, structure and function. Using a variety of methods such as the source-sink landscape index, land suitability assessment, and cropland pressure index, we assessed the TSR of the Yangtze River Economic Belt (YREB) from 2000 to 2020 and comprehensively analysed its spatial and temporal evolutionary characteristics. Through data analysis, we observe that the urban spatial resilience (RU) decreases and then increases, while the agricultural spatial resilience (RA) and the ecological spatial resilience (RE) show an increasing trend. The spatial clustering in TSR is apparent, and the distribution of hot and cold spots in RA and RE is reversed in the east–west direction. The changes in TSR are influenced by a combination of RU, RA and RE, which show unique geographical characteristics. Based on the average level and overall evolution of TSR, we divided the study area into five type zones and proposed development strategies for each of them.

Keywords: territorial spatial resilience; urban–agricultural–ecological space; optimisation path; Yangtze River Economic Belt

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1. Introduction

Territorial space is the spatial carrier of human activities. Rational development of territorial space is a prerequisite for the sustainable development of a country or region [1]. Under the background of global environmental change, China's territorial spatial pattern, which has experienced rapid urbanisation and industrialisation, has changed dramatically. The disorderly exploitation of urban, agricultural and ecological space by human beings has triggered problems such as environmental pollution, resource shortage and ecological damage [2]. Moreover, the imbalance within the territorial space and the different requirements of urban development for the functioning of the territorial space limits its sustainable development. Therefore, upgrading the functions of the territorial spatial system and enhancing its resilience has become a consensus for development in many countries [3,4].

To address these problems, western countries carried out extensive spatial planning practices after the 20th century and established a relatively comprehensive spatial planning system, intending to improve the territorial space use efficiency and promote coordinated regional development [5,6]. In this process, the concept of resilience was introduced into ecology by Holling [7], and has gradually been widely used in various fields such as disaster and public safety, agricultural management, community building, urban planning and economic management [8–10]. Building resilient territorial space is significant to sustainable economic and social development. TSR is a new attempt to combine resilience planning with territorial spatial research. China has made territorial spatial planning the primary basis for all types of development, protection and construction activities, as well as a spatial blueprint for sustainable development [11]. In particular, 'enhancing the spatial resilience of the national territory' is one of the guiding requirements in the code of practice for territorial and spatial planning at the provincial level. The 14th Five-Year Plan of China proposed the construction of 'resilient cities' for the first time, emphasising the prominence of ecology and safety in urban construction. Under the background of territorial spatial planning, linking urban economic development with the protection of arable land and ecological environment restoration to give targeted guidance in the process of planning practice is an important research topic.

Previous studies related to TSR have focused on its conceptual and theoretical exploration, quality assessment, evolutionary process and planning practice. Specifically, TSR is the capacity of the territorial space to absorb the impact generated by endogenous and exogenous factors and move towards a new dynamic equilibrium [12]. In risky societies, endogenous complexity and external uncertainty exacerbate the vulnerability of territorial space and may contribute to regional or urban–rural development imbalances [13]. At the same time, territorial space can adapt and recover from natural disasters and human activity disturbances. Many studies measure the magnitude of this capacity using the composite index method [14], principal component analysis [15] and semi-structured expert interviews [16] to evaluate the resilience of territorial space in a given region quantitatively or qualitatively. For example, Assumma et al. (2024) [17] assess TSR in the Champagne-Ardenne region of France in terms of social, technological, environmental, economic, and regional development capacities. Some studies tend to systematically analyse TSR from the perspective of spatial structure and landscape morphology [18,19]. On this basis, research on the functions, security, vulnerability and ecological restoration of territorial space has become increasingly rich [20–23]. Moreover, scholars continue to explore directions for incorporating resilience concepts into territorial spatial planning [24,25]. For example, spatial planning in Poland aims at increasing the resilience of spatial structures to natural and socio-economic threats [26]; and the Netherlands emphasises the importance of proactively addressing risks in spatial planning decisions, in particular concerning climate perturbations and flood risks [27]. Exploring ecological protection and restoration methods for territorial space under the resilience perspective, especially in countries that have experienced large-scale urban expansion, can provide new feasible paths for promoting the high-quality development of territorial space [28]. At present, international research on spatial resilience evaluation methods has matured, involving economic [29], ecological [30], infrastructure [31] and agricultural system resilience [32]; diversified community resilience evaluation and enhancement research have also been enriched [33]. However, most of the existing studies tend to focus on the resilience of a single subsystem of territorial space, which may be unable to capture the complex evolutionary characteristics of TSR under the influence of human activities. Therefore, based on the need to optimise the structure and enhance the function of territorial space, a comprehensive exploration of the spatio-temporal correlation and enhancement path of TSR is urgently needed.

As a development belt coordinating east, middle and west China, the YREB has experienced rapid urbanisation in recent decades, accompanied by a large number of land use changes and landscape transformations. Therefore, we take the YREB as a case study to investigate the spatial heterogeneity and evolutionary law of TSR and try to explore a reasonable optimisation path. Our specific research objectives are to (1) quantify TSR in different years and clarify its spatial evolution trend; (2) reveal the clustering characteristics and combination types of multi-dimensional TSR; and (3) propose optimisation paths for different types of TSR. The main contributions of this study are as follows. Firstly, we constructed a TSR assessment framework that included urban, agricultural and ecological space. The spatiotemporal heterogeneity characteristics of TSR in the YREB were explored using the three dimensions of elements, structure and function. It is a comprehensive view that highlights the integrity and interactivity of TSR. Compared with the common unidimensional indicators in previous studies, the framework can reflect the TSR characteristics more effectively and show the problems of territorial space more accurately. These provide empirical insights for prefecture-level city-scale TSR research. Secondly, we divided the study area into functional zones based on the combination of TSR and dynamic changes. Few previous studies have carried out functional zoning of a territorial space from a resilience perspective. Functional zoning can accurately identify the strengths and weaknesses of regional TSR and provide theoretical support and a practical reference for territorial spatial planning zoning. Thirdly, we examined the response history of TSR at different stages, based on which we explored the optimisation path of TSR under different combination modes. Previous studies have paid less attention to the coordination between TSR dimensions and lacked the dissection of the co-evolutionary process, which is insufficient to propose a comprehensive optimisation strategy. Our study will provide valuable theoretical references for promoting resilient territorial space construction.

2. Theoretical Framework

2.1. The Connotations of TSR

Territorial space is a complex formed by coupling natural ecosystems and human social systems; it is characterized by nested scales, coupled elements, spatial and temporal correlations and functional composites [34]. Resilience was introduced to ecology by Holling [7]; it pertains to the ability of an ecosystem to maintain its organisation and return to a stable state after a major disturbance. Territorial spatial resilience (TSR) is the ability of territorial space to maintain stability when disturbed by multiple risks, recover from damage and adapt to co-evolution with the environment [35]. The realisation of TSR relies on the stability and adaptability of the territorial spatial system's elements, structures and functions (Figure 1a). Driven by exogenous factors such as globalisation, industrialisation, urbanisation and informatisation, the territorial spatial system is affected and disturbed by various factors such as business enterprises, citizens and farmers, government departments and social organisations. By relying on specific location conditions, natural resources, economic base and cultural characteristics, the territorial spatial system is guided and constrained by development policies, land use regulation, remediation projects and market regulation [36]. In this process, the scale and attributes of the elements of the territorial spatial system change and the spatial structure and form transform, affecting the output and supply of its various functions and leading to the continuous evolution of the territorial spatial system. Territorial space is divided into three categories, namely, urban, agricultural and ecological space, according to the attributes of spatial elements and main functions [37]. Urban space mainly carries urban economic, social, political and cultural functions, agricultural space mainly carries agricultural production and rural life functions, and ecological space mostly provides ecological services or products. The territorial space system is a structured spatial organisation of three types of elements, namely, urban space, agricultural space and ecological space, forming various types of territorial functions [38]. TSR is realised in the functioning of the three types of spaces and their optimal coordination with each other [39].

TSR is embodied in the process of transformation of the three types of spatial elements, structural transformation and functional transformation, exhibiting characteristics such as robustness, restorability, redundancy and adaptability (Figure 1b). It is jointly influenced by economic resilience and social resilience and simultaneously provides support for the realisation of economic and social resilience. Specifically, TSR is characterised by the ability to withstand the specific pressures generated by the production and living activities of the actors under the action of exogenous drivers [40]. It can rely on the combined action of guiding constraints and supporting elements to maintain its main functions and adapt to changes in response to external socio-economic development to satisfy human needs continually [41]. Moreover, TSR evolution has obvious externalities, generates complex economic, social, ecological and environmental effects and has a decisive impact on food security, resource security, ecological security and livelihood security.

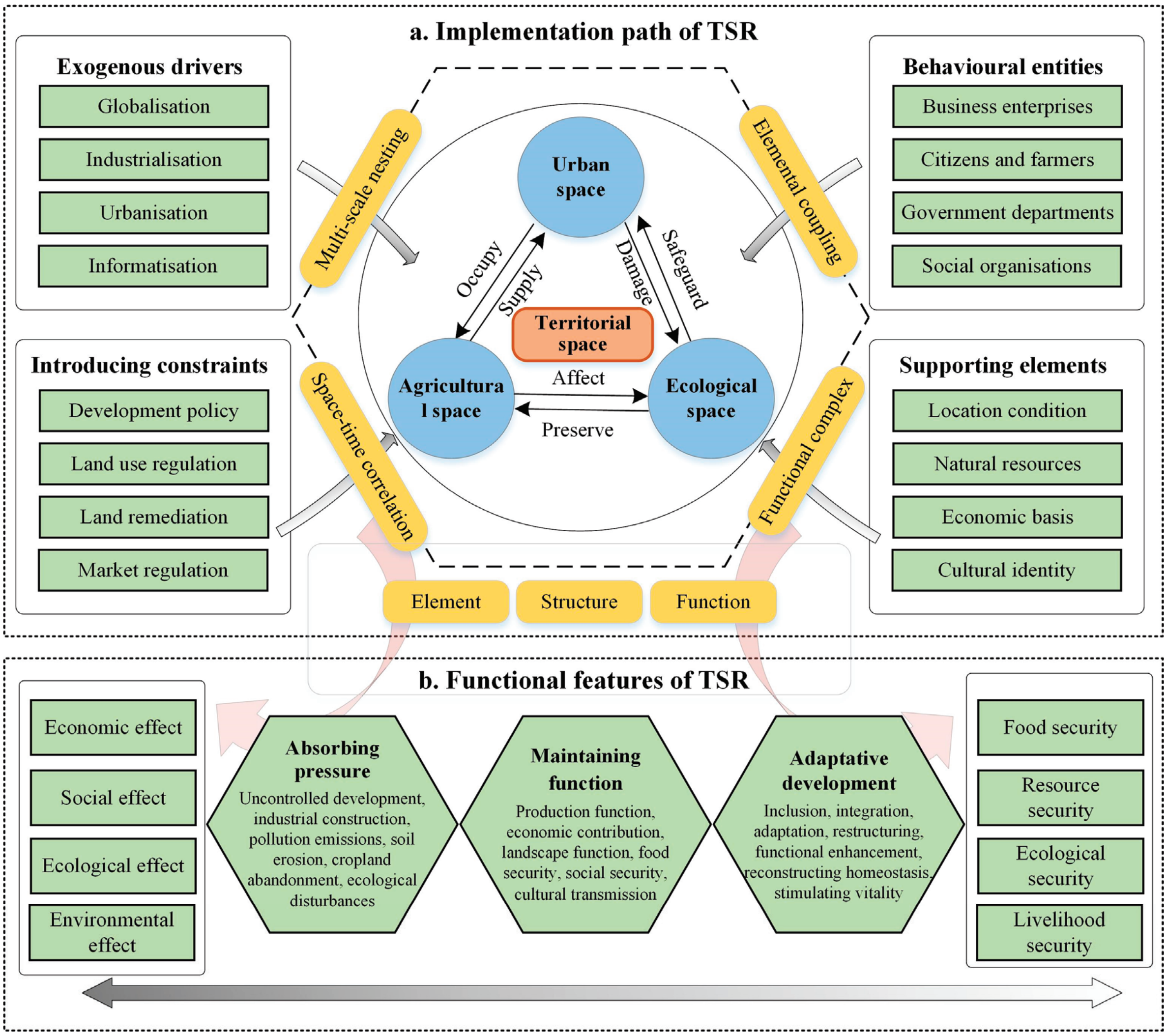

Figure 1. The connotations of TSR.

2.2. Technical Framework for TSR Assessment

The assessment of TSR should focus on the elements' scale, attributes and spatial structure characteristics of the territorial spatial system, as well as the realisation of the dominant functions. For urban space, scale is measured by built-up area, structure is evaluated by spatial form, and function is assessed by economic and population carrying density [42]. For agricultural space, element is measured by arable land quality, structure is assessed by arable land quality, and function is evaluated by arable land utilisation. For ecological space, the element is assessed by vitality, the structure is assessed by landscape pattern and ecological services assess the function (Figure 2).

As urban, agricultural and ecological spaces influence and constrain each other, the interaction of the three makes the TSR evolution characterised by multidimensional linkages. If urban space expands unchecked, the encroachment of neighbouring arable land and ecological landscapes will lessen the connectivity of the city's blue–green infrastructure, and their carbon sink benefits and ability to withstand construction disturbances will be weakened [43], leading to a decrease in urban spatial resilience (RU). At different spatial scales and environmental gradients, the quality of arable land shows differentiated characteristics, while population growth and economic development have continuously aggravated the pressure on arable land and triggered land degradation of varying degrees [44]. In this context, areas with low agricultural spatial resilience (RA) are vulnerable to strong shocks due to external impacts, such as natural disasters and the hollowing out of rural populations, which can threaten food security and social stability. Ecological space has self-regulating stability, which is mainly reflected in the integrity and sustainability of ecosystems, the fulfilment of ecological functions and the provision of ecological services [45]. In the context of global change, urban expansion and agricultural pollution have caused problems such as damage to ecological space, over-consumption of natural resources and fragmentation of ecological landscapes, decreasing ecological spatial resilience (RE) [46]. On the contrary, if targeted interventions are taken for territorial spatial governance, then highly resilient urban, agricultural and ecological space will form an interconnected positive feedback adjustment mechanism to promote positive interactions among systems of mountains, rivers, forests, fields, lakes, grasses and sands [47].

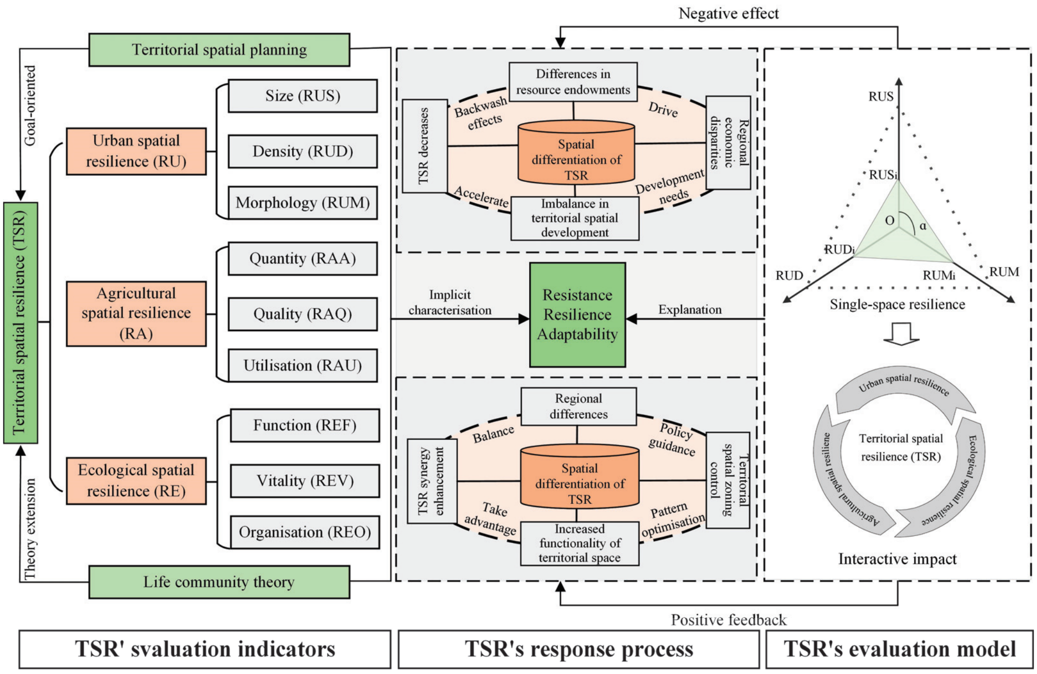

Figure 2. Technical framework of TSR assessment.

We built a model to measure the level of each dimension of TSR. Taking RU as an example, the origin represents the initial state of undeveloped urban space. The three axes represent element, structure and function, and the points representing the state of the regional RU system fall on the axes. The length of the straight line between the origin and the coordinate points is the standardised value of the indicator. The area formed by the three indicator values is the RU. With this model, we can obtain single-space resilience. Under the constraints of territorial spatial planning, urban space, agricultural space and ecological spatial resilience will gradually form their respective areas of strength [48]. A territorial spatial system that satisfies the maximisation of social, ecological and economic benefits will achieve functional optimisation and regional coordination [49]. High RU can promote urban economic development, provide funds and technology for agricultural development, improve the efficiency of arable land use, and thus improve RA. The improvement of RA reduces the encroachment of human activities on ecological space and is conducive to the improvement of RE. At the same time, high RE can provide ecological products for urban space, meet residents' demand for a high-quality environment, and promote the improvement of RU. The territorial space with multi-dimensional high resilience characteristics can lead to the synergistic progress of the regional TSR as a whole.

This study attempts to combine resilience theory with the dynamic process of coordinated development of territorial space, comprehensively consider the interactive influence characteristics of urban, agricultural and ecological spaces, and construct a technical framework for the assessment of TSR.

3. Materials and Methodology

3.1. Study Area

The YREB covers 11 provinces and municipalities (Figure 3), with a total area of 2,052,300 km^2. The YREB's gross domestic product (GDP) reached 56 trillion yuan in 2022, accounting for 45% of the country's total. Owing to its favourable climate and varied topography, the YREB is rich in agricultural resources and supports national food security as an important commodity grain base in China [50]. Moreover, ecological restoration is a prerequisite for the high-quality development of the YREB. According to the concept of 'ecological priority, green development', the shortage of resources, loss of arable land and environmental pollution that accompany urban expansion must be solved urgently [51]. The level of TSR has a direct impact on the region's capacity for sustainable development. The optimisation of territorial spatial patterns and resilience enhancement in YREB should be promoted to achieve coordinated development of the economy, society and ecology.

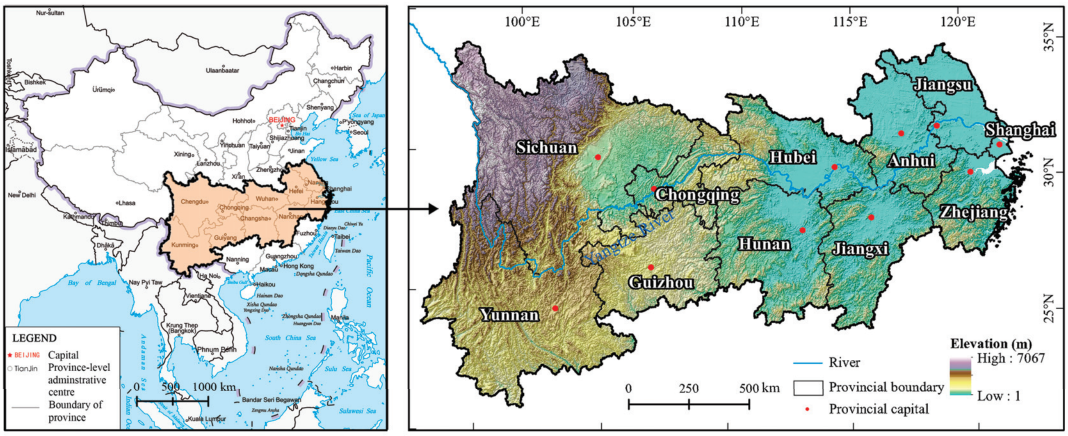

Figure 3. Location of the study area.

3.2. Data Source

We used multiple sources of spatial data and statistics in our study. (1) Land use raster data and normalised difference vegetation index (NDVI) data for 2000, 2010 and 2020 were obtained from the Resource and Environment Data Centre of the Chinese Academy of Sciences, with a spatial resolution of 30 m and 1 km, respectively (https://www.resdc.cn/, accessed on 22 October 2022). The DEM data used are SRTM1 elevation data derived from the USGS with a spatial resolution of 30 m. (2) The spatial data on administrative division boundaries, road networks and water systems were extracted from the standard map service of the National Geographic Information Public Service Platform of the Ministry of Natural Resources (https://www.tianditu.gov.cn/, accessed on 8 January 2023). (3) Socioeconomic data such as resident population and GDP of prefecture-level cities were obtained from the China Urban Statistical Yearbook. We obtained data on arable land and sown area from provincial and municipal statistical yearbooks, and some missing values were supplemented based on data from the National Agricultural Census. (4) Meteorological data used for the study were analysed and processed using daily precipitation products from the China Meteorological Administration. Soil quality data were downloaded from the World Soil Database at a resolution of 1 km.

3.3. Methods

3.3.1. Measurement of TSR

Based on the theoretical framework, according to the classification of urban, agricultural and ecological, we have systematically summarised the TSR measurement methods, as shown in Table 1.

Table 1. Quantitative measurement models for RU, RA and RE.

Name	Index	Formula	Explanation
RU	Size (RUS)	$RUS = \frac{L_S}{L_d}$	where RUS is the size resilience index of urban space, L_S is the area of land suitable for building and L_d is the area of existing building land.
	Density (RUD)	$ED = GDP/TS$ $PD = GDP/TP$ $RUD = (ED + PD)/2$	where ED is the city's economic density, PD is the city's population density, GDP is gross domestic product, TS and TP refers to the area and the resident population of the city, respectively.
	Morphology (RUM)	$L_d = \frac{\sum_{i=1}^{m} min(d_i)}{m}$ $RUM = L/L_d$	where RUM is the morphological density index of urban space, $min\ (d_i)$ is the minimum cost distance from source raster i to the nearest sink, m is the number of source raster in the study area, and L is the average distance index value for the source–sink landscape across the YREB.
RA	Quantity (RAA)	$S_{min} = \beta \frac{G_r}{p \times q \times k}$ $RAA = S_{min}/S$	where RAA is cropland pressure index, S_{min} and S are the minimum per capita cropland area and the actual per capita cropland area (hm^2/person), respectively, β is food self-sufficiency rate (%), p is the grain yield per unit area (kg/hm^2), q is the proportion of area sown to grain to total sown area (%), k is the replanting index, and G_r is the per capita food requirement (kg/person). With RAA = 1 as the early warning line, the greater the value of RAA, the greater the pressure on cropland protection and the lower the level of agricultural spatial security. With reference to international food security standards and actual food production, the per capita food requirements for 2000, 2010 and 2020 were set at 400, 420 and 440 kg, respectively. Since more than half of the provinces in the YREB are major food-producing areas, the food self-sufficiency rate is taken to be 100%.
	Quality (RAQ)	$RAQ = \frac{\sum_j^n A_j \times AS_j}{TA}$	where RAQ is the average arable land suitability, TA is the total area of agricultural space in the study unit, A_j is the area of image element j in agricultural land in the study area and AS_j is the agricultural suitability of image element j in agricultural land.
	Utilisation (RAU)	$RAU = AP/FA$	AP is the value of agricultural production in the study area and FA is the area of agricultural land.
RE	Function (REF)	$ESp_i = A_i \times ESc \times \frac{(100+SNc)}{100}$ $REF = \sum ESp$	where REF is the functional resilience of ecological space, ESp_i is the ecosystem service value of raster i, A_i is the area of raster i, ESc is the service coefficient of the ecosystem value for the land use type corresponding to raster i and SNc are the spatial neighbourhood coefficients.
	Vitality (REV)	$RAU = \frac{NIR-R}{NIR+R} = NDVI$	where NIR is the near-infrared band reflectance value, and R is the red band reflectance value. $NDVI$ can reflect the state of vegetation cover, with a range of values from -1 to 1. $NDVI < 0$ indicates that the ground cover is water, snow, ice or clouds; $NDVI > 0$ indicates that there is vegetation growing on the surface, and the higher the value, the better the grade of vegetation cover.
	Organisation (REO)	$REO = 0.3 \times SHDI + 0.2 \times FRAC + 0.3 \times PD + 0.2 \times CONTAG$	where REO is the organisational resilience of the ecological space, $SHDI$ is the Shannon diversity index, $FRAC$ is the fractal dimensionality index, PD is the patch density and $CONTAG$ is the landscape contagion index. This calculation was run using Fragstats 4.2.

(1) Measuring RU. With reference to the urban resilience assessment framework proposed by existing studies [52,53], we construct a resilience assessment system for urban space from the three dimensions of size, density and morphology.

We used a size resilience index to describe the relationship between the scale of urban construction and the appropriate scale. Ecological infrastructure (EI) indicates the enduring capacity of the natural landscape to support the city and can be used as a constraint to maintain RU. When the built-up area of a city spreads unchecked and minimum ecological infrastructure is not guaranteed, the city's ability to develop sustainably is compromised [54]. Thus, we measure the magnitude of the city's level of scale resilience through the relationship between the suitable built-up land boundary under EI constraints and the current state of built-up land. After taking into account the restrictive impacts of ecological functional areas such as mountains, forests and wetlands, spatial superimposition of elements, such as topography, slope, water system, road network, extent of built-up area, and land use type, the suitable construction land boundary that meets the minimum level of ecological safety needs to be obtained. When the built-up area of a city exceeds the area suitable for construction, it signifies that the resources of urban construction space have been exhausted.

Density resilience indicates the RU level in terms of construction density and intensity of human activity. Appropriate urban density is conducive to sustainable urban development, while excessively extreme urban density can lead to development problems. Thus, the combined value of GDP per capita and population density is used to characterise urban density resilience.

According to the source–sink theory of landscape ecology, the negative impacts of built-up land can be reduced by ecological land [55]. A well-mixed and balanced distribution of built-up and ecological land can improve urban resilience in terms of form. The accessibility of built-up land to ecological space was measured by extracting two landscape types, namely, sources and sinks, where sources include built-up land and sinks include woodlands, grasslands and watersheds. We calculated the minimum cost distance from each source raster to the nearest sink and averaged all the minimum cost distances in a prefecture-level city to obtain the average distance index. Finally, we compare it with the average value of the whole study area to obtain the morphological resilience index.

(2) Measuring RA. Agricultural spatial resilience is an important support for achieving stable agricultural production functions and sustainable use of arable land resources [56]. At present, the reduction in the area of arable land, the decline in the quality of arable land, the degradation of farming conditions and the uneven distribution of agricultural resources are seriously affecting the sustainable development of agricultural space [57]. Based on the above, we constructed an assessment system for agricultural spatial resilience in three dimensions: quantity, quality and utilisation.

We used the cropland pressure index to reflect the quantitative characteristics of agricultural space. We used the average agricultural suitability to reflect the qualitative characteristics and production conditions of the agricultural space. The study used the average land value of production to reflect the degree of intensification of agricultural space. In general, farmland with mechanised operations, good management techniques and marketable produce have a high average value of production.

(3) Measuring RE. Maintaining healthy ecosystems is essential to achieving sustainable development of territorial space. Strong ecosystem services, sustained dynamism and stable organisational structures characterise resilient ecological spaces. Based on the evaluation framework of ecosystem health [58], we constructed an assessment system of ecological spatial resilience from the three dimensions of function, vitality and organisation.

We used ecosystem service values to measure the functional characteristics of ecological space [59]. To measure the interactions between different ecosystems objectively, we consider the role of spatial proximity of various land use types. The ecosystem services of the raster are determined by a combination of its land use type and the land use types of its four neighbours. Ultimately, the functional resilience of each city's ecological space is quantified as the sum of ecosystem service values. The NDVI characterised the ecological space's vitality level. The organisation of the ecological space was quantitatively assessed using the integrated landscape pattern index.

(4) Measuring dimensions of TSR. This study applies the polygon method to measure TSR in each dimension. The length of the straight line between the origin and the vertex of the polygon is the standardised value of the indicator, and the area of the polygon is the value of the spatial resilience sub-dimension of the territorial space.

$$R_i = \frac{1}{6} sin\alpha (A_a \times A_b + A_b \times A_c + A_c \times A_a)$$

where R_i is the TSR index in each dimension, A_a~A_c are the standardised values of the indicators and α is the angle between the indicators.

3.3.2. Standard Deviation Ellipse

We used the standard deviation ellipse (SDE) to reveal the overall characteristics of the spatial distribution and the spatio-temporal evolution process of TSR. The centre of the SDE is the mean centre of the spatial distribution of geographic elements, its azimuth reflects the overall trend of the distribution of the elements, and the long and short semi-axes indicate the direction and extent of the distribution of the elements, respectively. The calculation formulas are as follows:

$$SDE_x = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$$

$$SDE_y = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}$$

$$\sigma_x = \frac{\sqrt{\sum_{i=1}^{n} (w_i \overline{x_i} cos\theta - w_i \overline{y_i} sin\theta)}}{\sum_{i=1}^{n} w_i^2}$$

$$\sigma_y = \frac{\sqrt{\sum_{i=1}^{n} (w_i \overline{x_i} sin\theta - w_i \overline{y_i} cos\theta)}}{\sum_{i=1}^{n} w_i^2}$$

where (SDE_x, SDE_y) is the centre of SDE, n is the total number of cities in the study area, σ_x and σ_y represent the standard deviation of the two axes, θ is the azimuth of the ellipse, (x_i, y_i) represents the coordinates of the spatial location of each element and w_i is the weight.

3.3.3. Getis-Ord Gi* Statistics

Getis-Ord Gi* statistics was used to identify spatial clustering characteristics of TSR. The formula is defined as follows:

$$G_i^* = \left(\sum_{j=1}^{n} W_{ij} X_j\right) / \left(\sum_{j=1}^{n} X_j\right)$$

$$Z(G_i^*) = \frac{\sum_{j=1}^{n} W_{ij} X_j - \sum_{j=1}^{n} W_{ij}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} W_{ij}{}^2 - \left(\sum_{j=1}^{n} W_{ij}\right)^2\right]}{n-1}}}$$

where W_{ij} is the spatial weight, X_j is the magnitude of variable X at city j, $\overline{x}$ is the sample mean and S is the sample variance. For positive z-scores that are statistically significant, the higher the z-score, the tighter the clustering of hot spots. Conversely, the lower the z-score, the tighter the clustering of cold spots.

4. Results

4.1. Spatiotemporal Analysis of TSR

The distribution of RU at different stages shows differentiated characteristics (Figure 4). Low-level districts are mainly located near provincial capitals or large cities that are the first to urbanise, while high-level districts are mostly located at provincial borders. Specifically, in 2000, the high level of RU was concentrated in the borders of five provinces and municipalities, Hubei, Hunan, Chongqing, Sichuan and Guizhou. The low level was mainly in the plains of the middle and lower reaches of the Yangtze River, central and western Sichuan and the northern part of Yunnan Province. Influenced by the national regional development policy, urbanisation and industrialisation in the lower reaches of the Yangtze River are earlier than in the middle and upper reaches of the Yangtze River, so areas with a relatively lagging urbanisation process and suitable location for development show great potential for development; that is, they have higher RU. In 2010, along with the implementation of the strategy of the rise of central China and the development of western China, the construction of cities in the middle reaches of the Yangtze River and the Chengdu–Chongqing region accelerated, so RU declined. Meanwhile, the Yangtze River Delta (YRD) region gradually transformed towards optimising the structure of economic growth and improving the comprehensive carrying capacity of cities. The development patterns of the YRD, the middle reaches of the Yangtze River and the Chengdu–Chongqing urban agglomeration in 2020 have been relatively stable, while the provincial border areas of Hunan, Guizhou and Yunnan have a low intensity of urban space utilisation and sufficient developable reserve land resources.

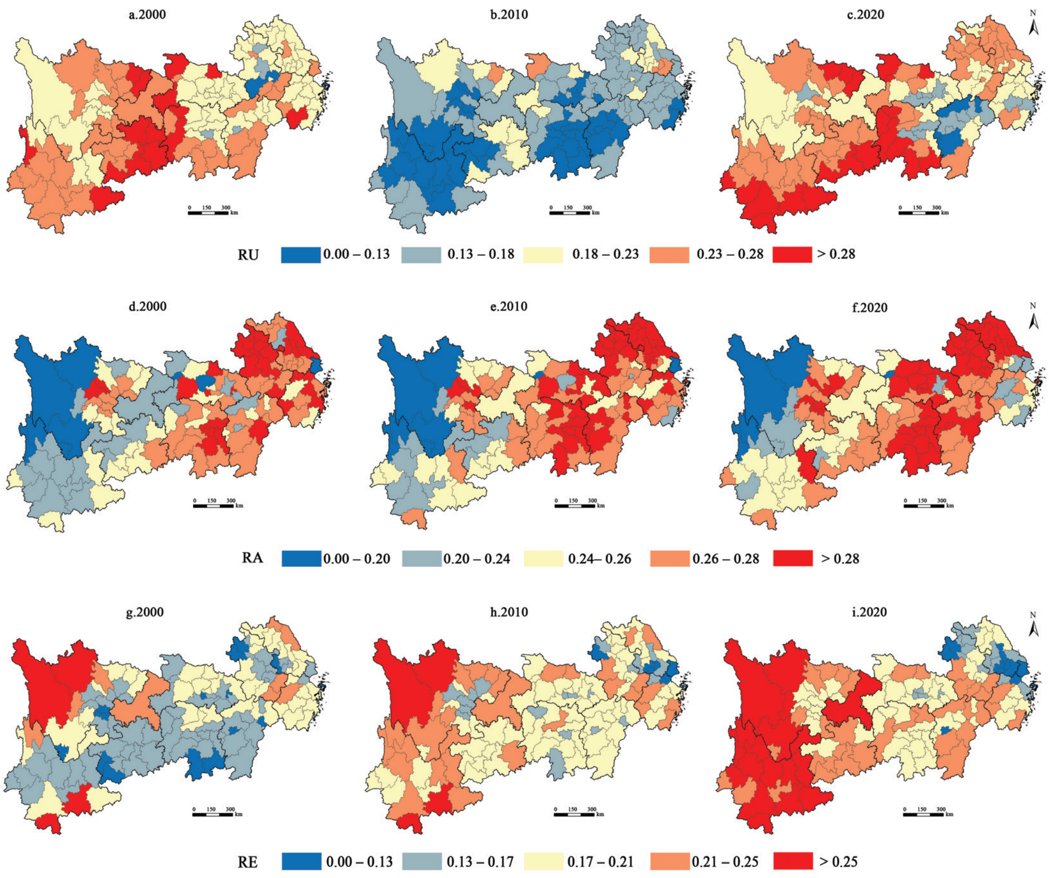

Figure 4. Temporal and spatial evolution of TSR in the YREB.

The RA of the YREB has experienced a gradual upward change process, showing a distribution of low in the west and high in the east. Given the strict constraints of natural conditions, agricultural suitability has obvious regional characteristics. Although the pressure on arable land increases in most cities as the population grows, the comprehensive agricultural production capacity also rises, resulting in an overall upward trend in RA. From 2000 to 2020, RA in the middle and lower reaches of the Yangtze River is consistently dominated by a high level, with its scope expanding over time. In contrast, RA in the upper reaches of the Yangtze River, bounded by the western part of Hunan province in Hubei, is predominantly a low-level area. Significant changes are reflected in the decrease in RA in Zhejiang Province mainly because Zhejiang Province is one of the main grain marketing areas in China and the pressure on its arable land increases with urban development.

RE exhibits a pattern of spatial differentiation between the high west and the low east, which has been strengthening over time, creating an apparent spatial mismatch with RA. Areas in the upper reaches of the Yangtze River with high RE tend to have low RA, while the middle and lower reaches of the Yangtze River, where high values of RA are dense, are prone to have low values of RE. In 2020, a significant decline in RE was observed in the YRD region, with most of the remaining regions experiencing increases. The differences between regions are gradually expanding, forming a distribution characteristic of the highest in the west, the second highest in the centre and the lowest in the east. The middle and lower reaches of the Yangtze River need to be given more consideration in the future to achieve coordinated development of the ecological environment, the economy and society to improve the TSR.

4.2. Spatial Clustering Characteristics of TSR

The results of the SDE analysis are shown in Figure 5. From 2000 to 2020, the centre of the RU in the YREB moved first to the northeast and then to the southwest, and its azimuth first increased and then decreased, changing from 70.01° to 68.57°. The centre of RA has shifted slightly to the southwest. Given that RA primarily depends on the endowment differences in natural conditions, although RA has increased or decreased in some areas, these changes have not been deemed significant in the whole study area. The centre of RE gradually shifted to the south–west direction from 2000 to 2020. The standard deviation of the short axis gradually increases, indicating that the RE distribution tends to be discrete in the south–north direction. The standard deviation of the long axis gradually decreases, indicating that the RE distribution tends to contract in the southeast–northwest direction. This decrease is mainly due to the accelerated development of the urban agglomeration in the middle reaches of the Yangtze River, which poses a certain threat to the ecological environment.

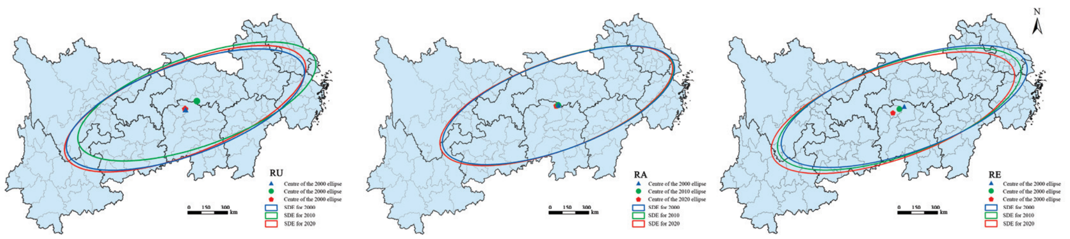

Figure 5. SDE of the TSR in the YREB.

We further reveal the spatial clustering characteristics of the TSR of the YREB through Getis-Ord Gi* statistics (Figure 6). The 2000 RU hot spot areas are concentrated along the borders of Chongqing, Guizhou and Hunan provinces, where urbanisation is lagging. Cold spot areas are concentrated in Anhui and eastern Hubei provinces, where construction land is concentrated and population density is high. In 2010, two main hot spot distribution areas were formed. In addition to Chongqing and its neighbouring areas, where hot spot distribution was formed earlier, the hot spot cluster in the YRD region was formed with Shanghai as the core to drive the quality of urbanisation in the surrounding areas. In 2020, hot spot areas were mainly clustered in western Hunan, eastern Guizhou and southern Yunnan, with a distinct cold spot area forming within the junction of Hubei, Hunan and Jiangxi. In recent years, the integrated development of the urban agglomerations in the middle reaches of the Yangtze River has contributed to the spread of urban space, causing territorial space to carry higher pressure for economic activities. There is ample suitable land for building in the traditional agricultural areas of the Midwest Junction, but urban economic and population growth is weak, so the hotspot clustering effect of the RU has diminished.

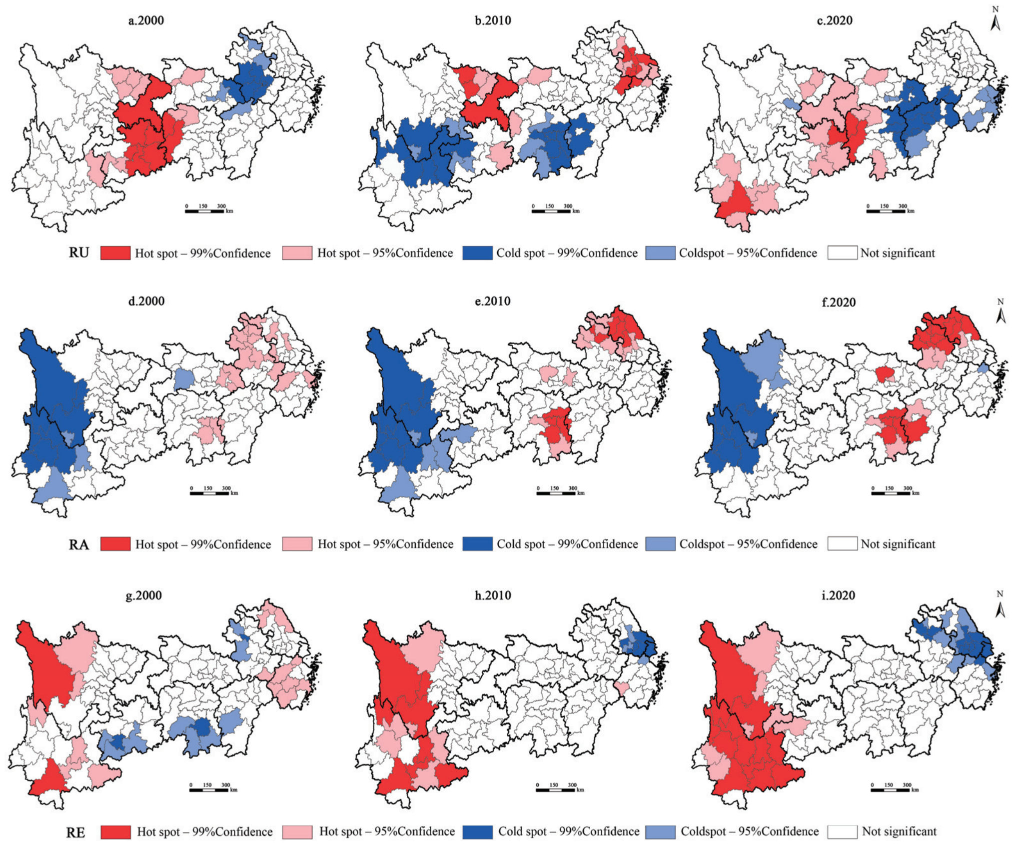

Figure 6. Distribution of hot and cold spots of the TSR in the YREB.

During the study period, the number of hot spots of RA gradually increased, and two centralised distribution areas centred on Anhui–Suzhou and Hunan–Jiangxi gradually formed, indicating a positive mutual reinforcement of RA among prefecture-level cities. The cold spot areas of RA were mainly concentrated in the mountainous areas of Sichuan and Yunnan Provinces, with the number increasing and then decreasing over time. Poor agricultural growing conditions and frequent geological disasters are the main reasons restricting the growth of RA. The clustering trend of RA low in the west and high in the east is intensifying, mainly because of topography and climate. The middle and eastern parts of the YREB have flat topography and abundant precipitation, so the agricultural economy is well developed. In contrast, the western region is mostly mountainous, with fragmented arable land, which is not conducive to agricultural production, so RA is low.

In contrast to the RA, the RE hotspot areas continue to concentrate in areas with little disturbance from human activities, such as Sichuan and Yunnan. Cold spot areas were scattered in southern Guizhou, Hunan Province and northwestern Anhui Province in 2000 and then clustered towards Shanghai and the surrounding areas. Despite the government's increased demand for ecological protection in the YREB, the eastern coastal cities are facing increasing population pressure, and the conflict between economic development and ecological protection is significant, showing a growing concentration of cold spots. A mismatch is identified between economic development and ecological construction in the YRD region, and the protection and control of the quality of the ecological environment should be strengthened in the development of territorial space.

4.3. Functional Classification of TSR in the YREB

We analysed the combining forms of the three types of resilience. Taking the average of the whole YREB as a judgement criterion (Table 2), we define each spatial resilience greater than the average as high resilience and the rest as low resilience. We levelled the city according to the combination of the dimensions, setting areas with high values in all three dimensions RU, RA and RE as excellent, areas with high values in any two dimensions as good, areas with high values in only one dimension as fair and the rest as poor.

Table 2. Mean value of each dimension of TSR in the YREB.

Name	**RU**			**RA**			**RE**		
	2000	**2010**	**2020**	**2000**	**2010**	**2020**	**2000**	**2010**	**2020**
YREB	0.234	0.147	0.231	0.256	0.263	0.266	0.169	0.194	0.201

As shown in Figure 7, only seven cities in the YREB in 2000 had an excellent combination of TSR. They are mainly located in the north of Zhejiang Province and the south of Anhui Province, which have strong resilience and high development potential in territorial space. Approximately 52.8% of the cities have a good TSR combination, with the most notable development of RA and RE in harmony. A prosperous agricultural economy and stable ecological landscape structure are important reasons for their grouped layout. A total of 62 cities have fair TSR combinations. Cities with high RU are mainly located in the Yunnan–Guizhou region and the Hubei–Hunan border. Cities with high RA are the most widely distributed, and those with high RE are mainly located in the western part of Sichuan Province and the central part of Hubei Province. The number of regions with excellent and good TSR combinations increased in 2010, and the types with excellent combinations were scattered in Jiangsu and Anhui provinces. The total number of fair combination areas decreased to 54, the concentrated RU–RA combination areas of high-value in southern Hunan Province were transformed into single RA high-value areas, and some cities in central and western Yunnan Province were transformed from RU high-value areas to RE high-value areas. The phenomena are all related to the massive expansion of urban construction land from 2000 to 2010. In implementing new-type urbanisation and ecological civilisation, a marked improvement is found in the TSR combination in the YREB. Approximately 60.8% of TSR combinations were excellent or good in 2020. The RU–RE combination is concentrated in Yunnan, Guizhou and Sichuan, and the RU–RA combination is grouped in Jiangsu and Anhui. The type of poor combination in this period is mainly found in cities with a high level of economic development.

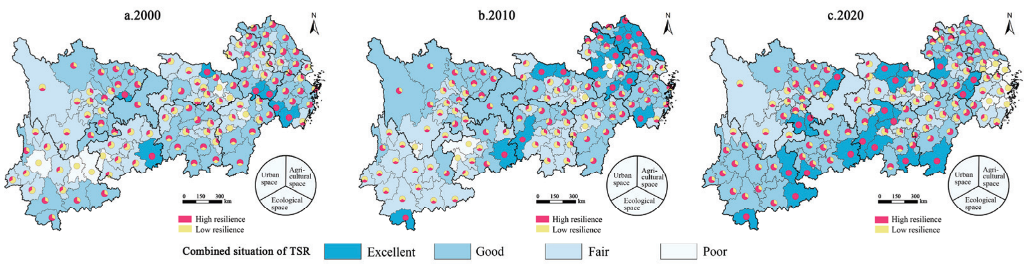

Figure 7. Combined classification based on RU, RA and RE in the YREB.

Taking the mean values of RU, RA and RE from 2000 to 2020 as the classification basis, we applied the K-means function to divide spatial units with high similarity into the same interval for TSR functional classification. When the value of k is 5, the sum of squares within the group is characterised by a strong inflexion point. Thus, the study area is divided into five functional types, including three dominant types of RU, RA and RE and two combined lagging types of RU–RA and RU–RE (Figure 8). The clustering results passed the significance test.

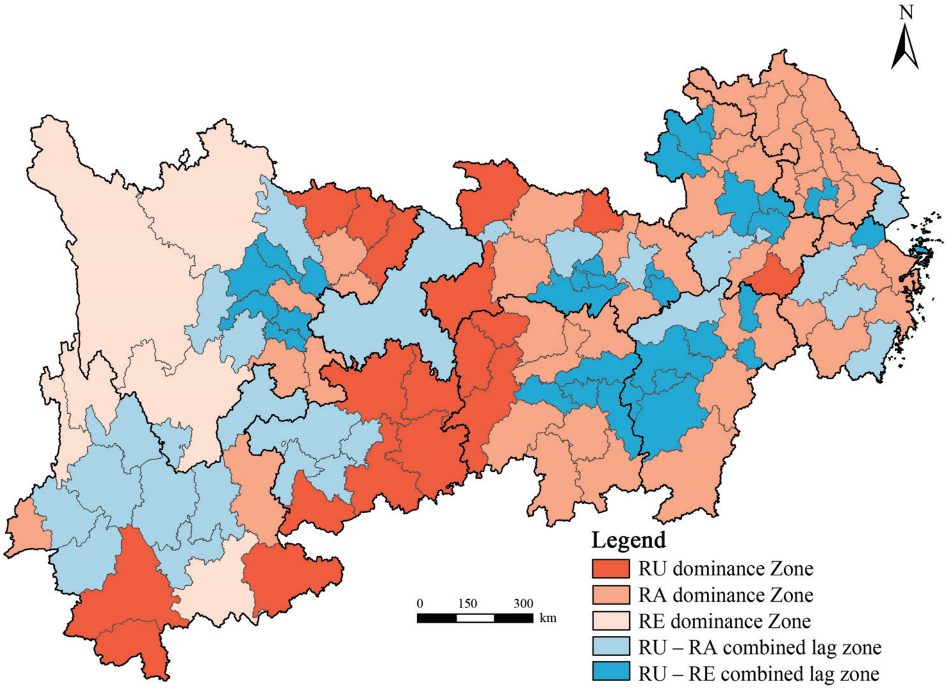

Figure 8. Functional zoning of TSR in the YREB.

RU dominant regions are cities with sufficient land for suitable construction and maintain a medium level of RA and RE, which can be properly strengthened with infrastructure to stimulate urban vitality. The RA dominant regions are concentrated in the middle and lower plains of the Yangtze River, which have the strongest agricultural suitability, medium level of RU and the lowest level of RE. Such cities should accelerate the resolution of agricultural productivity inefficiencies to alleviate the pressure on ever-increasing arable land. At the same time, they should focus on building green infrastructure to enhance the carrying capacity of the ecological environment. The RE dominant region is concentrated in the predominantly mountainous western area, which has the highest level of RE, higher level of RU and lower level of RA. These areas should continue to strengthen the synergistic restoration of ecological corridors and ecological functional areas, enhance the ability of mountains to withstand soil erosion and stabilise the ecological service functions of forest, grass and water systems. The RU–RA lagging areas are distributed in a more dispersed chain, with RU and RA at low-to-medium levels and RE at high-to-medium levels. Such cities should focus on development strategies that optimise urban form. Simultaneously, they should promote the development of traditional agriculture towards the integration of agro-tourism, modern urban agriculture, agro-entertainment and other industries. RU–RE lag zones have the potential for agricultural development, but their ecological regulation capacity is weakened with excessive urban development. Improving the quality of urban agglomeration development is the main direction for the optimal development of this category of cities.

5. Discussion

5.1. Response of TSR to Urban–Agricultural–Ecological Space in Different Stages

The changes in TSR are caused by the combined effect of RU, RA and RE. This effect is phased and spatially varied, driving a spiralling trend in TSR.

During the period of rapid economic and social development (2000–2010), when cities were in a state of expansion, the evolution of TSR in the YREB was mainly dominated by RU, with relatively little change in RA and RE. Although territorial spatial management began to explore structural optimisation in that period, irrational urban space development and unsound policy systems still led to a series of problems. Moreover, regional economic development and natural environment differences exacerbate structural differences in the evolution of TSR patterns. Strongly influenced by human activities, the RU in the YREB has experienced a process of decreasing and then increasing, which can be corroborated by the results of existing studies [60]. It has been shown that rapid urbanisation and industrialisation are the main factors leading to changes in TSR during this period [61]. Given its economic and policy advantages, Zhejiang Province has increased its urban development during this period, making its RU lower than the average level of the YREB. However, the combination of TSR in most cities in Zhejiang Province is generally in poor condition in the later period due to the shrinkage of agricultural and ecological space triggered by early urban spatial expansion. Although the implementation of the strategy of western development and the rise of central China has promoted the urbanisation of the central and western provinces, there are still shortcomings such as a weak industrial base and a lack of prominent location advantages, so the RU has declined. The phenomenon suggests a correlation between functional areas. A low level of resilience in a single space has an impact on the resilience of other spaces.

During the period of coordinated economic and social development (2011 to the present), urbanisation has transitioned from rapid growth to a focus on high-quality development. Concurrently, the TSR of the YREB has shifted from being RU-dominant to the development to a mode emphasizing the protection mode of the simultaneous rise of RA–RE. The spatial resilience of 36.2% of the cities in the YREB is on an upward trend, with the number of cities with a good combination increasing from 46.2% to 60.8%, but the causes of the improvement vary from place to place. Wu et al. (2023) [62] found a gradual rise in RUs in the LRD after 2013. Ye et al. (2022) [63] provided similar evidence for the YREB. This is influenced by a number of factors, including nature, economics and policy. Natural geographic features have laid the foundation for RA and RE, and improved agricultural technology and stronger ecological protection have contributed to higher RA and RE. The upward trend in the Yunnan–Guizhou region is the most significant, as evidenced by the significant increase in RE. The high ecological vulnerability of the Yunnan–Guizhou region is a major factor limiting its development, and the long-term implementation of ecological restoration projects has improved the natural environment and increased the level of RE. Even if the expansion of urban and agricultural space is limited, its TSR has continued to develop to a high level. Moreover, the implementation of strict arable land protection policies in the middle and lower reaches of the Yangtze River has contributed to the intensification of urban and agricultural spaces. In addition, policy factors play an important role. The development plan of the city in that period called for strengthening the composite use of various types of land space, so the combination of RU and RA or RU and RE became better. The interaction of RU, RA and RE is critical in influencing changes in TSR. Significant evidence for this view can be found in the study on homestead space utilisation by Qu et al. (2023) [11]. Thus, in the process of rationally optimising the spatial layout of the territory, the crux of the problem that hinders the enhancement of TSR must be identified to promote the enhancement of RU and RA under the premise of guaranteeing ecological function.

5.2. Pathways to Optimise TSR in the YREB

According to the evaluation results of the TSR level of the YREB, to achieve the optimisation goals of high efficiency of urban space, improvement of the quality of agricultural space and conservation of ecological space, differentiated countermeasures should be taken to address different development problems. From the systematic and holistic features of the territorial space, the production function, ecological function and living function of the region should be comprehensively enhanced (Figure 9).

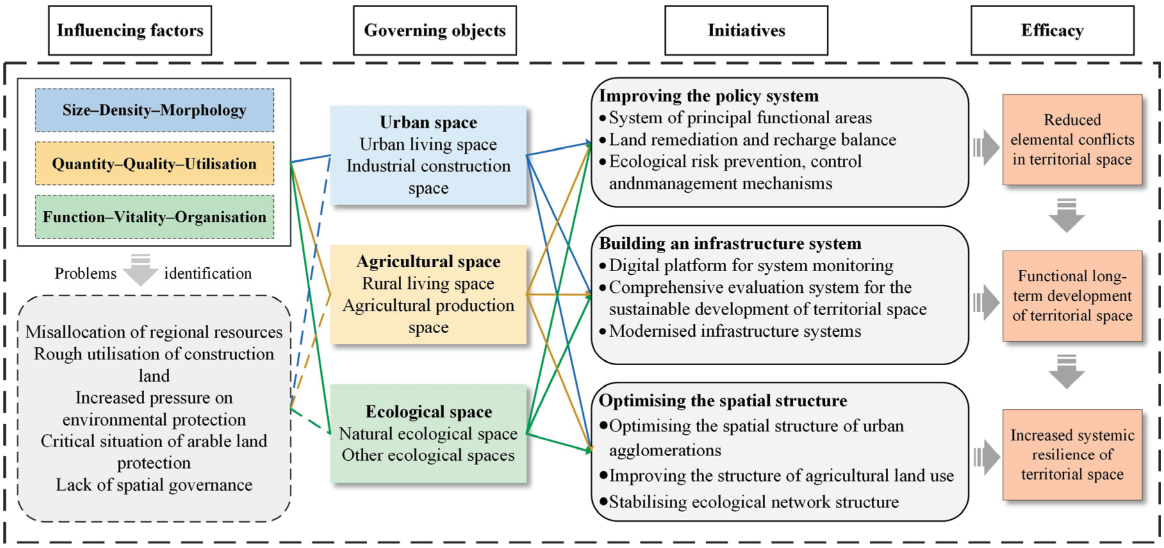

Figure 9. Comprehensive governance system of TSR.

(1) Promoting institutional innovation and policy implementation. Although many land use policies have been put forward in China, these policies need continuous improvement and vigorous pursuit. We should gradually establish and improve the management mechanism of the three land-management "red lines", i.e., urban growth boundaries (UGBs), ecological protection redlines (EPRs), and basic farmland protection zones (BFPZs) to alleviate the risks of territorial space development. Therefore, it is necessary to continue to promote the improvement of the ecosystem and to implement the main functional area strategy. Optimising requisition-compensation balance of farmland policy is necessary to achieve a dynamic balance of the total amount of arable land. Particular attention should be paid to the over-occupation of arable land by urban construction, agricultural restructuring and pollution of arable land. To achieve efficient use of the stock of construction land and optimise the layout, it is necessary to strengthen the three-dimensional composite development of space and guide the flexible adjustment of land use and composite use. The government should continue to innovate mechanisms for preventing, controlling and regulating ecological risks; implement strict use control in areas of the middle reaches of the Yangtze River where ecological space is vulnerable to urban spatial encroachment; accelerate the construction of water system restoration; and regulate the order of resource development.

(2) Strengthening the construction of infrastructure systems. We should strengthen infrastructure development including public services, transportation infrastructure, water conservancy facilities, energy facilities and emergency facilities. For example, Shanghai, as a mega-city, should focus on optimising the overall layout of public service facilities, municipal infrastructures and disaster prevention and evacuation facilities in the compilation of territorial spatial planning, so as to improve its adaptive capacity to cope with various types of disturbances. In traditional agricultural areas, the Government should strengthen agricultural infrastructure to increase the scale and efficiency of agriculture through modern plants, mechanised farming patterns and intelligent cultivation techniques in order to strengthen the monitoring and repair of nature reserves in RE dominant areas, build biodiversity protection networks and ecological corridors, and give full play to the supporting role of ecological functions in the improvement of RU and RA.

(3) Optimising the structure of territorial space enhances the spatial structure of urban agglomerations in line with the requirements of urban renewal, urban–rural integration and regional coordination and to improve the comprehensive carrying capacity

of urban space. This approach includes accelerating the restructuring of the industrial structure, transforming traditional industries and building a green and ecological economic system. In response to the widespread fragmentation of arable land and the high degree of intertwining of towns and farmland in the Yangtze River Basin, it is imperative to rationally configure the structure of arable land use. For example, arable land and cities, forests and grasslands, rivers and lakes and wetlands should be regarded as interrelated wholes, the ecological environment of farmland should be improved, and the production potential of agricultural space should be fully tapped. In addition, efforts should centre on integrating and optimising the protection and restoration patterns of mountains, water, forests, fields, lakes, grasses and sands and improving the quality and resilience of ecosystems using zonal diagnosis and precise restoration.

5.3. Shortcomings and Prospect

Our research still has deficiencies. Firstly, we have not sufficiently analysed the territorial spatial system's scale effect characteristics and element coupling characteristics. Moreover, the driving modes of TSR changes vary considerably in different regions, and conducting in-depth studies in the various areas is necessary, especially in those regions where TSR changes are relatively rapid. In subsequent research, we will further study the process and mechanism of TSR differentiation and transformation in different areas to regulate optimally the development and protection behaviour of land space more scientifically and effectively and to achieve sustainable use of the territorial space.

6. Conclusions

This study assessed TSR from three types of urban, agricultural and ecological space, and three dimensions of elements, structure and function, and a comprehensive judgement is made through the combined state of the three. We have developed a comprehensive system of indicators to accurately quantify TSR, which emphasises the coordination of urban, agricultural and ecological spaces.

The main conclusions are as follows: (1) There is a complex dynamic evolutionary process of TSR. From 2000 to 2020, the RU of the YREB declined first and then rose, with the low-value areas mainly distributed around the big cities and the high-value areas primarily located at the provincial borders. RA has an upward trend, and the equilibrium between the regions is enhanced, with the characteristics of the pattern of high in the west and low in the east becoming more and more significant. RE values continued to rise, but the differences between regions are widening, creating a spatial mismatch with RA. (2) The spatial clustering phenomenon of TSR is evident. The TSR combination of the YREB improved during the study period, with the widest distribution of single high RA. In the context of promoting high-quality development, the combination of RU–RA and RU–RE presents developmental advantages. According to the TSR evolution characteristics, the YREB is divided into three spatial resilience advantage areas of urban, agriculture, and ecology, as well as two combined spatial resilience lagging areas of RU–RA and RU–RE. (3) The evolution of TSR is generated by the joint action of the three spatial categories of RU–RA–RE and is dominated by the RU changes, which affect the RA and RE responses. The key to regulation is to mitigate internal conflicts in the territorial space through policy innovation. The support system for TSR is further strengthened. The focus is on optimising the multifunctional structure of the territorial space to facilitate the continuous improvement of TSR.

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References

1. Assiri, M.; Barone, V.; Silvestri, F.; Tassinari, M. Planning sustainable development of local productive systems: A methodological approach for the analytical identification of Ecoregions. *J. Clean. Prod.* **2021**, *287*, 125006. [CrossRef]
2. Hu, Q.; Shen, W.; Zhang, Z. How does urbanisation affect the evolution of territorial space composite function? *Appl. Geogr.* **2023**, *155*, 102976. [CrossRef]
3. Brunetta, G.; Ceravolo, R.; Barbieri, C.A.; Borghini, A.; de Carlo, F.; Mela, A.; Beltramo, S.; Longhi, A.; De Lucia, G.; Ferraris, S.; et al. Territorial Resilience: Toward a Proactive Meaning for Spatial Planning. *Sustainability* **2019**, *11*, 2286. [CrossRef]
4. Menzori, I.D.; de Sousa, I.; Gonçalves, L.M. Urban growth management and territorial governance approaches: A master plans conformance analysis. *Land Use Policy* **2021**, *105*, 105436. [CrossRef]
5. Frantzeskaki, N. Seven lessons for planning nature-based solutions in cities. *Environ. Sci. Policy* **2019**, *93*, 101–111. [CrossRef]
6. Remøy, H.; Street, E. 'The dynamics of "post-crisis" spatial planning: A comparative study of office conversion policies in England and The Netherlands. *Land Use Policy* **2018**, *77*, 811–820. [CrossRef]
7. Holling, C.S. Resilience and Stability of Ecological Systems. *Annu. Rev. Ecol. Syst.* **1973**, *4*, 1–23. [CrossRef]
8. Leitner, H.; Sheppard, E.; Webber, S.; Colven, E. Globalizing urban resilience. *Urban Geogr.* **2018**, *39*, 1276–1284. [CrossRef]
9. Cumming, G.S. Spatial resilience: Integrating landscape ecology, resilience, and sustainability. *Landsc. Ecol.* **2011**, *26*, 899–909. [CrossRef]
10. Labeyrie, V.; Ouadah, S.; Raimond, C. Social network analysis: Which contributions to the analysis of agricultural systems resilience? *Agric. Syst.* **2024**, *215*, 103832. [CrossRef]
11. Qu, Y.; Dong, X.; Su, D.; Jiang, G.; Ma, W. How to balance protection and development? A comprehensive analysis framework for territorial space utilization scale, function and pattern. *J. Environ. Manag.* **2023**, *339*, 117809. [CrossRef]
12. Assumma, V.; Bottero, M.; De Angelis, E.; Lourenco, J.M.; Monaco, R.; Soares, A.J. A decision support system for territorial resilience assessment and planning: An application to the Douro Valley (Portugal). *Sci. Total Environ.* **2021**, *756*, 143806. [CrossRef] [PubMed]
13. Xia, C.; Zhai, G. Territorial spatial vulnerability assessment based on PSO-BP neural network: A case study in Shenzhen, China. *Ecol. Inform.* **2023**, *75*, 102088. [CrossRef]
14. Qu, Y.; Wang, S.; Tian, Y.; Jiang, G.; Zhou, T.; Meng, L. Territorial spatial planning for regional high-quality development—An analytical framework for the identification, mediation and transmission of potential land utilization conflicts in the Yellow River Delta. *Land Use Policy* **2023**, *125*, 106462.
15. 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] [PubMed]
16. Stotten, R. The natural domain and its social representation in the community resilience concept. *Sustain. Dev.* **2024**, *32*, 1458–1470. [CrossRef]
17. Assumma, V.; Bottero, M.; Ishizaka, A. Enhancing territorial resilience assessment with a decision-aiding model in regional planning of Socio-Ecological Systems. *Environ. Sci. Policy* **2024**, *154*, 103691. [CrossRef]
18. Zhao, Y.; Zhang, M.; Zhao, D.; Duo, L.; Lu, C. Optimizing the ecological network of resource-based cities to enhance the resilience of regional ecological networks. *Environ. Sci. Pollut. Res.* **2024**, *31*, 17182–17205. [CrossRef]
19. Egerer, M.; Annighöfer, P.; Arzberger, S.; Burger, S.; Hecher, Y.; Knill, V.; Probst, B.; Suda, M. Urban oases: The social-ecological importance of small urban green spaces. *Ecosyst. People* **2024**, *20*, 2315991. [CrossRef]
20. Fistola, R.; Gargiulo, C.; La Rocca, R.A. Rethinking vulnerability in city-systems: A methodological proposal to assess "urban entropy". *Environ. Impact Assess. Rev.* **2020**, *85*, 106464. [CrossRef]
21. García-Ayllón, S.; Pilz, J. Territorial spatial evolution process and its ecological resilience. *Front. Environ. Sci.* **2024**, *12*, 1373672. [CrossRef]
22. Qu, Y.; Wang, S.; Li, Y.; Zhu, W.; Wang, S. Characteristics of potential conflicts of territorial space and optimization pattern in the Yellow River Delta based on multi-functional suitability. *Sci. Geogr. Sin.* **2023**, *43*, 301–312.
23. Ran, Y.; Lei, D.; Li, J.; Gao, L.; Mo, J.; Liu, X. Identification of crucial areas of territorial ecological restoration based on ecological security pattern: A case study of the central Yunnan urban agglomeration, China. *Ecol. Indic.* **2022**, *143*, 109318. [CrossRef]
24. Marando, F.; Heris, M.P.; Zulian, G.; Udías, A.; Mentaschi, L.; Chrysoulakis, N.; Parastatidis, D.; Maes, J. Urban heat island mitigation by green infrastructure in European Functional Urban Areas. *Sust. Cities Soc.* **2022**, *77*, 103564. [CrossRef]
25. Zhai, G.; Xia, C. Strategic emphasis on the construction of resilient cities in China. *City Plan. Rev.* **2021**, *45*, 44–48.
26. Rogatka, K.; Starczewski, T.; Kowalski, M. Urban resilience in spatial planning of polish cities—True or false? Transformational perspective. *Land Use Policy* **2021**, *101*, 105172. [CrossRef]

27. Lu, P.; Stead, D. Understanding the notion of resilience in spatial planning: A case study of Rotterdam, The Netherlands. *Cities* **2013**, *35*, 200–212. [CrossRef]
28. Datola, G. Implementing urban resilience in urban planning: A comprehensive framework for urban resilience evaluation. *Sust. Cities Soc.* **2023**, *98*, 104821. [CrossRef]
29. Feng, Y.; Lee, C.C.; Peng, D.Y. Does regional integration improve economic resilience? Evidence from urban agglomerations in China. *Sust. Cities Soc.* **2023**, *88*, 104273. [CrossRef]
30. Oliver, T.H.; Heard, M.S.; Isaac, N.; Roy, D.B.; Procter, D.; Eigenbrod, F.; Freckleton, R.; Hector, A.; Orme, D.L.; Petchey, O.L.; et al. Biodiversity and Resilience of Ecosystem Functions. *Trends Ecol. Evol.* **2015**, *30*, 673–684. [CrossRef] [PubMed]
31. Zhou, Q.; Zhu, M.; Qiao, Y.; Zhang, X.; Chen, J. Achieving resilience through smart cities? Evidence from China. *Habitat Int.* **2021**, *111*, 102348. [CrossRef]
32. Meuwissen, M.; Feindt, P.H.; Spiegel, A.; Termeer, C.; Mathijs, E.; de Mey, Y.; Finger, R.; Balmann, A.; Wauters, E.; Urquhart, J.; et al. A framework to assess the resilience of farming systems. *Agric. Syst.* **2019**, *176*, 102656. [CrossRef]
33. Imperiale, A.J.; Vanclay, F. Conceptualizing community resilience and the social dimensions of risk to overcome barriers to disaster risk reduction and sustainable development. *Sustain. Dev.* **2021**, *29*, 891–905. [CrossRef]
34. Zou, L.; Zhang, L.; Liang, Y.; Wen, Q. Scientific cognition and research framework of territorial space function in the New Era. *J. Nat. Resour.* **2022**, *37*, 3060–3072. [CrossRef]
35. Deng, C.; Liu, C.; Li, Z. Research Path on the Resilience of Watershed Territorial Space under the Background of Ecological Restoration. *China Land Sci.* **2022**, *36*, 11–20.
36. Li, S.; Zhao, X.; Pu, J.; Miao, P.; Wang, Q.; Tan, K. Optimize and control territorial spatial functional areas to improve the ecological stability and total environment in karst areas of Southwest China. *Land Use Policy* **2021**, *100*, 104940. [CrossRef]
37. Liu, Y.S.; Zhou, Y. Territory spatial planning and national governance system in China. *Land Use Policy* **2021**, *102*, 105288. [CrossRef]
38. Long, H.; Tu, S.; Ge, D.; Li, T.; Liu, Y. The allocation and management of critical resources in rural China under restructuring: Problems and prospects. *J. Rural Stud.* **2016**, *47*, 392–412. [CrossRef]
39. Song, W.; Cao, S.; Du, M.; He, Z. Aligning territorial spatial planning with sustainable development goals: A comprehensive analysis of production, living, and ecological spaces in China. *Ecol. Indic.* **2024**, *160*, 111816. [CrossRef]
40. Zhang, C.; Zhao, L.; Song, X.; Zhang, Q.; Zhang, X. Spatial-temporal coupling characteristics and interaction effects of economic resilience and people's livelihoods and well-being: An analysis of 78 cities in the Yellow River Basin. *Sust. Cities Soc.* **2024**, *112*, 105638. [CrossRef]
41. Liu, C.; Cheng, L.; Li, J.; Lu, X.; Xu, Y.; Yang, Q. Trade-offs analysis of land use functions in a hilly-mountainous city of northwest Hubei Province: The interactive effects of urbanization and ecological construction. *Habitat Int.* **2023**, *131*, 102705. [CrossRef]
42. Dhar, T.K.; Khirfan, L. A multi-scale and multi-dimensional framework for enhancing the resilience of urban form to climate change. *Urban Clim.* **2017**, *19*, 72–91. [CrossRef]
43. Shi, C.; Zhu, X.; Wu, H.; Li, Z. Assessment of Urban Ecological Resilience and Its Influencing Factors: A Case Study of the Beijing-Tianjin-Hebei Urban Agglomeration of China. *Land* **2022**, *11*, 921. [CrossRef]
44. Volkov, A.; Morkunas, M.; Balezentis, T.; Streimikiene, D. Are agricultural sustainability and resilience complementary notions? Evidence from the North European agriculture. *Land Use Policy* **2022**, *112*, 105791. [CrossRef]
45. 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]
46. Ghosh, S.; Das Chatterjee, N.; Dinda, S. Urban ecological security assessment and forecasting using integrated DEMATEL-ANP and CA-Markov models: A case study on Kolkata Metropolitan Area, India. *Sust. Cities Soc.* **2021**, *68*, 102773. [CrossRef]
47. Wei, X.; Shen, L.; Liu, Z.; Luo, L.; Wang, J.; Chen, Y. Comparative analysis on the evolution of ecological carrying capacity between provinces during urbanization process in China. *Ecol. Indic.* **2020**, *112*, 106179. [CrossRef]
48. Hu, Q.; Zhang, Z.; Niu, L. Identification and evolution of territorial space from the perspective of composite functions. *Habitat Int.* **2022**, *128*, 102662. [CrossRef]
49. Xu, Y.; Zhao, X.; Huang, P.; Pu, J.; Ran, Y.; Zhou, S.; Zhao, Q.; Feng, Y.; Tang, Y.; Tao, J.; et al. A new framework for multi-level territorial spatial zoning management: Integrating ecosystem services supply-demand balance and land use structure. *J. Clean. Prod.* **2024**, *441*, 141053. [CrossRef]
50. Cui, X.; Cai, T.; Deng, W.; Zheng, R.; Jiang, Y.; Bao, H. Indicators for Evaluating High-Quality Agricultural Development: Empirical Study from Yangtze River Economic Belt, China. *Soc. Indic. Res.* **2022**, *164*, 1101–1127. [CrossRef]
51. Zhang, R.; Tai, H.; Cheng, K.; Zhu, Y.; Hou, J. Carbon emission efficiency network formation mechanism and spatial correlation complexity analysis: Taking the Yangtze River Economic Belt as an example. *Sci. Total Environ.* **2022**, *841*, 156719. [CrossRef] [PubMed]
52. Sharifi, A. Urban form resilience: A meso-scale analysis. *Cities* **2019**, *93*, 238–252. [CrossRef]
53. Xiu, C.; Wei, Y.; Wang, Q. Evaluation of urban resilience of Dalian city based on the perspective of 'Size-Density-Morphology'. *Acta Geogr. Sin.* **2018**, *73*, 2315–2328.
54. Feng, X.; Xiu, C.; Bai, L.; Zhong, Y.; Wei, Y. Comprehensive evaluation of urban resilience based on the perspective of landscape pattern: A case study of Shenyang city. *Cities* **2020**, *104*, 102722. [CrossRef]

55. Dai, L.; Liu, Y.B.; Luo, X.Y. 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]
56. Urruty, N.; Tailliez-Lefebvre, D.; Huyghe, C. Stability, robustness, vulnerability and resilience of agricultural systems. A review. *Agron. Sustain. Dev.* **2016**, *36*, 15. [CrossRef]
57. Ye, S.; Song, C.; Shen, S.; Gao, P.; Cheng, C.; Cheng, F.; Wan, C.; Zhu, D. Spatial pattern of arable land-use intensity in China. *Land Use Policy* **2020**, *99*, 104845. [CrossRef]
58. Peng, J.; Liu, Y.; Li, T.; Wu, J. Regional ecosystem health response to rural land use change: A case study in Lijiang City, China. *Ecol. Indic.* **2017**, *72*, 399–410. [CrossRef]
59. Xie, G.; Zhang, C.; Zhen, L.; Zhang, L. Dynamic changes in the value of China's ecosystem services. *Ecosyst. Serv.* **2017**, *26*, 146–154. [CrossRef]
60. Wang, Y.; Cai, Y.; Xie, Y.; Chen, L.; Zhang, P. An integrated approach for evaluating dynamics of urban eco-resilience in urban agglomerations of China. *Ecol. Indic.* **2023**, *146*, 109859. [CrossRef]
61. Song, Y.; Xue, D.; Dai, L.; Wang, P.; Huang, X.; Xia, S. Land cover change and eco-environmental quality response of different geomorphic units on the Chinese Loess Plateau. *J. Arid Land* **2020**, *12*, 29–43. [CrossRef]
62. Wu, P.; Duan, Q.; Zhou, L.; Wu, Q.; Deveci, M. Spatial-temporal evaluation of urban resilience in the Yangtze River Delta from the perspective of the coupling coordination degree. *Environ. Dev. Sustain.* **2023**, 1–23. [CrossRef] [PubMed]
63. Ye, C.; Hu, M.; Lu, L.; Dong, Q.; Gu, M. Spatio-temporal evolution and factor explanatory power analysis of urban resilience in the Yangtze River Economic Belt. *Geogr. Sustain.* **2022**, *3*, 299–311. [CrossRef]

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Article

Dynamic Matching and Spatial Optimization of Land Use and Resource-Environment Constraints in Typical Regions of the Yellow River Basin in China

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Abstract: Accurately identifying the matching relationships between territorial space evolution and the resources and environment carrying capacity will directly guide the sustainable use of territorial space. Based on the evaluation of the territorial space dynamics of the lower Yellow River, this paper evaluates the suitability of territorial space development by focusing on ecological protection, agricultural development, and urban construction. Specifically, the resources and environment carrying capacity is estimated by identifying and mediating potential conflicts in the development of territorial space. The matching relationship between the evolution of territorial space and the resources and environment carrying capacity is identified using the matching degree model. The results demonstrated that: (1) Between 2000 and 2020, the agricultural space of the lower Yellow River was relatively stable, while the ecological space was generally shrinking, and the urban space continued to increase; (2) The characteristics of suitability for the agricultural development and urban construction of the lower Yellow River are characterized by landform and land-sea differentiation. The carrying scale of resources and the environment is based on agricultural space and is increasing yearly, followed by ecological space, which is gradually decreasing, and urban space, which first increased and then decreased; (3) Between 2000 and 2020, the matching index of the ecological and agricultural space evolution and the resource and environmental carrying capacity in the lower Yellow River exhibited a downward trend, while the regional difference increased. Furthermore, the matching index of urban space and the resources and environment carrying capacity indicated an upward trend, while the regional difference decreased.

Keywords: territorial space; potential conflict; resources and environment carrying capacity; matching; regulation; Yellow River

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1. Introduction

At present, China is in the stage of accelerated urbanization and industrialization. The increasing intensity of territorial space development and utilization and the imbalance in social-ecological systems has challenged the sustainable use of territorial space [1]. Several Opinions on Establishing a Land Spatial Planning System and Supervising Its Implementation proposed that "we should scientifically and orderly co-ordinate the layout of ecological, agricultural, urban and other functional spaces based on suitability evaluation and resources and environment carrying capacity of territorial space development (referred to as "dual evaluation")". In practice, "dual evaluation" provides important technical support for the zoning of territorial functions [2] and the optimal regulation of territorial space [3,4], and it also contributes to promoting the compilation of regional territorial space planning and the construction of an ecological civilization [5].

The “dual evaluation” refers to the evaluation of the carrying capacity of the environment and the evaluation of the suitability of the spatial development of territorial space. The suitability evaluation can be traced back to the land ecological suitability evaluation method [6]. The evaluation object is from the initial agricultural land to the construction land, and then to the entire territorial space [7,8]. The carrying capacity has gradually expanded to include the ecological carrying capacity, resource carrying capacity, and environmental carrying capacity [9–11]. The resources and environment carrying capacity is the standard for measuring whether social and economic activities are overloaded. It has multiple attributes, such as objectivity [12], and is an important research topic in the field of international sustainable development [13]. From a theoretical perspective, many theories, such as the Growth Limit Theory [14–16], serve as the theoretical bases for understanding the resources and environment carrying capacity, and finally form a diverse, multi-scale, and multi-objective-oriented research paradigm [17]. From the perspective of research methods, massive methods, such as the Pressure State Response Model, have attracted much attention [18–21], and finally form the framework of the resource and environmental carrying capacity represented by the Driver-Pressure-State-Impact-Response (DPSIR) framework [22]. Furthermore, the process of resource and environmental carrying capacity deduction is centered on building an indicator evaluation system based on the resource carrying capacity, environment carrying capacity, and ecological carrying capacity [23,24]. From the perspective of achievements application, it covers extensive fields, such as spatial layout optimization, industrial layout and planning, and post-disaster reconstruction [25–29]. The achievements application emphasizes the fundamental support of the resource and environmental carrying capacity and its core lies in the interaction between human activities and the resource environment.

The compilation of land spatial planning requires the notion of “dual evaluation”. Many scholars have focused on the logical relationship between the resources and environment carrying capacity and the suitability of territorial space development in the “dual evaluation” [30–32]. They have proposed the correlation logic that “suitability determines the space for development and carrying capacity identifies the scale of development” [33]. Specifically, the resources and environment carrying capacity is regarded as having the potential to better guide territorial space planning and sustainable utilization. More importantly, the resources and environment carrying capacity emphasizes the balance and decomposition of the resources and environment carrying capacity among the ecological protection, agricultural production, and urban construction functions in the same administrative unit. In addition, in the current context of increasingly significant territorial space changes, how and whether the matching relationship between the evolution of territorial space and the resources and environment carrying capacity breaks through the bottom line of resource and environment constraints is crucial [34]. Despite exploring resources and environment carrying capacities that possess theoretical and practical implications, limited empirical attention has been paid to it.

This paper selects cities in the Yellow River basin of Shandong Province as the study area for the following reasons. (1) Compared with the entire Yellow River basin, it has complex geomorphological differences. The plateau, hills, and plains are distributed in steps, and the natural conditions are complex. (2) At the same time, the Yellow River basin is one of the regions with the highest level of socio–economic development and urbanization in China. This area covers 77 counties. Therefore, the representativeness of the research area selected in this paper lies in its obvious differentiation characteristics in terms of its natural geographical environment and social economic pattern, which can be regarded as the epitome of the Yellow River basin. Specifically, Shandong Province, the only province located entirely in the lower reaches of the Yellow River, spans across nine cities in western Shandong and covers an area of 83×104 km^2. Thus, there are significant differences in the upper, middle, and lower sections of the region. Specifically, the upper section is an important grain producing area, the middle section is the provincial capital economic circle, and the lower section is an ecologically fragile area that is important for the ecosystem services dominated by the Yellow River Delta. The Yellow River basin in Shandong Province thus conforms to the overall pattern of ecological protection, agricultural production, and urban construction in the Yellow River basin. Therefore, this paper takes the Yellow River basin in Shandong Province as the research object. Firstly, the spatial evolution and the resources and environment carrying capacity are incorporated into the coupling framework of the social economy and the resources and environment to reveal the spatial evolution of the territory. Secondly, this paper establishes an evaluation system for the suitability of territorial space development and identifies the resources and environment carrying capacity through potential conflict mediation. The goal is to uncover the matching relationship between the evolution of territorial space development and the resources and environment carrying capacity. The findings could provide a path for optimizing territorial space.

This paper makes five contributions. Firstly, this paper proposes a framework for determining the alignment between the territorial space and the resource and environmental carrying capacity, as well as realizing the resource and environmental carrying capacity. The framework provides a theoretical basis for understanding the sustainable use of territorial space. Secondly, this paper introduces technical guidelines for assessing the resource and environmental carrying capacity. It emphasizes the importance of identifying and mediating potential conflicts in land and space, thus aiding in the identification of the resource and environmental carrying capacity of regional multi-functional areas. Thirdly, this paper provides a supporting framework for optimizing land structure and pattern reconfiguration. The researchers have conducted an in-depth empirical study in an important ecological region of the Yellow River basin, thus providing a concrete and practical reference for the sustainable development of territorial space. Fourthly, as one of the significant ecological regions in the Yellow River basin, our research area plays a crucial role in supporting the conservation and development of the inlet area and other important ecological regions within the basin. This is achieved through the analysis of the spatial evolution, the matching relationship of resource and environmental carrying capacity, and the ecology-agriculture-urban space. Fifthly, our database on territorial space, resources, and the environment in typical areas of the lower reaches of the Yellow River provides a foundation for the formulation and implementation of the relevant government policies.

2. Theoretical Framework

2.1. A Framework for Matching Territorial Space and Resources and Environment Carrying Capacity

The matching relationship between the evolution of territorial space and the resources and environment carrying capacity is a representation of the interaction between humans and environmental systems. This relationship impacts the optimization and sustainable use of the territorial spatial pattern. Territorial space is the home for people's survival and development and the material basis for the sustainable development of eco-social systems and natural geographic systems [3]. At the same time, territorial space is also an advanced manifestation of the spatialization of land use [35]. According to the Growth Limit Theory, there are limits to both socio–economic development and the resource environment. When this limit is exceeded, it will hinder and curb sustainable development [14]. The two major systems of social economy, represented by territorial space utilization, and natural objects, represented by the resources and environment, constitute the resources and environment carrying capacity; it has to be noted that there is a highly coupled relationship between these two systems [12] (Figure 1). The environmental carrying capacity is a comprehensive and scientifically based evaluation method that serves as a crucial indicator for assessing the long-term sustainability of ecosystems [36]. The impact of socio–economic development on the resources and environment is increasing. In other words, urban space is expanding while ecological space is shrinking, and the utilization of territory reaches the bottom line of resource and environmental constraints. As a result, the matching relationship between the evolution of territorial space and the carrying capacity of the resources and environment has shifted to a mismatched one. To achieve the sustainable utilization of space, differentiated regulation plans should be adopted according to the matching relationship between the evolution of territorial space and the carrying capacity of the resources and environment. Specifically, mismatched areas should be limited to expand the territorial space, near-mismatched areas should be reasonably allocated to ensure that it does not exceed the bottom line of resource and environmental constraints, and well-matched areas should improve the utilization quality of the territorial space. Finally, meeting the resource and environmental constraints in utilizing all types of territorial space would be achieved. Therefore, clarifying the trend of change in the relation between the evolution of territorial space and the carrying capacity of the resources and environment plays an important role in the sustainable use of territorial space.

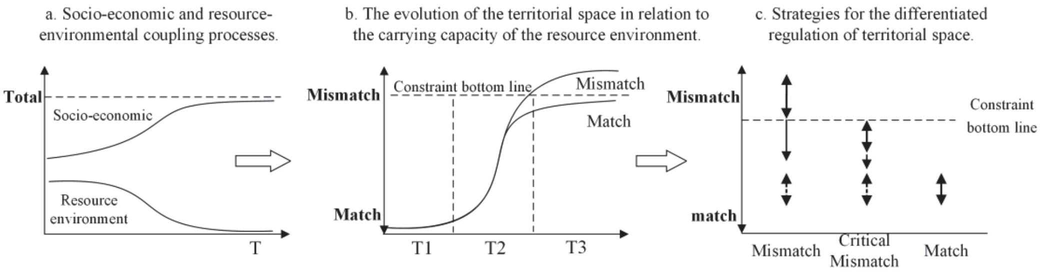

Figure 1. Theoretical basis.

2.2. The Process of Implementing Resource and Environmental Carrying Capacity

At present, there are two commonly used methods for evaluating the resources and environment carrying capacity. The first is to select socio–economic and resource environment indicators for evaluation [37,38]. This method is able to uncover the difference in the carrying capacities of different regions. The second method is used to calculate the carrying capacity based on the results of an agricultural production and urban construction suitability evaluation. This method emphasizes the background conditions, in accordance with the "Technical Guidelines for Evaluating the Carrying Capacity of Resources and Environment and the Suitability of Land and Space Development (Trial)". As the territorial spatial planning system was established, the latter approach received increasing attention. However, most existing studies emphasize suitability, while weakening the carrying capacity, thus leading to many problems. For instance, the calculated resource and environmental carrying capacity in the results is too large. Furthermore, there are difficulties in determining the resources and environmental carrying capacity in cases where different areas are considered suitable at the same time. There is also a lack of consideration for the decomposition of territorial space with different functional spatial orientations and the support for the optimization of the territory spatial structure and pattern reconstruction is relatively weak. Identifying and regulating potential conflicts contributes to pinpointing regions with multiple suitabilities and reconstructing the regional spatial pattern. Moreover, this process also has a bridging role as it identifies the resources and environmental carrying capacity. This paper adopts the method of "dual evaluation" to carry out the study, and the specific research process is shown in Figure 2. Firstly, a system of indicators for ecological protection, agricultural production, and urban construction is established around land and water resources, and environment and ecological factors are established in order to conduct a suitability evaluation of the spatial development. Secondly, we construct a territorial spatial potential conflict model that includes no potential conflicts, mild potential conflicts, moderate potential conflicts, and severe potential conflicts. Land use planning requirements act as a binding bottom line to regulate potential conflicts through rigid effects. The remaining areas employ the current status of land use to achieve elastic adjustment. Finally, the paper obtains the scale of the resource and environmental carrying capacity centered around ecology, agriculture, and urban space.

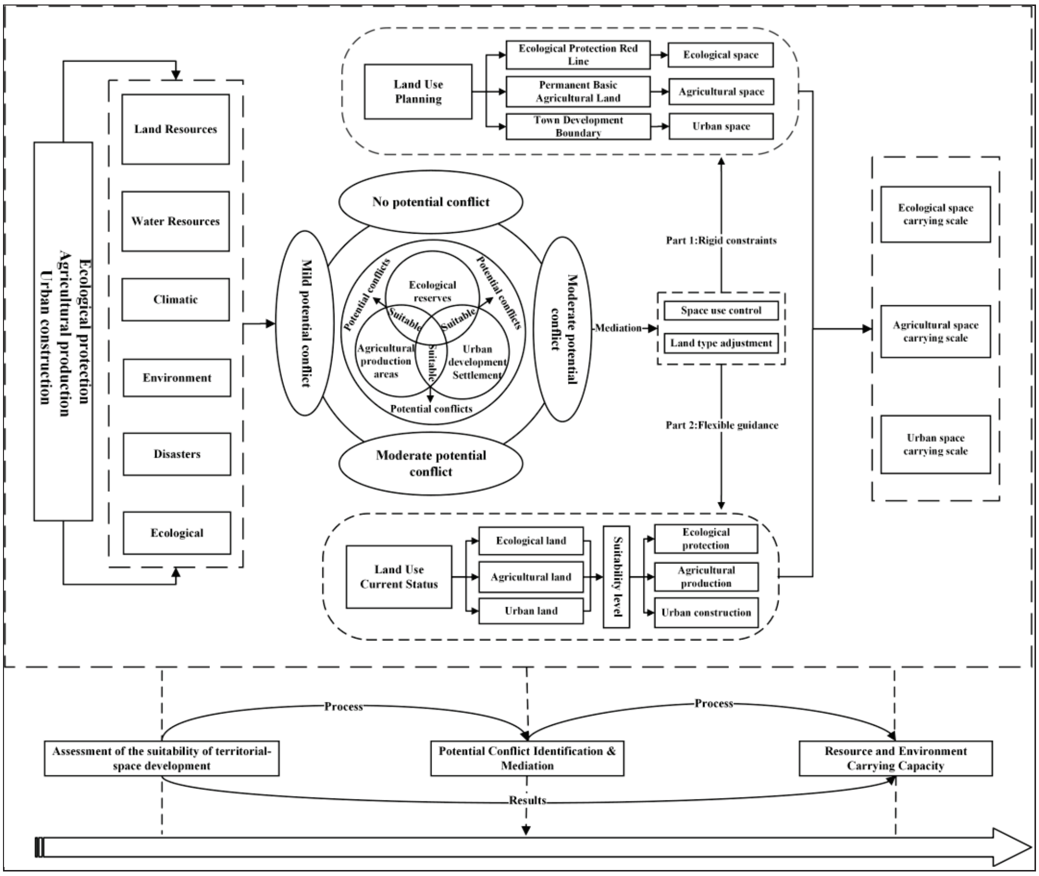

Figure 2. The realization process of resources and environment carrying capacity.

However, there are certain limitations to the current "dual evaluation". Firstly, the "dual evaluation" is based on the simultaneous adaptation of different spaces in the territorial space, and there is still in-depth research to be conducted on the corresponding resource and environmental carrying categories and their capacities. Secondly, there is a clear lack of consideration of the overall planning of multifunctional territorial spaces and the mutual support and constraint relationships between natural background elements and humans, i.e., there is still a lack of corresponding practical research.

3. Research Methods and Data Sources

3.1. Research Methods

3.1.1. Measuring the Spatial Evolution of the Territory

The degree of territorial spatial dynamics is a quantitative evaluation of the rate of change of territorial spatial types. It is divided into a single degree of territorial spatial dynamics and an integrated degree of territorial spatial dynamics.

The degree of spatial dynamics of a country is used to express the degree of evolution of the spatial pattern of the national territory over a period of time. The equation for this, Equation (1), is as follows:

$$K = \frac{U_y - U_x}{U_x \cdot T} \times 100\% \quad (1)$$

where K represents the degree of evolution of the spatial pattern of a country in a certain time period. U_x, U_y denote the area of the initial and final territorial space type, respectively. Moreover, T represents the length of the study period.

The degree of integrated territorial spatial dynamics characterizes the degree of overall territorial spatial evolution over a certain time period. The equation for this, Equation (2), is as follows:

$$C = \left[\frac{\sum_{i=1}^{n} \Delta U_{i-j}}{2\sum_{i=1}^{n} U_i} \right] \times \frac{1}{T} \times 100\% \tag{2}$$

where C represents the extent of the overall spatial evolution of a country over a certain time period, while U_i denotes the area of the initial category i land space type. ΔU_{i-j} represents the absolute value of the area of spatial type i converted to other spatial types during the study period. Lastly, n represents the number of territorial space types.

3.1.2. Identifying the Carrying Capacity of the Resource Environment

1. Assessment of the suitability of territorial spatial development

According to the Technical Guidelines for the Evaluation of the Suitability of Resource and Environmental carrying capacity and Territorial Spatial Development (for Trial Implementation), an ecological protection evaluation is primarily focused on identifying areas with regional ecosystem service functions and a high degree of ecological fragility (shown in Table 1). At the same time, with reference to the relevant research results [39–42], this evaluation accounts for two key aspects: ecosystem service functions and ecological sensitivity. Specifically, it emphasizes the presence of factors related to sanding and salinization sensitivity.

Table 1. Evaluation index system of ecological protection importance.

Target	Aspects	Factors	Formulations
Ecological protection (Fe)	Ecosystem service functions	Biodiversity conservation (e_1)	$e_1 = NPP_{mean} \times F_{pre} \times F_{temp} \times (1 - F_{ait})$
		Water conservation (e_2)	$e_2 = NPP_{mean} \times F_{sic} \times F_{pre} \times \left(1 - F_{slp}\right)$
		Soil and water conservation (e_3)	$e_3 = NPP_{mean} \times (1 - K) \times \left(1 - F_{slp}\right)$
		Windbreak and sand-fixation (e_4)	$e_4 = NPP_{mean} \times K \times F_q \times D$
	Ecological sensitivity	Soil erosion sensitivity (e_5)	$e_5 = \sqrt[4]{R \times K \times LS \times C}$
		Desertification sensitivity (e_6)	$e_6 = \sqrt[4]{I \times W \times K \times C}$
		Salinization sensitivity (e_7)	$e_7 = \sqrt[4]{I \times M \times D \times K}$

Note: NPP_{mean} is net primary productivity of vegetation; F_{pre} is perennial average rainfall; F_{temp} is the perennial average temperature; F_{alt} is the altitude factor; F_{sic} is the soil seepage factor; F_{slp} is the slope factor; K is the soil erodibility factor; F_q is the perennial average climate erodibility factor; D is the surface roughness factor; R is the rainfall erosivity factor; LS is the topographic relief factor; C is the vegetation cover factor; I is the dryness index; W is the number of sand-blowing days greater than 6 m/s in winter and spring; M is the groundwater salinity; and D is the groundwater burial depth. The normalized threshold of each factor is between 0 and 1.

The evaluation of the suitability of agricultural production and urban construction reflects the suitability of the national land space for agricultural production and the needs of urban residents, in terms of land, water, environment, meteorology, and disasters, and is focused on the resources and environment. The suitability of agricultural production emphasizes the influence of factors such as precipitation, light and heat conditions, soil environmental capacity, and meteorological hazards (shown in Table 2). On the other hand, the suitability of urban construction highlights the influence of factors such as climate comfort, water and air environmental capacity, and geological hazards (shown in Table 3). The evaluation system variables and grade classification used in this study are based on *the Guidelines for the Evaluation of the Carrying Capacity and Suitability of the Resource Environment* [43,44].

Table 2. Evaluation index system of agricultural production suitability.

Target	Aspects	Factors	Grade and Scores 0	1	3	5	7	Weight
Agricultural production (Fa)	Land	slope/(°) (a_1)	≥25	15~25	6~15	2~6	<2	0.15
		silt content/% (a_2)	≥80	60~80	40~60	20~40	<20	0.12
	Water	precipitation/mm (a_3)	<200	200~400	400~800	800~1200	≥1200	0.16
		total water resources/10,000 m^3 (a_4)	<3	3~8	8~13	13~25	≥25	0.14
	Climate	light and heat conditions/°C (a_5)	<1500	1500~4000	4000~5800	5800~7600	≥7600	0.15
	Environment	soil environmental capacity (a_6)	Greater than 150% of the risk control value	100~150% of the risk control value	The risk screening value is 70 to 100%	Greater than the risk screening value but less than or equal to 70% of the risk control value	Below or equal to the risk screening value	0.14
	Disaster	frequency of meteorological disasters/%(a_7)	>80	60~80	40~60	20~40	≤20	0.14

Note: The soil environmental capacity classification standard is based on the "Soil Environmental Quality Agricultural Land Soil Pollution Risk Control Standard (Trial) (GB 15618-2018)".

Table 3. Evaluation index system of urban construction suitability.

Target	Aspects	Factors	Grade and Scores 0	1	3	5	7	Weight
Urban construction (*Fc*)	Land	slope/(°) (c_1)	>25	15~25	8~15	3~8	≤3	0.17
		altitude/m (c_2)	>50	30~50	20~30	10~20	≤10	0.13
	Water	total water resources/(m^3/km^2) (c_3)	<50,000	50,000~100,000	100,000~200,000	200,000~500,000	≥500,000	0.17
	Climate	Thermal Comfort/(THI) (c_4)	<32 or >90	32~41 or 82~90	41~51 or 73~82	51~60 or 65~73	60~65	0.12
	Environment	atmospheric environmental capacity index (c_5)	≤0.2	0.2~0.4	0.4~0.6	0.6~0.8	>0.8	0.09
		water environmental capacity/(t/km^2) (c_6)	<0.04 <0.8	0.04~0.14 0.8~2.9	0.14~0.39 2.9~7.8	0.39~0.96 7.8~19.2	≥0.96 ≥19.6	0.10
	Disaster	distance from fault zone/m (c_7)	<30	30~100	100~200	200~400	>400	0.08
		peak ground acceleration/g (c_8)	≥0.30	0.20	0.15	0.10	≤0.05	0.07
		cumulative land subsidence/mm (c_9)	>2400	1600~2400	800~1600	200~800	<200	0.06

Note:① The comfort degree is represented by the temperature and humidity index, THI = T − 0.55 × (1 − f) × (T − 58). THI is the temperature-humidity index; T is the monthly average temperature (in Fahrenheit); and f is the monthly average relative humidity of the air. ② the water environmental capacity is controlled by COD and NH_3-N.

The ecological protection importance is categorized into three levels using the natural breakpoint method and the stepwise correction method (Equation (3)). The three levels are classified as extremely important, important, and generally important.

$$Fe = max(E_1, E_2, E_3, E_4, E_5, E_6, E_7) \tag{3}$$

where *Fe* represents the ecological protection importance level. E_1, E_2, E_3, E_4, E_5, E_6, and E_7 denote biodiversity maintenance, water conservation, soil conservation, wind and sand control, erosion sensitivity, sand sensitivity, and salinity sensitivity, respectively.

The evaluation of the suitability of agricultural production and town construction is conducted using the factor assignment-restrictive integrated evaluation method. This builds upon the deductions made for ecological protection. The weights of the factors are determined using the expert assessment method, and are assigned in a hierarchical manner using the corresponding specifications:

$$F_i = \begin{cases} 0 \ (f_{ij} = 0) \\ \sum_{i=1}^{n} w_{ij} \times f_{ij} \ (f_{ij} \neq 0) \end{cases} \tag{4}$$

where F_i denotes the suitability level of the *i* evaluation unit, while w_{ij} represents the index weight of factor *j* in the *i-th* evaluation unit. Furthermore, f_{ij} denotes the index score of factor *j* in the *i-th* evaluation unit. When $F_i = 0$, it is considered unsuitable. Conversely, when $F_i \neq 0$, it is classified as generally suitable and suitable according to the natural breakpoint method.

2. Identification of the resources and environment carrying capacity based on potential conflict mediation.

The three-step process of identifying potential conflicts in land and space, reconciling them, and identifying the resource and environmental carrying capacity is used to establish the scale of the resource and environmental carrying capacity for ecological, agricultural, and urban spaces.

Step 1: Ecologically critical areas are potentially conflict-free. Mild potential conflict is present when at least two of the three suitability evaluations result in the lowest rating. Furthermore, a potential conflict is considered moderate when the assessment of the ecological importance is generally important and the assessment of the suitability for agricultural production and urban construction is generally suitable or higher. It is also moderate when the assessment of the ecological importance is important and at least one of the assessments of the suitability for agricultural production and urban construction is generally suitable or higher. Finally, a potential conflict is considered heavy when the assessment of the ecological importance is categorized as important, and the suitability for agricultural production and urban construction is considered suitable [45,46].

Step 2: The "three red lines" (the ecological protection red line, permanent basic agricultural land protection red line, and urban development boundary) are adopted as a constraint and guidance mechanism for potential conflict mediation. Firstly, the "three red lines" are divided into three categories of national land space. Then, the existing land types are maintained for areas without potential conflicts. According to the current land use status, identify and reconcile land classes with mismatched suitability classes in mild and severe potential conflict areas. The current ecological land is not subject to mediation. According to the highest level of suitability, achieve potential conflict mediation by achieving one-way or two-way conversion between ecological land, agricultural land, and construction land for moderate potential conflict areas. While ecological land is maintained in its current state, construction land and agricultural land in ecologically important areas are adjusted to ecological space. Moreover, construction land in areas suitable for agricultural production is adjusted to agricultural space, while agricultural land in areas suitable for urban construction is adjusted to urban space.

Step 3: In order to co-ordinate the decomposition and balance of the resource and environmental carrying capacity within different administrative regions, it is measured according to the ecological, agricultural, and urban space scales. It is based on the results of the reconciliation of potential conflicts within the national territory.

3.1.3. Matching Relationship between Spatial Evolution of Territories and Resource and Environmental Carrying Capacity and Optimal Zoning

Based on the matching relationship between the evolution of territorial space and the resources and environmental carrying capacity, this paper explores whether the evolution of territorial space exceeded the threshold of the resources and environment, as well as the degree of stress borne by the resources and environment (Equation (5)).

$$D = \begin{cases} D_z/D_x \\ D_y/D_z \end{cases} \quad (5)$$

where D represents the matching index between the evolution of territorial space and the carrying capacity of the resources and environment. D_Z denotes the resource and environmental carrying capacity, while D_x represents the current scale of ecological space, and D_y denotes the scale of agriculture and urban space. In short, the existing scale is compared with the carrying scale. As ecological conservation is given priority, the more scales other than the carrying scale for ecological space exist, the better; therefore, for ecological space accounting, use D_z/D_x. For agricultural and urban spaces, the fewer scales other than the carrying scale exist, the better; therefore, use D_y/D_z. When $D < 1$, the spatial evolution of territory does not exceed the threshold of the resources and environment and there is a matching relationship between the two. Conversely, when $D > 1$, the spatial evolution of territory exceeds the threshold of the resources and environment, and there is a mismatch. According to the existing studies [47], this paper classifies the matching relationships into seven distinct categories (Table 4).

Table 4. Matching relationship between territorial space evolution and resources and environment.

Matching index interval	[0, 0.2)	[0.2, 0.4)	[0.4, 0.6)	[0.6, 0.8)	[0.8, 1)	[1, 1.2)	[1.2, +∞)
Matching degree	Severe match	High match	Mild match	Low match	Critical match	Mild mismatch	Severe mismatch

To identify single and combined types of territorial space in different regulatory areas and propose regulatory strategies, this paper complies with the following requirements: (1) It refers to the matching index of ecological, agricultural, and urban space and the carrying capacity of the resources and environment of each administrative unit in 2022; (2) Following the principle of "Mismatch first, low degree matching second, and high degree matching third", this paper identifies severe mismatch and mild mismatch units as priority regulation areas. Critical match and low degree match units are identified as key regulatory areas, while moderate and above match units are considered as moderate regulatory areas.

3.2. Data Source and Processing

The land use status and planning data in this paper are taken from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences and the General Land Use Planning of Shandong Province (2006–2020), respectively. The digital elevation product SRTMDEMUTM is derived from the Geospatial Data Cloud (http://gscloud.cn/) with a resolution of 90 m. The water resource data from long time series precipitation observations of meteorological stations in and adjacent to the study area in 2020 are obtained from the Resource and Environment Science and Data Centre of the Chinese Academy of Sciences (http://www.resdc.cn). The soil data are taken from the investigation of soil pollution status in and around the research area in 2020. The climate data are sourced from the accumulated temperature and wind speed of the annual average daily temperature ≥ 0 °C at the meteorological stations within the research area in 2020. Finally, the Normalized Difference Vegetation Index (NDVI) is obtained from the resource and environment data cloud platform of the Chinese Academy of Sciences (https://www.resdc.cn/), with a resolution of 1 km. Using the ArcGIS operation platform, the resource, environment, and spatial zoning data were extracted to construct a database of the land space and resource environment in typical areas of the lower reaches of the

Yellow River, in which precipitation, temperature, and other meteorological data were processed using the Kriging interpolation method of the ArcGIS software (ArcGIS 10.8.2). The types of land space were classified into ecological space, agricultural space, and urban space based on the existing literature [45].

4. Results

4.1. Spatial Evolutionary Characteristics of the Territory

The degree of territorial spatial dynamics exhibited a slight decrease, followed by a sharp increase, resulting in significant changes in the spatial structure, as shown in Figure 3. The percentages for the periods of 2000–2005, 2005–2010, 2010–2015, and 2015–2020 were 0.167%, 0.091%, 0.079%, and 1.707%, respectively. Specifically, the expansion of ecological space is centered in the outer-side of the Yellow River Delta, the mountainous parts of Central Lu, and around the South Four Lakes. Conversely, the reduction areas are concentrated in the landward extension of the Yellow River Delta. The extension regions of agricultural space are located in the Yellow River Delta, while a decrease is observed around the towns of the administrative regions. Finally, regarding the urban space, the majority of the increments are distributed in the periphery of the central city, with a minimal reduction.

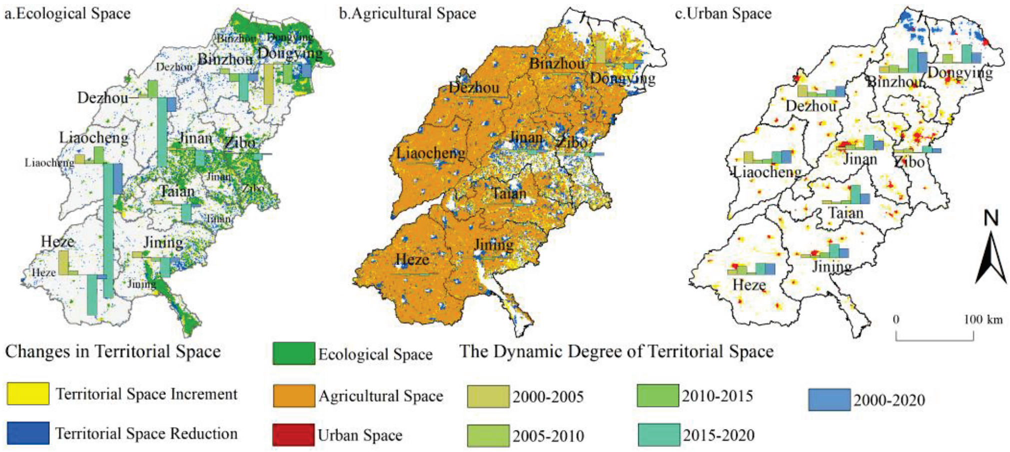

Figure 3. Evolution of territorial space in the Shandong section of the Yellow River basin from 2000 to 2020.

The extent to which the ecological spatial dynamics are affected is characterized by fluctuations between 2000 and 2020. Except for a small number of areas that experienced increases between 2000 and 2005 and between 2010 and 2015, the research period is dominated by a reduction in ecological space. The spatial dynamics of agriculture remained stable between 2000 and 2020, with a trend of shrinking agricultural space in each administrative region. However, the rate of shrinkage was relatively low. The spatial dynamics of towns and cities in all boroughs exhibited growth between 2000 and 2020.

4.2. Resource and Environmental Carrying Capacity Status

4.2.1. Suitability of Land for Spatial Development

The importance of ecological protection (Figure 4a) exhibits a gradient distribution along the rivers, coast, and mountains, and extends inland. Approximately 12.82% of the extremely important ecological protection areas are primarily concentrated in the mountainous areas of central Lu and in ecological reserves along the rivers, lakes, and coastline. The suitability of agricultural production (Figure 4b) demonstrates an overall decrease from inland to coastal and mountainous areas. Nearly 86.96% of the agricultural production areas are suitable or above, and these areas are mainly restricted by the slope of the central terrain and the soil texture. The overall spatial characteristics of the urban construction suitability (Figure 4c) exhibit a decrease from the periphery to the center.

Nearly 86.06% of the urban construction areas are suitable or above, and these areas are mainly constrained by the slope of the terrain and the risk of geological hazards.

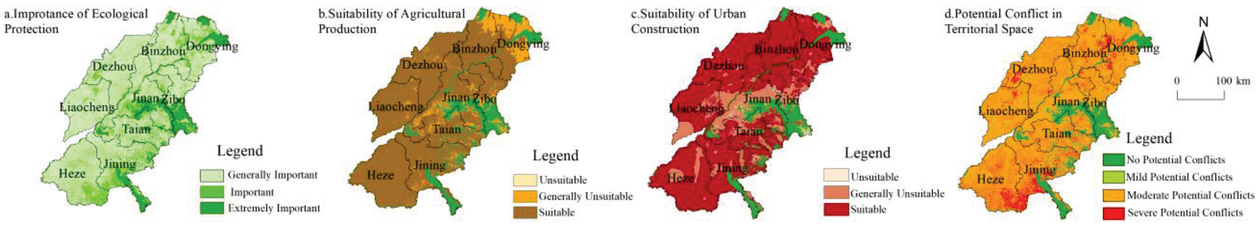

Figure 4. Suitability and potential conflict of territorial space development.

4.2.2. Potential Conflicts in Territorial Space

The intensity of potential conflicts in typical areas of the lower Yellow River is characterized by moderate potential conflicts (Figure 4d). The area share of each potential conflict intensity, in descending order, is as follows: light potential conflict (0.58%), heavy potential conflict (9.13%), no potential conflict area (13.08%), and moderate potential conflict (77.21%). The potential conflict intensity decreases from the plains to the mountains, with some regional variations.

4.2.3. Resource and Environmental Carrying Capacity

The ecological, agricultural, and urban space orientation of the carrying capacity of the resources and environment reflects the dynamic evolution of human activities and resources towards sustainable development. In quantitative terms, the scale of the resource and environmental carrying capacity in the lower reaches of the Yellow River between 2000 and 2020 is dominated by agricultural space, followed by ecological space, and finally urban space, which has the lowest proportion. Specifically, the ecological space decreased from 15,344.82 km^2 to 10,498.27 km^2, showing a decreasing trend year by year. Conversely, the agricultural space increased from 60,316.11 km^2 to 65,959.59 km^2, showing an increasing trend year by year. The spatial scale of the urban areas changed from 8144.92 km^2 to 7345.11 km^2, showing an upward and then downward trend. The ecological spaces are mainly distributed in the Yellow River Delta, the Luzhong mountainous area, and the Weishan Lake area, with ecosystem service functions such as water connotation and soil conservation (Figure 5). Lastly, the agricultural spaces are distributed over the majority of western and southwestern Lu. The towns are distributed in patches within the administrative districts.

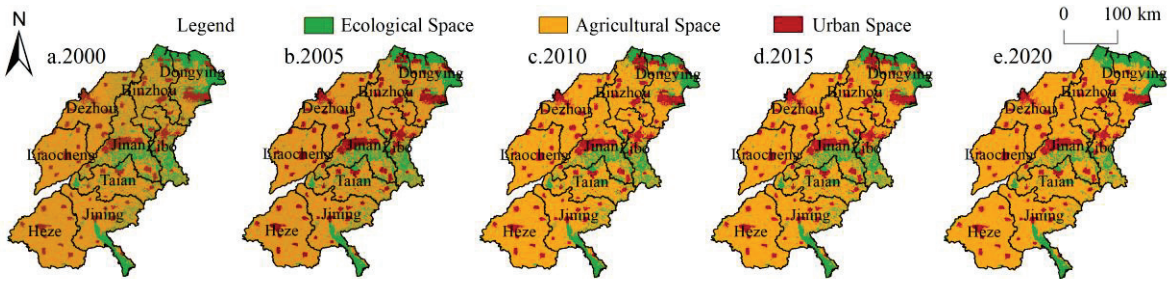

Figure 5. The carrying scale of resources and environment directed by ecological-agriculture-urban space.

4.3. Matching Relationship Analysis

4.3.1. Overall Matching Relationship

Between 2000 and 2020, the index reflecting the alignment between the evolution of ecological space and the carrying capacity of the resources and environment had a decreasing trend. Even though the stress level on ecological space caused by human activities significantly decreased, the coefficient of variation has slightly increased. Furthermore, despite this overall improvement, local areas still faced threats to their ecological space.

Between 2000 and 2020, the match index between the spatial evolution of agriculture and the carrying capacity of the resources and environment exhibited a decreasing trend. This indicates a decrease in the degree of stress that agricultural space imposes on environmental resources. However, the regional disparities in the match relationship have widened over time. Namely, the spatial evolution of towns and cities, as well as the matching index of the carrying capacity of the resources and environment, exhibited an upward trend from 2000 to 2020. The coefficient of variation consistently decreased, thus indicating a reduction in the variability of the matching index across different regions. In addition, the spatial impact of towns and cities on the resources and environment gradually increased, as shown in Table 5.

Table 5. Mathematical statistics on the matching relationship between the evolution of territorial space and the carrying capacity of resources and environment.

Year	Ecological Space			Agricultural Space			Urban Space		
	Mean	SD	COV	Mean	SD	COV	Mean	SD	COV
2000	1.09	0.36	0.33	1.15	0.15	0.13	0.20	0.13	0.65
2005	0.92	0.32	0.34	1.11	0.14	0.13	0.26	0.15	0.58
2010	0.91	0.32	0.35	1.10	0.14	0.13	0.32	0.16	0.49
2015	0.90	0.32	0.36	1.09	0.14	0.13	0.37	0.17	0.47
2020	0.73	0.32	0.43	1.01	0.16	0.15	0.77	0.34	0.44

4.3.2. Partial Matching Relationship

Between 2000 and 2020, the relationship between the evolution of the ecological spatial patterns and the matching of the resource and environmental carrying capacity exhibited a spatial divergence. Namely, it transitioned from a south–north pattern to a center-periphery ring (Figure 6a–e). At the early research stage, Binzhou and Dezhou exhibited a severe mismatch in their respective resource and environmental carrying capacities. Furthermore, Liaocheng, as well as the eastern parts of Tai'an and Jinan, were predominantly characterized by low and critical matches. In the final research stage, a low match area formed around the provincial capital of Jinan, while a mismatch was observed in the Yellow River Delta and in localized areas of Heze and Liaocheng. The main reason for these changes is attributed to the influence of topography. In the early research stage, the unused plains in the north and northwest were reclaimed as arable land, resulting in the shrinkage of ecological space. In contrast, the southeastern region, which is part of the TaiShan Mountains, has a relatively intact ecological base. Additionally, ecological space in the provincial capital increased in later years due to the construction of the forest city of Jinan in 2010. However, ecological protection source areas, such as the Yellow River Delta, have still been significantly disturbed by human activities.

During the research period, the relationship between the spatial evolution of agriculture and the matching of the resource and environmental carrying capacity exhibited a spatial divergence characterized by a northwest–southeast gradient (Figure 6f–j). At the beginning of the study—with the exception of Tai'an and Zibo, which exhibited a locally critical matching relationship—all of the other areas demonstrated a mismatching relationship. In particular, Dongying experienced a severe mismatching relationship. The mismatch improved towards the end of the research period, even though northwestern areas, such as Dezhou, still exhibited a more pronounced mismatch. The main reason for this is that the northwestern region features a plain terrain with abundant resources that are favorable for agricultural production, leading to over-exploitation. In contrast, the southeastern region has a more undulating terrain, which is not conducive to agricultural farming.

The relationship between the spatial evolution of towns and cities and the matching of the carrying capacity of the resources and environment between 2000 and 2020 is characterized by a spatial divergence in the form of a center-periphery ring (Figure 6k–o). At the beginning of the research period, the entire region exhibited a matching relationship, with the exception of Jinan, which had a critical matching relationship. Towards the end of the study, the non-municipal areas showed a serious mismatch, while the remaining parts were predominantly characterized by a matching relationship. The main reason for this is the slow pace of urbanization in the early years. In later years, even though industrialization and urbanization motivated the expansion of urban space, the scale of the resource and environmental carrying capacity was insufficient to support the intensified human activities. This was particularly evident in the pressure exerted on the resources and environment due to the construction of small towns.

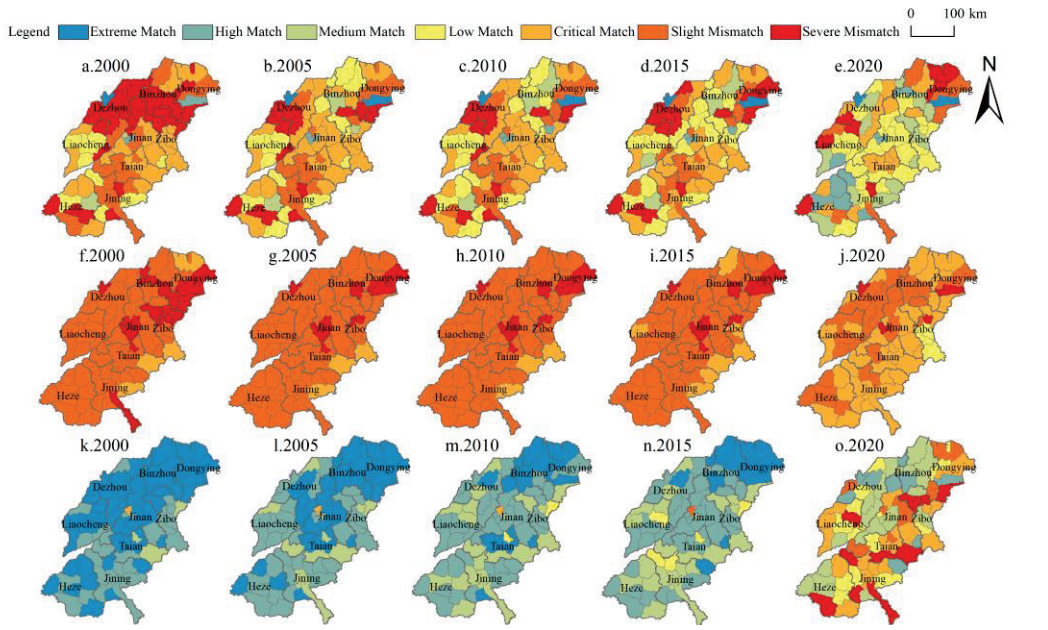

Figure 6. The matching relationship between territorial space evolution and resources and environment.

5. Discussion

5.1. Research Contribution

Our paper found that the urban space in the lower reaches of the Yellow River continued to expand and the ecological space shrank during the specific study period. In this paper, we concluded that the expansion of urban space squeezes the ecological space and leads to the shrinkage of ecological space. Tang et al. concluded that urban expansion is increasingly interfering with the ecological environment, which is in line with our study [42]. Global urban spatial expansion has the same effect on agricultural space, which is the same as the research result of Talema and Nigusie [43]. After that, the resource and environmental carrying scale derived from the evaluation of the national land space suitability and the conflict and regulation of space use in this study has been confirmed to be reasonable by Qu et al. and Wang et al. [35,44]. There is already a foundation of related research on which we developed the framework used in this study. The inherent factors in the construction of the framework have a co-ordinated relationship, and our aim is to change the disordered pattern to establish an orderly and sustainable pattern. Moreover, the results of this research can be applied to the practice of territorial spatial planning, and similar studies are as follows [48,49]. The effectiveness of spatial planning strategies in curbing urban sprawl and environmental protection has been proven in countries and regions [50]. The research pattern helps to provide a basis for decision-making.

This paper proposes a framework for determining the alignment between territorial space and the resource and environmental carrying capacity, as well as realizing the resource and environmental carrying capacity. The framework provides a theoretical basis for understanding the sustainable use of territorial space. Specifically, the matching relationship between the spatial evolution of national land and the carrying capacity of the resources and environment serves as a representation of the interaction between human-environment systems, with implications for the optimization and sustainable management of spatial patterns. By elucidating the changing trends in the relationship between the spatial evolution and carrying capacity of the resources and the environment, differentiated control paths can be developed. In areas with a mismatch relationship, restrictions should be placed on the expansion of territorial space. Furthermore, in areas with a small mismatch, territorial space should be reasonably allocated to ensure that the bottom line of resource and environmental constraints is not breached. Finally, in matched areas, the quality of territorial space use should be improved, aligning the use of various types of territorial space with the resource and environmental constraints.

This paper introduces technical guidelines for assessing the resource and environmental carrying capacity. It emphasizes the importance of identifying and mediating potential conflicts in land and space, thus aiding in the identification of the resource and environmental carrying capacity of regional multi-functional areas. The paper provides a supporting framework for optimizing land structure and pattern reconfiguration.

The authors of this research have conducted an in-depth empirical study in an important ecological region of the Yellow River basin, thus providing a concrete and practical reference for the sustainable development of territorial space. Lastly, as one of the significant ecological regions in the Yellow River basin, our research area plays a crucial role in supporting the conservation and development of the inlet area and other important ecological regions within the basin. This is achieved through the analysis of the spatial evolution, the matching relationship of the resource and environmental carrying capacity, and the ecology-agriculture-urban space. Moreover, our database on territorial space, resources, and the environment in typical areas of the lower reaches of the Yellow River provides a foundation for the formulation and implementation of the relevant government policies.

5.2. Territorial Spatial Optimization and Regulation Strategies

The spatial optimization zoning of typical areas in the lower reaches of the Yellow River is determined by the alignment of the regional control objectives and the variations in the control targets over a specific period. A "three zones and seven categories" spatial optimization pattern facilitates the implementation of tailored control measures, highlighting the urgency of distinct regional control strategies (Figure 7).

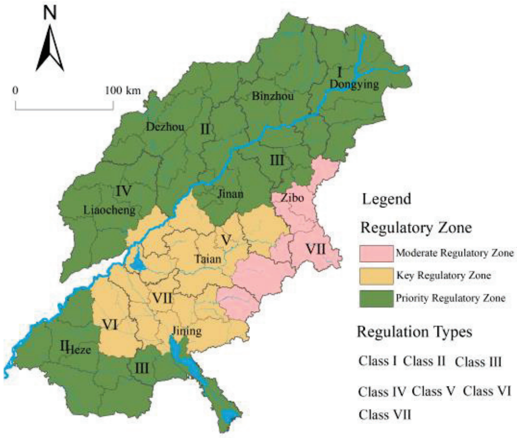

Figure 7. Territorial spatial optimization pattern in typical areas of the lower Yellow River.

The priority control zone encompasses four types of control: ecology-led (I), agriculture-led (II), urban-led (III), and ecology-agriculture synergy (IV). The objective is to address the mismatch between territorial space, on one hand, and the resources and environment, on the other, in order to ensure that the land use aligns with the resource and environmental constraints. This category comprises six administrative regions, primarily located in the Yellow River Delta. This paper recommends establishing an interconnected ecological security pattern of "source-sink-corridor" based on the ecological protection red line. Category II comprises 25 administrative districts, primarily located in northwest and southwest Lu.

Although these regions have a rich agricultural history, they are faced with challenges in terms of water resources availability. We recommend actively implementing fallow rotations on arable land to maintain soil fertility and alleviate water pressure. Category III encompasses 12 administrative districts, all characterized by the expansion of urban construction land. This paper suggests strict control over the expansion of urban land, based on the delineation of urban development boundaries. Emphasis should be placed on pursuing a path of intensive urbanization development by using the potential of existing urban stock. Category IV comprises nine administrative districts, primarily situated in western Lu, where the ecological and agricultural space faces significant challenges. To address them, this paper suggests prioritizing the establishment of ecological corridors. In addition, it is crucial to promote agricultural intensification and large-scale operations through the utilization of modern agricultural machinery. This approach will contribute to the development of a synergistic mechanism for the co-ordinated development of both ecological and agricultural space.

The key control zone encompasses three types of control: ecological town synergy (V), agricultural town synergy (VI), and ecological-agricultural town synergy (VII). The objective is to ensure the rational allocation and use of national space, while also ensuring that it remains within the limits of the resource and environmental carrying capacity. Category V comprises four administrative districts, located in the central part of Lu. All of these districts are influenced by topographical conditions. In urban planning, this paper suggests prioritizing the shaping of ecological space within built-up areas. In addition, there should be a strong emphasis on promoting the construction of landscape and forest cities. Category VI comprises two administrative regions situated in southwest Lu. These regions exhibit high suitability levels for agricultural production and town construction. This paper recommends undertaking a rational planning of the spatial layout and scale of the agriculture and towns. Furthermore, it is important to establish a spatial symbiosis of agriculture and towns based on urban development. Finally, category VII encompasses 12 administrative districts, located in the Dawen River basin. The focus in this category is on the sustainable use of territorial space. This is accomplished by emphasizing the strategic leadership of territorial space planning and recognizing the role of resources and the environment in controlling the use of territorial space.

The moderate control zone comprises the ecological-agricultural-town synergy type (VII), which aims to ensure the stability of spatial utilization. Firstly, it is essential to ensure ecological spatial integrity and connectivity, as this enhances the quality of the living environment and facilitates industrial transformation. Secondly, it is recommended to actively use agricultural development models, such as special agriculture, sightseeing agriculture and picking agriculture, while focusing on exploring the mechanisms required to achieve agricultural ecology. Finally, it is important to prioritize ecological security while focusing on utilizing the existing stock of construction land. This can be achieved by promoting the intensive use of construction land and striving for the co-ordinated development of national land.

5.3. Limitations and Future Research Direction

There are certain shortcomings to this paper, which need to be addressed. Firstly, the research area is rather limited as it is restricted to the typical areas in the lower reaches of the Yellow River. It thus fails to cover the entire Yellow River basin. To provide more comprehensive coverage, future studies should expand the research scope and cover the entire Yellow River basin, thus exploring the spatial evolution patterns of ecology, agriculture, and towns in different areas, as well as the matching relationship between the carrying capacity of the resources and environment.

Furthermore, due to the limitations of data availability and precision, this paper requires further refinement with regards to the relationship of ecological-agricultural-urban space. The delineation criteria can be further improved by drawing on other relevant theories and experiences. In addition, this paper only considers the bearing scale from the perspective of resource background and natural endowment, thus failing to account for the socio–economic factors related to the spatial development and use of territory. This limitation impacts the accurate identification of the carrying scale. In order to assess the carrying capacity in a more comprehensive manner, future studies should incorporate socio–economic indicators, such as population density, the economic development level, and infrastructure development. Such a comprehensive analysis will help to better guide the sustainable development and rational use of territorial space.

Finally, the territorial spatial planning system contains five levels of planning: national, provincial, city, county, and township level. Therefore, exploring the multi-dimensional decomposition and transmission of the territorial spatial pattern from the perspective of multi-scale correlation will aid in understanding and planning the sustainable development of territorial space.

6. Conclusions

This paper structures the role of potential conflict identification and mediation between the suitability of territorial space development and the carrying capacity of the resources and environment. It further identifies the problems of territorial space utilization in typical areas of the lower reaches of the Yellow River by investigating the matching relationship between the evolution of territorial space and the carrying capacity of the resources and environment.

Firstly, the rate of change to the territorial space in 2000–2005, 2005–2010, 2010–2015, and 2015–2020 period is 0.167%, 0.091%, 0.079%, and 1.707%, respectively. These data show the fluctuating shrinkage of ecological space, a relatively stable agricultural space, a continuous increase in urban space, and significant changes in the territorial space structure.

Secondly, the spatial development suitability of the land in typical areas of the lower reaches of the Yellow River exhibits topographic and land-sea divisions. Namely, the intensity of potential conflicts is dominated by moderate potential conflicts. Furthermore, the spatially directed resource and environmental carrying capacity of the ecology, agriculture, and towns reflects the dynamic evolutionary processes of human activities and the resources and environment, which tend towards sustainable development.

Thirdly, between 2000 and 2020, the index of matching the ecological and agricultural spatial evolution with the resource and environmental carrying capacity experienced a decreasing trend, with expanding regional differences. Conversely, the index of matching urban space and the resource and environmental carrying capacity showed an increasing trend, leading to smaller regional differences. The development of "three zones and seven categories" of national spatial optimization and the control strategy to achieve them can help in the sustainable use of national spatial areas by adopting differentiated control paths.

Finally, this paper proposes strategies for the optimal regulation and control of the use of sustainable territories. This paper only explores the matching relationship between the territorial spatial evolution and the bearing capacity of resources and the environment from the perspective of scale. The research on matching human activities and the resources and environment under the perspective of multi-dimensional coupling requires further corroboration. In addition, it is important to note that this paper solely focuses on the matching analysis between the spatial evolution of national land and the carrying capacity of the resources and environment at the present stage. However, the typical areas in the lower reaches of the Yellow River are currently undergoing a critical period of transition. Therefore, the spatial evolution of national land in this area is of significant importance and requires further investigation.

The priority control zone encompasses four types of control: ecology-led (I), agriculture-led (II), urban-led (III), and ecology-agriculture synergy (IV). This paper suggests prioritizing the establishment of ecological corridors. In addition, it is crucial to promote agricultural intensification and large-scale operations through the utilization of modern agricultural machinery. The key control zone encompasses three types of control: ecological town synergy (V), agricultural town synergy (VI), and ecological-agricultural town synergy (VII). In urban planning, this paper suggests prioritizing the shaping of ecological space within built-up areas. In addition, there should be a strong emphasis on promoting the construction of landscape and forest cities. The moderate control zone comprises the ecological-agricultural-town synergy type (VII). Firstly, it is essential to ensure ecological spatial integrity and connectivity, as this enhances the quality of the living environment and facilitates industrial transformation. Secondly, it is recommended to actively use agricultural development models, such as special agriculture, sightseeing agriculture, and picking agriculture.

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Data Availability Statement: The land use status and planning data in this paper are taken from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences and the General Land Use Planning of Shandong Province (2006–2020), respectively. The digital elevation product SRTMDEMUTM is derived from the Geospatial Data Cloud (http://gscloud.cn/). The water resource data from the long time series precipitation observations of meteorological stations in and adjacent to the study area in 2020 are obtained from the Resource and Environment Science and Data Centre of the Chinese Academy of Sciences (http://www.resdc.cn). The soil data are taken from the investigation of soil pollution status in and around the research area in 2020. The climate data are sourced from the accumulated temperature and wind speed of the annual average daily temperature ≥ 0 °C at the meteorological stations within the research area in 2020. Finally, the Normalized Difference Vegetation Index (NDVI) is obtained from the resource and environment data cloud platform of the Chinese Academy of Sciences (https://www.resdc.cn/).

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

References

1. 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]
2. Li, S.; Zhao, X.; Pu, J.; Miao, P.; Wang, Q.; Tan, K. Optimize and control territorial spatial functional areas to improve the ecological stability and total environment in karst areas of Southwest China. *Land Use Policy* **2021**, *100*, 104940. [CrossRef]
3. Zhao, X.-Q.; Li, S.-N.; Pu, J.-W.; Tan, S.-C.; Chen, J.-X. Optimal partitions and control of territorial space in karst mountainous areas of Yunnan province. *J. Nat. Resour.* **2020**, *35*, 2339–2357. [CrossRef]
4. Jia, K.; He, H.; Zhang, H.; Guo, J. Optimization of territorial space pattern based on resources and environment carrying capacity and land suitability assessment. *China Land Sci.* **2020**, *34*, 43–51.
5. Gu, S.Z.; Hu, Y.J.; Zhou, H. Ecological civilization construction: Scientific connotation and basic paths. *Resour. Sci.* **2013**, *35*, 2–13.
6. McHarg, I.L. *Design with Nature*; Rui, J.W., Translator; Press of Tianjin University: Tianjin, China, 1967.
7. Zhang, S.M.; Zhang, B.L. The suitability pattern of territorial development in the Yellow River Delta under national strategy. *Resour. Sci.* **2016**, *38*, 837–846.
8. Wu, Y.J.; Yang, Y.Z.; Yang, L.; Zhang, C.; You, Z. Land spatial development and suitability for city construction based on ecological-living-industrial space: Take Ningbo City as an example. *Resour. Sci.* **2016**, *38*, 2072–2081.
9. Arrow, K.; Boln, B.; Costanza, R.; Dasgupta, P.; Folke, C.; Holling, C.S.; Jansson, B.-O.; Levin, S.; Mäler, K.-G.; Perrings, C.; et al. Economic growth, carrying capacity and the environment. *Science* **1995**, *268*, 89–90. [CrossRef] [PubMed]
10. Rees, W.E. Ecological footprints and appropriated carrying capacity: What urban economics leaves out? *Environ. Urban.* **1992**, *4*, 121–130. [CrossRef]
11. Daily, G.C.; Ehrlich, P.R. Socioeconomic equity, sustainability, and Earth's carrying capacity. *Ecol. Appl.* **1996**, *6*, 991–1001. [CrossRef]
12. Fan, J.; Zhou, K.; Wang, Y.F. Basic points and progress in technical methods of early-warning of the national resource and environmental carrying capacity (V 2016). *Prog. Geogr.* **2017**, *36*, 266–276.
13. United Nations. *Transforming Our World: The 2030 Agenda for Sustainable Development*; United Nations: New York, NY, USA, 2015.

14. Meadows, D.H.; Randers, J.; Meadows, D.L. *Limits to Growth: The 30-Year Update*, 3rd ed.; Chelsea Green Publishing: White River Junction, VT, USA, 2004.
15. Chen, X.P.; Fang, K.; Peng, J.; Liu, A.-Y. New insights into assessing the carrying capacity of resources and the environment: The origin, development and prospects of the planetary boundaries framework. *J. Nat. Resour.* **2020**, *35*, 513–531.
16. Galaz, V. Planetary Boundaries Concept Is Valuable. *Nature* **2012**, *486*, 191. [CrossRef] [PubMed]
17. Chen, X.P.; Wu, C.F.; Fang, K. Differentiation and comparison of the paradigms for the carrying capacity of resources and the environment. *China Land Sci.* **2020**, *34*, 17–24.
18. Duan, X.J.; Wang, Y.Z.; Kang, J.Y.; Bai, P. Theoretical foundations and measurement system of resource and environmental carrying capacity for village and town development. *Resour. Sci.* **2020**, *42*, 1236–1248. [CrossRef]
19. 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]
20. Meng, L.; Chen, Y.; Li, W.; Zhao, R. Fuzzy comprehensive evaluation model for water resources carryi ng capacity in Tarim River Basin, Xinjiang, China. *Chin. Geogr. Sci.* **2009**, *19*, 89–95. [CrossRef]
21. Wang, S.-H.; Wang, Y.-C.; Song, M.-L. Construction and analogue simulation of TERE model for measuring marine bearing capacity in Qingdao. *J. Clean. Prod.* **2017**, *167*, 1303–1313. [CrossRef]
22. Du, Y.-W.; Li, B.-Y.; Quan, X.-J. Construction and application of DPPD model for evaluating marine resources and environment carrying capacity in China. *J. Clean. Prod.* **2020**, *252*, 119655. [CrossRef]
23. Feng, Z.; Yang, Y.; Yan, H.; Pan, T.; Li, P. A review of resources and environment carrying capacity research since the 20th Century: From theory to practice. *Resour. Sci.* **2017**, *39*, 379–395.
24. Huang, J.; Xue, D.Q.; Dai, L.H. Spatial differentiation and influencing factors of resource and environmental carrying capacity in main agricultural production areas: Taking Linze County of Gansu Province as an example. *Resour. Sci.* **2020**, *42*, 1262–1274. [CrossRef]
25. Zhou, K.; Li, J.Y.; Wang, Q. Evaluation on agricultural production space and layout optimization based on resources and environmental carrying capacity: A case study of Fujian Province. *Sci. Geogr. Sin.* **2021**, *41*, 280–289.
26. Zhou, X.-Y.; Lei, K.; Meng, W.; Khu, S.-T. Industrial structural upgrading and spatial optimization based on water environment carrying capacity. *J. Clean. Prod.* **2017**, *165*, 1462–1472. [CrossRef]
27. Gao, X.L.; Chen, T.; Fan, J. Analysis of the population capacity in the reconstruction areas of 2008 Wenchuan Earthquake. *J. Geogr. Sci.* **2011**, *21*, 521–538. [CrossRef]
28. Kong, X.; Jiang, X.; Liu, Y.; Jin, Z. 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.
29. Wei, S.Y.; Ju, X.; Xun, W.H. Spatial-temporal coupling relationship between land development intensity and carrying capacity of regional resources and environment: A case study in Shenyang Economic Region. *China Land Sci.* **2018**, *32*, 58–65.
30. Yue, W.-Z.; Wu, T.; Wang, T.-Y.; Xia, H.-X. "Double evaluations" for territorial spatial planning: Challenges and responses. *J. Nat. Resour.* **2020**, *35*, 2299–2310. [CrossRef]
31. Kuang, W.H. Issues regarding spatial pattern change of territorial space and its overall implementation on beautiful vision in new era. *Resour. Sci.* **2019**, *41*, 23–32.
32. Liu, M.; Liu, C.L. Early warning evaluation and warning trend analysis of resource and environment carrying capacity in Hunan Province. *Econ. Geogr.* **2020**, *40*, 187–196.
33. Gai, M.; Nie, C.; Ke, L.N. Carrying capacity and coordinated development of ERE system in the coastal Area of Bohai Sea. *Econ. Geogr.* **2018**, *38*, 163–172.
34. Zou, L.; Liu, Y.; Wang, J.; Yang, Y.; Wang, Y. Land use conflict identification and sustainable development scenario simulation on China's southeast coast. *J. Clean. Prod.* **2019**, *238*, 117899. [CrossRef]
35. Qu, Y.B.; Dong, X.; Su, D.; Jiang, G.; Ma, W. How to Balance Protection and Development? A Comprehensive Analysis Framework for Territorial Space Utilization Scale, Function and Pattern. *J. Environ. Manag.* **2023**, *339*, 117809. [CrossRef] [PubMed]
36. Wang, J.; Zhang, F.; Tan, M.L.; Shi, J.; Johnson, V.C.; Kung, H.-T. Remote Sensing Evaluation of Chinese Mainland's Comprehensive Natural Resources Carrying Capacity and Its Spatial-Temporal Variation Characteristics. *Environ. Impact Assess. Rev.* **2023**, *101*, 107104. [CrossRef]
37. Liu, Q.Q.; Zhao, H.F.; Wu, K.N.; Yu, X.; Zhang, Q. Identifying potential land use conflict based on competitiveness of different land use types in Beijing, China. *Resour. Sci.* **2014**, *36*, 1579–1589.
38. Zhou, M.; Feng, X.; Liu, K.; Zhang, C.; Xie, L. Spatial-Temporal Matching between Green Space and Typical Elements of Economic Development: A Case Study on Zhejiang Province. *China Land Sci.* **2021**, *35*, 107–114.
39. Qu, Y.B.; Wang, S.L.; Tian, Y.Y.; Jiang, G.H.; Zhou, T.; Meng, L. Territorial Spatial Planning for Regional High-Quality Development—An Analytical Framework for the Identification, Mediation and Transmission of Potential Land Utilization Conflicts in the Yellow River Delta. *Land Use Policy* **2023**, *125*, 106462. [CrossRef]
40. Yu, Z.L.; Zhang, W.X.; Liang, J.S.; Zhuang, L. Progress in evaluating suitability of spatial development and construction land. *Prog. Geogr.* **2015**, *34*, 1107–1122.
41. Zhou, D.J.; Xu, Y.; Wang, Y.F.; Zhou, K.; Liu, B.Y.; Li, J.Y.; Fan, J. Methodology and Role of "Double Evaluation" in Optimization of Spatial Development Pattern. *J. Chin. Acad. Sci.* **2020**, *35*, 814–824. [CrossRef]

42. Tang, J.; Zhou, L.; Dang, X.; Hu, F.; Yuan, B.; Yuan, Z.; Wei, L. Impacts and Predictions of Urban Expansion on Habitat Quality in the Densely Populated Areas: A Case Study of the Yellow River Basin, China. *Ecol. Indic.* **2023**, *151*, 110320. [CrossRef]
43. Talema, A.H.; Nigusie, W.B. Impacts of Urban Expansion on the Livelihoods of Local Farming Communities: The Case of Burayu Town, Ethiopia. *Heliyon* **2023**, *9*, e14061. [CrossRef]
44. Wang, S.; Qu, Y.; Zhao, W.; Guan, M.; Ping, Z. Evolution and Optimization of Territorial-Space Structure Based on Regional Function Orientation. *Land* **2022**, *11*, 505. [CrossRef]
45. Qu, Y.; Wang, S.; Zhu, W.; Ping, Z. Spatial-temporal differentiation characteristics and driving force of territorial space evolution in the Yellow River Delta. *Trans. Chin. Soc. Agric. Eng.* **2021**, *37*, 252–263.
46. Zhu, Z.; Mei, Z.; Li, S.; Ren, G.; Feng, Y. Evaluation of Ecological Carrying Capacity and Identification of Its Influencing Factors Based on Remote Sensing and Geographic Information System: A Case Study of the Yellow River Basin in Shaanxi. *Land* **2022**, *11*, 1080. [CrossRef]
47. Li, S.; Congmou, Z.; Li, Y.; Dong, B.; Tan, K.; Deng, X. Agricultural Space Function Transitions in Rapidly Urbanizing Areas and Their Impacts on Habitat Quality: An Urban–Rural Gradient Study. *Environ. Impact Assess. Rev.* **2023**, *99*, 107019. [CrossRef]
48. Qiao, W.; Hu, Y.; Jia, K.; He, T.; Wang, Y. Dynamic Modes and Ecological Effects of Salt Field Utilization in the Weifang Coastal Area, China: Implications for Territorial Spatial Planning. *Land Use Policy* **2020**, *99*, 104952. [CrossRef]
49. Tan, R.; Liu, P.; Zhou, K.; He, Q. Evaluating the Effectiveness of Development-Limiting Boundary Control Policy: Spatial Difference-in-Difference Analysis. *Land Use Policy* **2022**, *120*, 106229. [CrossRef]
50. Perrin, M.; Bertrand, N.; Vanpeene, S. Ecological Connectivity in Spatial Planning: From the EU Framework to Its Territorial Implementation in the French Context. *Environ. Sci. Policy* **2022**, *129*, 118–125. [CrossRef]

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The Impact of Urban Renewal on Spatial–Temporal Changes in the Human Settlement Environment in the Yangtze River Delta, China

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Abstract: China's rapid urbanization drive, marked by extensive urban renewal projects, necessitates a meticulous examination of their transformational impact on the human settlement environment (HSE) across urban landscapes. This study investigates the impact of China's urban renewal progress on the spatial–temporal changes in the HSE from 2009 to 2019, using data from 40 prefecture-level cities in the Yangtze River Delta. Our findings reveal an overall positive relationship between the spatio–temporal evolution of urban renewal and the HSE, suggesting that urban renewal projects have had a beneficial impact, particularly following the announcement of China's New Urbanization policy in 2014. However, the extent of this positive impact varied among different areas, with more significant improvements observed in core cities and economically developed areas. Additionally, our study uncovered significant variations in how urban renewal influenced the HSE over time. We found that the primary influencing factor shifted from material renewal to industrial renewal. These findings offer valuable insights for improving the HSE during urban renewal processes, both in China and other regions undergoing rapid urbanization.

Keywords: urban renewal; spatial–temporal evolution; human settlement environment; the Yangtze River Delta

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1. Introduction

The human settlement environment (HSE) is a multidimensional construct, embodying the physical, socio-economic, and ecological facets of inhabited spaces across urban, suburban, and rural landscapes, where individuals dwell, engage in economic activities, and foster social connections. Since the United Nations' establishment of the Human Settlements Programme (UN-Habitat) in 1978, the HSE concept has risen to prominence on the international stage. It has emerged as a focal point for urban strategists, researchers, and policymakers worldwide, with leading regions like North America and Europe, among others, integrating HSE enhancement at the core of their urban planning frameworks [1]. China has also acknowledged the escalating importance of nurturing a healthy human settlement environment, prompting a strategic pivot in land management policy from a strategy of 'enclosure' to one of 'destocking' [2], echoing a global commitment to sustainable urban development and a people-centric approach to urbanization. This paradigm shift underscores the nation's recognition of the HSE as a cornerstone in its drive towards balanced and equitable urban–rural development, aligning with international efforts towards sustainable living environments for all inhabitants.

Urban renewal is viewed as a critical initiative for rejuvenating and enhancing urban areas facing decay or decline, and it stands as a key component of China's 'destocking' land use policy [3]. Globally, this policy intervention is esteemed for its ambitions to elevate residents' living standards, stimulate economic prosperity, and nurture sustainable, lively communities. Achieving these ends often entails initiatives such as infrastructure modernization, public space enhancements, housing restoration, investment stimulation, and the fostering of cultural and recreational facilities. Amid the surging prominence of urban renewal on municipal agendas worldwide, academic inquiry has intensified, either delving into the intricacies of urban renewal's scientific and rational foundations [4,5] or adopting urban renewal as a prism to explore its multifarious societal implications through sociological, urban planning, and rural planning perspectives, among other lenses [6–8]. This body of research collectively paints a detailed tapestry of the theoretical and applied facets of urban renewal, guiding prospective policy formulation and implementation. Nonetheless, while the linkage between urban renewal and enhancements to the HSE seems evident, concrete empirical evidence substantiating this association remains scant. This paucity of research is particularly pressing in the Chinese context, given its unparalleled pace and scale of urbanization, coupled with marked evolutions in urban renewal strategies.

In comparison to developed nations, China's urban renewal strategy is intimately intertwined with the objective of fostering urban-led economic progress. The unique dual land system in the country empowers local governments with extraordinary leverage for developmental land utilization. Since the 1990s, in a bid to ignite regional economic expansion, administrations have executed "strategic land allocation" tactics, marshaling resources to optimize fiscal revenues. A plethora of studies attest to local governments' monopoly over land provision, with officials leaning on high GDP performance to ascend the ranks under the nation's cadre promotion system [9]. Empirical evidence solidifies the notion that land allocation bolsters the local economy positively [10]. Consequently, residential and commercial plots are frequently auctioned publicly to capitalize on earnings [11], whereas industrial terrain is customarily negotiated to entice investments and invigorate the local economic landscape [12,13]. Amidst this epoch, urban rejuvenation endeavors in Chinese metropolises were predominantly fueled by rental discrepancies, culminating in the proliferation of gated micro-district communities [14]. Simultaneously, ad hoc demolition and reconstruction efforts have posed formidable obstacles to the cityscape's human habitat, exacerbating disparities in urban maturation [15]. Thus, urban renewal initiatives in the initial years of the new millennium prioritized less the amelioration of the human settlement environment.

Since crossing the 50% urbanization threshold in 2010 and steadily advancing towards the 80% benchmark characteristic of developed nations, China's swift urban growth trajectory has ignited concerns surrounding sprawl, land resource depletion, and environmental deterioration [16]. In response, the government's strategy has pivoted from a predominantly market-led model to a more directive approach in urban renewal policy. This shift was marked by the State Council's introduction of "ten measures to stimulate domestic demand" in 2008, which spotlighted shantytown renovation as a pivotal livelihood and development endeavor. The launch of the "National New Urbanization Plan (2014–2020)" further underscored a focus on enhancing urbanization quality, transforming development paradigms, and advocating people-oriented urbanization principles. Complementing these, the "Opinions of the State Council on Deepening New Urbanization Construction" in 2016 accentuated the urgency of revamping shantytowns, urban villages, and substandard housing. The 20th National Congress in 2021 reinforced this commitment, advocating for megacity development model reforms and urban renewal strategies, outlining a roadmap for people-centered urbanization in the contemporary era. Nowadays, Chinese cities are transitioning from expansive growth to a phase of optimized land use, with the revitalization of *three olds*—shantytowns, micro-renewal projects, and minor transformations—emerging as key catalysts for urban evolution. These interventions, targeting enhanced human settlement environments and enriched urban functionality, signify a strategic pivot towards sustainable and quality-focused urban development.

In light of the government's assertive stance on urban renewal, a critical evaluation is warranted to ascertain the efficacy of China's recent endeavors in achieving the intended improvements to the HSE. Unpacking the fundamental drivers of these outcomes is equally vital. Given the protracted timeline and expansive scope of urban renewal projects, discerning potential spatial heterogeneities in the impact on HSEs across diverse urban locales emerges as a pivotal research avenue. Moreover, elucidating the temporal and spatial dynamics of urban renewal's influence on the HSE is paramount. Attending to these inquiries holds significant implications for capitalizing on urban renewal strategies to augment the HSE and nurture environmentally sustainable and socially equitable urban progress.

This research endeavors to scrutinize the transformations in the HSE instigated by China's urban renewal ventures within the Yangtze River Delta from 2009 to 2019, harnessing data from a cohort of 40 municipalities. The outcomes suggest an overarching trend of amelioration in the region, albeit with a deceleration in the pace of improvement over time. Urban renewal endeavors emerge as pivotal in this narrative, facilitating infrastructural advancements, catalyzing industrial expansion, and driving urban sprawl. This study contributes to our understanding in several ways: it firstly forges a nationwide connection between urban renewal and the enhancement of the HSE; secondly, it impartially gauges the repercussions of urban renewal by homing in on individual cities and scrutinizing the fallout of large-scale interventions such as shantytown rehabilitation programs; and thirdly, it acknowledges the differential impact of urban renewal strategies across cities and temporal epochs, thereby furnishing insights for tailored policy formulation reflective of local contexts.

In the next section, we explore the theoretical framework for assessing the HSE and the relationship between urban renewal and the HSE in China. Section 3 outlines the methods and empirical strategy employed in this study. The presentation of the results and discussion follows in Section 4. Finally, we conclude the paper in Section 5.

2. Theoretical Framework

2.1. Assessing the Human Settlement Environment

Scholarly investigations into the HSE are bifurcated into two principal categories, each defined by the focal point of inquiry. The first category is centered on rural contexts, with an emphasis on understanding and elevating living conditions through a sociological lens. Researchers like Wang et al. have employed rigorous methodologies, such as structural equation modeling, to underscore the critical role of government support in spurring rural households to participate in environmental improvement initiatives [17]. This stream of research has evolved to encompass analyses of governance structures, advocating for more participatory, multi-stakeholder approaches in rural settings [18], alongside efforts to establish comprehensive evaluation frameworks for measuring sustainability in rural human settlements [19,20].

Conversely, the second category of research fixates on the complexities of urban habitats, encompassing several focal points. Chen's work, for instance, underscores the vulnerabilities within urban clusters and identifies the determinants of urban settlement patterns, emphasizing the centrality of regional economic strength [21,22]. Complementary to this, Zhou's research develops a resilience assessment model for urban settlements in China, elucidating the factors that bolster urban resilience [23]. Further, studies akin to Stal et al.'s transatlantic comparison highlight the socioeconomic benefits of strategic urban renewal plans, particularly in addressing urban poverty by tailoring interventions to the needs of disadvantaged groups [24].

These dual strands of inquiry collectively enrich our understanding of the multifaceted dynamics characterizing both rural and urban human settlements. Drawing on preceding scholarly work, the HSE is interpreted as a composite concept intimately tied to wellbeing and happiness. A superior HSE is paramount to fulfilling the escalating aspirations of populations for enhanced living standards. To facilitate analytical clarity, we parse the HSE into two discernible components: the economic environment and the ecological environment. An appraisal framework for the HSE is consequently erected upon these dual pillars (depicted in Table 1) to systematically gauge the conditions of the HSE of each city.

Table 1. Indicator system for evaluating the HSE.

Dimension	Indicator	Description
Economic environment	Income distribution	Theil's index; measures income disparities between urban and rural population.
	Per capita consumption expenditure	Per capita spending, indicative of living standards
	Engel's coefficient	Proportion of income spent on food; lower values signal higher living standards.
Ecological environment	Waste management efficiency	The annual volume of industrial wastewater discharged per city; measures the waste disposal practices for environmental sustainability.
	Green area of parks	Ratio of parks and gardens to urban area for improved wellbeing.
	Greening coverage in built-up areas	Measures the vegetative layer that exists amidst buildings, roads, and other concrete structures, serving as a vital element of urban ecology.

Note: the entropy weight method [25] is employed to objectively assign weights to these indicators based on their variability and significance in the dataset, enhancing the assessment's accuracy and robustness.

Specifically, the "economic environment" dimension encompasses metrics such as the Theil index of rural–urban income disparity, per capita consumption expenditure, and Engel's coefficient—a gauge of food expenditure as a share of total household income. Conversely, the "ecological environment" is characterized by indicators including the waste management efficiency, park green areas, and the extent of greening coverage within built-up locales. This strategy endeavors to distill complexity while retaining the essence of what constitutes a high-caliber HSE, pivotal to addressing the escalating desires for a more fulfilling existence among urban dwellers.

2.2. Theoretical Nexus of Urban Renewal and the HSE

The intricate nexus between urban renewal and the HSE stands as a subject of profound interest transcending disciplinary boundaries, engaging scholars in economics, urban planning, environmental science, and sociology alike. Studies have dissected the multifaceted impacts of urban renewal through varied theoretical lenses, encompassing the restructuring of urban functions [26], metabolic efficiency enhancements [27], land policies [28], and human structures [29,30]. As the "people-oriented" development paradigm gains ascendancy, scholarly pursuits must prioritize examining how urban renewal efforts enhance the living environment in targeted renewal zones and, more broadly, the entire urban human settlement context. This focal shift aligns with the cardinal aspiration of urban renewal initiatives, viz., elevating the general urban environmental quality and fostering superior living standards.

A synthesis of the existing literature reveals a myriad of theoretical frameworks explicating the HSE, coupled with in-depth explorations of governance rationales tailored to distinct contextual milieus. These inquiries have shed light on key determinants and operative mechanisms influencing the rural HSE, charting pathways for improvement and their real-world implementations [31]. Notwithstanding these advances, a conspicuous imbalance in research focus prevails, with the urban HSE receiving relatively scant attention. Moreover, a gap persists in our understanding of the intricate, reciprocal interactions between processes of urban renewal and the evolution of the urban HSE. In view of the ubiquitous implementation of urban renewal interventions across cities worldwide since the dawn of the 21st century, their transformative impact on the urban habitat is undeniable.

Therefore, there arises an urgent need to systematically probe the evolutionary mechanisms driving changes in the urban HSE against the backdrop of ongoing urban renewal efforts. Such an endeavor promises to unravel the nuanced interdependencies and reciprocal feedback mechanisms that mold urban landscapes, informing the formulation of more efficacious and environmentally sustainable strategies for urban renewal. Our study adopts a comprehensive framework, designed to systematically evaluate the repercussions of urban renewal on the human settlement environment. As depicted in Figure 1, the theoretical intersection of urban renewal and the HSE manifests in multifarious ways, underscoring the transformative potential of renewal initiatives on infrastructural, industrial, and urban construction fronts.

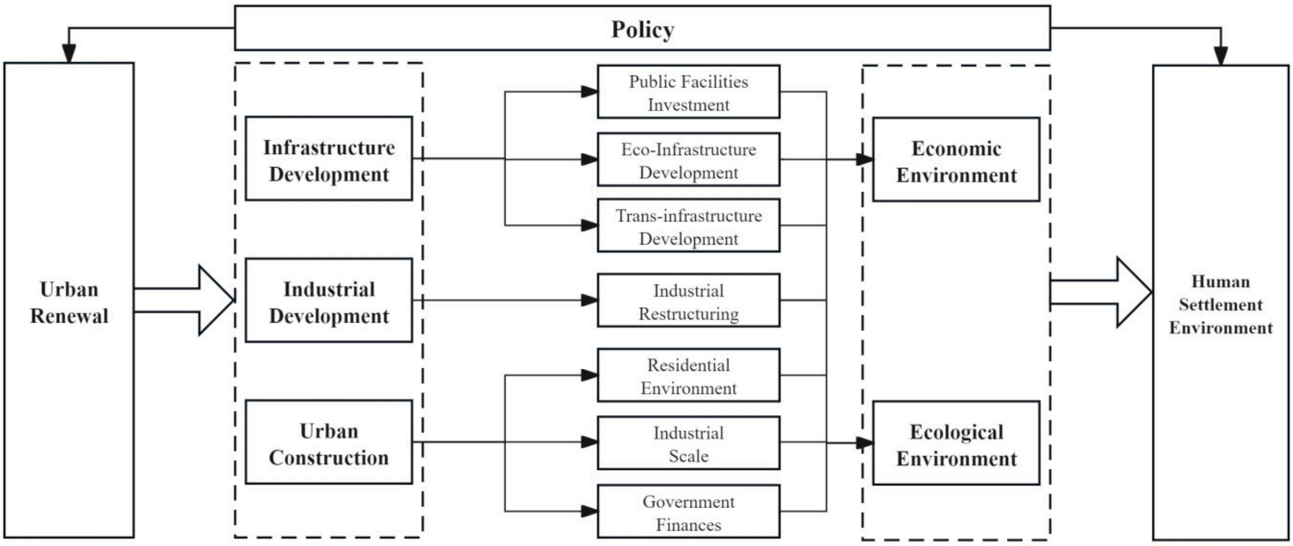


Figure 1. Theoretical nexus of urban renewal and the HSE.

Firstly, urban renewal plays a pivotal role in enriching infrastructure development, which, in turn, significantly bolsters the HSE. This encompasses large-scale projects aimed at modernizing urban infrastructure, congruent with national smart and sponge city agendas. Activities ranging from the rehabilitation of dilapidated housing to the revitalization of obsolete industrial zones and road network enhancements engender economic vibrancy by generating employment and boosting resident incomes. Moreover, improvements to public service amenities [32], commercial zones, and consumer experiences elevate living standards, stimulate economic expansion, and foster an optimized economic milieu. Investments in eco-friendly infrastructure, such as advanced drainage systems and waste management facilities, contribute to environmental amelioration and augment the city's ecological resilience.

Secondly, the impact of urban renewal on the HSE is discernible through its capacity to optimize industrial layouts and recalibrate industrial structures. Historically, haphazard urban growth has resulted in inefficient land use patterns and hindered urban vitality. By strategically integrating renewal efforts with industrial strategies, cities can invigorate their economies. Theoretical frameworks posit a directional shift toward higher-value-added sectors, facilitating the migration of lower-efficiency industries and spatial rearrangement [33]. This transition, aligned with China's push for high-quality economic development, rationalizes industrial structures, fostering knowledge-intensive industries [34] and realizing harmonious city–industry integration. Concurrently, the phase-out of polluting industries through renewal activities promotes environmental sustainability, transforming former industrial sites into green spaces that augment the ecological environment.

Lastly, urban renewal exercises a profound influence on the HSE by comprehensively transforming the physical fabric of urban construction through extensive improvements. This multidimensional process intertwines demographic shifts, social dynamics, economic transformations, and governance strategies, necessitating a multidisciplinary approach grounded in urban planning, economics, sociology, and engineering sciences. In the Chinese context, urban renewal constitutes a strategic governmental endeavor. Local governments actively participate by financing public infrastructure improvements, issuing policy incentives to attract investments, and orchestrating spatial planning guided by high standards and digital technologies. These measures not only expedite urban construction but also catalyze industrial clusters, steer population migrations toward favorable urban nodes, exploit agglomeration economies, and heighten the appeal of human settlement environments. Collectively, these dimensions of urban renewal coalesce to forge a more resilient, prosperous, and sustainable HSE.

3. Materials and Methods

3.1. Study Area and Data

In the realm of urban renewal studies, cities constitute the epicenter of implementation, with the Yangtze River Delta region, nestled along China's eastern seaboard, exemplifying a prime locale for such endeavors. Endowed with exceptional advantages, the region boasts well-developed transportation infrastructure and a wealth of ecological assets, furnishing a sturdy groundwork for the execution of urban renewal ventures. Characterized by brisk economic progress, the Yangtze River Delta harbors a constellation of large- and medium-sized cities, vibrant economic development zones, and robust intercity economic linkages, concurrently serving as a magnet for significant population influx. Premised on its heightened urbanization pace and pioneering role in initiating expansive urban renewal schemes, the region has cultivated a rich academic terrain for investigation. Consequently, this study envelops cities falling under the administrative ambit of three provinces within the Yangtze River Delta—Jiangsu, Zhejiang, and Anhui (Figure 2). This encompasses a total of 40 cities at the prefecture level or above, notable among them being Nanjing, Hangzhou, and Hefei. Notably, Shanghai, due to its uniquely vast economic scale and distinct development trajectory, was excluded from our study area.

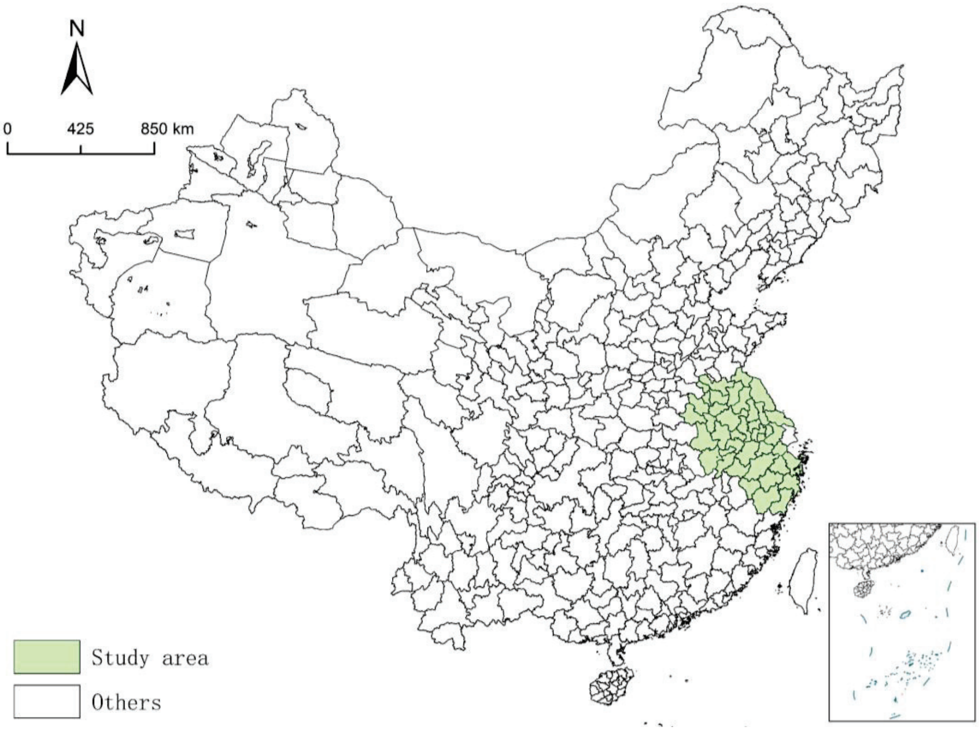


Figure 2. Study area.

To empirically ground our analysis, data spanning from 2009 to 2019 were compiled. These data were meticulously sourced from the *China City Statistical Yearbook* and provincial statistical yearbooks of Jiangsu, Zhejiang, and Anhui. Deliberately capping the data at 2019 aligns with our study's focus on policy dynamics related to shantytown transformation, revitalization of old industrial zones, and urban village renovations, which were piloted in the Yangtze River Delta and largely concluded pre-2020, marking the advent of fresh developmental epochs. Observations suggest that comparable renewal endeavors are currently unfolding in less economically mature regions, thereby underscoring the broader relevance of our findings.

3.2. Baseline Model

In accordance with the methodologies established by prior scholars in [35–37], we adopted a rigorous two-way fixed-effects model to rigorously assess the influence of urban renewal on the human settlement environment. The analytical framework we employed is delineated below, echoing the precedent set by these seminal works to ensure both methodological soundness and the comparability of our findings.

$$HSE_{it} = \alpha_0 + \sum_{j=1}^{8} \alpha_j UR_{it} + \alpha_2 Policy_{it} + \sum_{k=1}^{4} \beta_j X_{it} + \mu_i + \lambda_i + \varepsilon_{it} \quad (1)$$

where i and t represent cities and years, respectively. The dependent variable (HSE_{it}) signifies the index measuring the quality of the urban human settlement environment for city i in year t. The explanatory variables central to our analysis encompass UR_{it}, an indicator quantifying the extent of urban renewal activities in a given city and year; and $Policy_{it}$, a binary policy dummy variable marking the onset of urban renewal policy initiatives aligned with the National New Urbanization Plan in each city. This variable assumes a value of 0 preceding the policy's execution and flips to 1 post-implementation, thereby capturing the temporal shift in policy influence. Additionally, a suite of control variables, collectively represented as X_{it}, is included to account for potential confounding factors. To isolate the unique impacts of our variables of interest, we incorporate individual (μ_i) and time (λ_i) fixed effects, mitigating any unobserved heterogeneity tied to specific cities or time periods. Lastly, ε_{it} symbolizes the stochastic error term encapsulating residual variability not explained by the model's predictors, ensuring the integrity of our estimations. This comprehensive model specification thereby facilitates a nuanced understanding of the dynamic interplay between urban renewal initiatives and the evolution of human settlement environments across varying spatial and temporal contexts.

3.3. The Geographically and Temporally Weighted Regression (GTWR) Model

Following the method outlined by [38], we employed the geographically and temporally weighted regression (GTWR) model to delve deeper into the spatial and temporal heterogeneities in the influence exerted by diverse urban renewal endeavors on the HSE. The basic formulation of the GTWR model is delineated as follows:

$$HSE_{it} = \beta_0(u_i, v_i, t_i) + \sum_{j=1}^{8} \beta_j(u_i, v_i, t_i) UR_{it} + \beta_2(u_i, v_i, t_i) Policy_{it} + \sum_{k=1}^{4} \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i \quad (2)$$

where the tuple (u_i, v_i, t_i) symbolizes the spatio–temporal coordinates for city i, with u_i representing the longitude and latitude, respectively, and t_i denoting the chronological marker. The term $\beta_0(u_i, v_i, t_i)$ signifies the location and time-specific intercept for city i. The coefficients $\beta_j(u_i, v_i, t_i)$ and $\beta_2(u_i, v_i, t_i)$ denote the geospatially and temporally varying regression weights associated with the independent variables, reflecting the differential impacts of various urban renewal projects (UR_{it}) and policy interventions ($Policy_{it}$) across space and time. Similarly, $\beta_k(u_i, v_i, t_i)$ embodies the adaptable coefficients for the control variables (X_{ik}), capturing their contextual influence. All remaining variables retain their meanings consistent with those defined in Equation (1). This sophisticated modeling approach permits nuanced insights into how the effects of urban renewal strategies dynamically interact with geographical context and evolve over time.

3.4. Variables

3.4.1. Dependent Variable

The focal point of inquiry in Equations (1) and (2) rests on the HSE, a construct meticulously delineated by the evaluative framework presented in Table 1. Acknowledging the plausible implications of migratory dynamics and ancillary impacts instigated by urban renewal processes, it becomes imperative to scrutinize the presence of spatial correlation within the HSE, a premise supported by preceding scholarly endeavors. To ascertain this spatial interdependence, we employed *Moran's I* index, a statistical measure that elucidates spatial autocorrelation patterns. The mathematical expression for calculating *Moran's I* is thereby formulated as follows:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{3}$$

where i and j represent region i and region j, S^2 is the sample variance, $\overline{Y}$ is the sample mean, and W_{ij} is the spatial weight matrix representing the spatial relationships between regions, including the adjacency matrix, geographic matrix, economic–geographic matrix, etc. The value of *Moran's I* typically ranges from -1 to 1, where a larger absolute value indicates a stronger correlation. Specifically, if the *Moran's I* value is positive, it indicates positive spatial correlation. If the *Moran's I* value is zero, it indicates no spatial correlation. If the *Moran's I* value is negative, it indicates a negative spatial correlation. Due to the strong economic characteristics of the human settlement environment, constructing a weight matrix based solely on geographical distance cannot objectively reflect its economic associations. Therefore, this study selected an economic–geographic weight matrix [39] (W_1) and an economic–geographic nested weight matrix [40] (W_2) to measure the spatial relationships. W_1 is constructed by taking the reciprocal of the distance between city i and city j multiplied by the product of the ratio of the average per capita GDP of city i to the average per capita GDP of all cities. $W_2(\psi) = (1-\psi)w_n^G + \psi w_n^E$, where W_n^G and W_n^E represent the geographic distance weight matrix and the economic distance weight matrix, respectively. In this study, the geographic matrix and the economic matrix were considered to have equal weights, with ψ set to 0.5.

3.4.2. Key Independent Variable

In our research, the pivotal independent variable revolves around the degree of urban renewal undertaken in a given city at a specific temporal juncture. Urban renewal, recognized as a multidimensional phenomenon, not only entails the physical revitalization of spaces but also embraces advancements in the intangible facets of urbanity. To measure the intensity of urban renewal, we adopted a suite of indicators that collectively encapsulate the breadth and depth of urban transformation. These indicators are structured under three principal categories: urban infrastructure development, industrial development, and urban construction. Firstly, urban infrastructure development (Infra) is assessed through metrics such as the total completed fixed asset investments in municipal public facilities (Invest), the length of urban drainage pipeline networks (Pipe), and the per capita availability of the road surface area (Road). Secondly, the industrial development (Industry) is gauged by examining the shares of the secondary (Second) and tertiary sectors (Third) in the city's Gross Domestic Product (GDP), highlighting structural shifts and economic diversification. Lastly, urban construction (Urban) encompasses fiscal health and spatial expansion, measured via the local government's general public budget revenue (Income), the area designated for residential land use (Floor), and the allocation for industrial land (Industrial). This ensemble of indicators furnishes a comprehensive perspective on the multifaceted dimensions of urban renewal efforts in the studied cities.

3.4.3. Control Variable

Given the presence of various factors that can influence the urban human settlement environment, this study focused on representative variables from four key aspects: population density, external investment, employment situation, and human capital level.

(1) Population density (Pop): The rapid urbanization process has resulted in a significant influx of rural population into cities. High population density can exert considerable pressure on urban transportation, the ecological environment, and living conditions, leading to frequent urban challenges. To measure population density, this study used the number of people per square kilometer.

(2) External investment (Foreign): As comprehensive national strength grows, capital investments from foreign countries or regions play a crucial role in driving urban development and improving the living standards of urban residents. To represent the intensity of external investment, this study employed the number of contracted projects for foreign direct investment.
(3) Unemployment (Unemployed): Unemployment directly affects household income and consumption levels for the majority of the urban population, consequently impacting the urban economic environment. To evaluate the level of unemployment, this study utilized the number of registered unemployed individuals in the city.
(4) Human capital (Education): The level of human capital in cities directly reflects the quality of the urban economic environment. Enhanced human capital can increase individual employment opportunities, elevate income levels, and subsequently influence urban consumption levels. To measure the level of human capital in cities, this study considered the proportion of higher education students to the registered population.

4. Result and Discussion

4.1. Mapping the Spatial Variability and Temporal Trajectories of the HSE

Figure 3 graphically represents the city-level distribution of the HSE scores for the years 2009, 2014, and 2019, employing the natural breaks classification methodology. The visual depiction reveals stark spatial heterogeneity in the HSE, with a conspicuous trend of elevated scores clustering along the eastern coastal belt relative to the more inland, western territories. Over the decade under scrutiny, a pervasive trend of improvement in HSE is evident across the Jiangsu, Zhejiang, and Anhui provinces. Initially, in 2009, the aggregate mean HSE score for the 40 surveyed cities stood at roughly 0.3. By the conclusion of the study period in 2019, this mean had ascended appreciably to approach 0.4. This temporal evolution is further underscored by a broad-based enhancement across all score categories, evidenced by the lowest recorded HSE value escalating from 0.107 in 2009 to a peak of 0.919 in 2019. Collectively, these observations attest to a salutary shift in the HSE landscape throughout the timeframe investigated, underscoring the efficacy of urban renewal and development strategies in fostering more livable and sustainable human settlements.

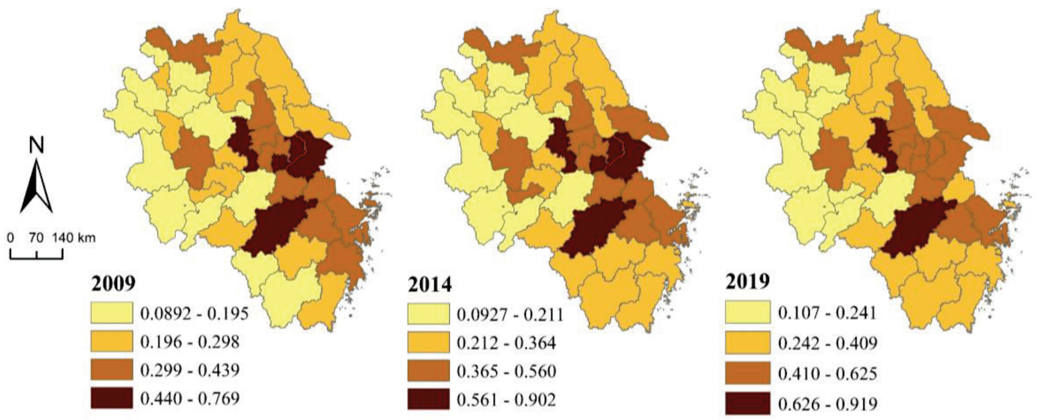
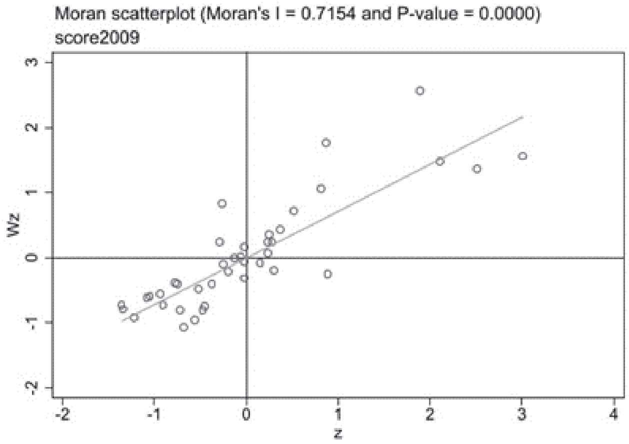
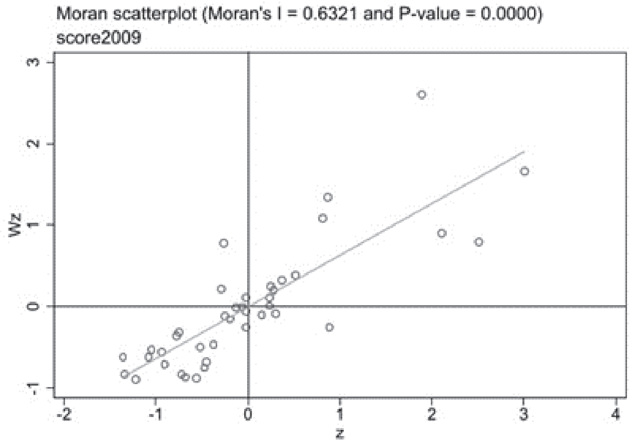


Figure 3. Geospatial depiction of HSE scores across cities, 2009–2019.

To further unravel the intricate spatio–temporal dynamics of the HSE, we computed *Moran's I* index for every city within the tri-provincial domain encompassing Jiangsu, Zhejiang, and Anhui from 2009 through 2019 (detailed in Table 2). Focusing on the landmark years 2009, 2014, and 2019 as illustrative instances, the HSE scores were classified into four quadrants—high–high, low–high, low–low, and high–low—reflecting varying combinations of spatial autocorrelation. These classifications facilitate the understanding of the clustering of high or low HSE scores in geographical proximity. To visualize these patterns explicitly, Local Indicators of Spatial Association (LISA) scatterplots (Figure 4) were constructed, offering a graphical interpretation of the HSE's specific distributional characteristics across time and space. These visual analyses provide critical insights into the geographic concentrations of HSE performance and potential drivers behind the observed trends.



(**A**)



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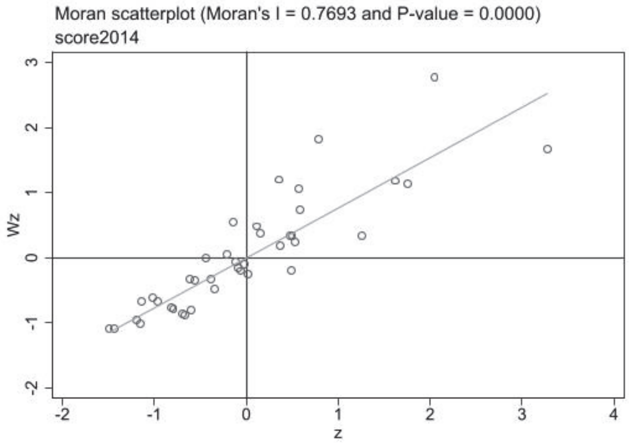

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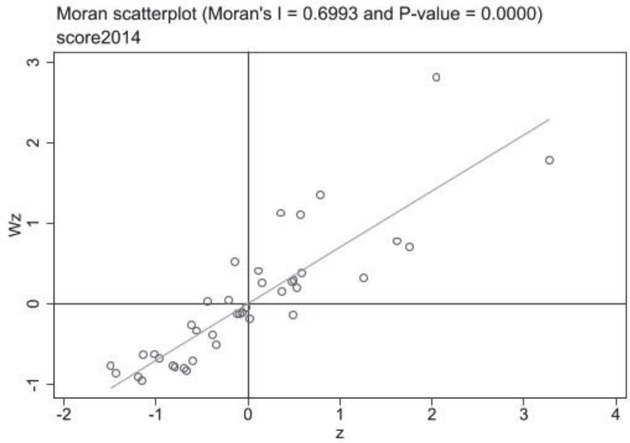

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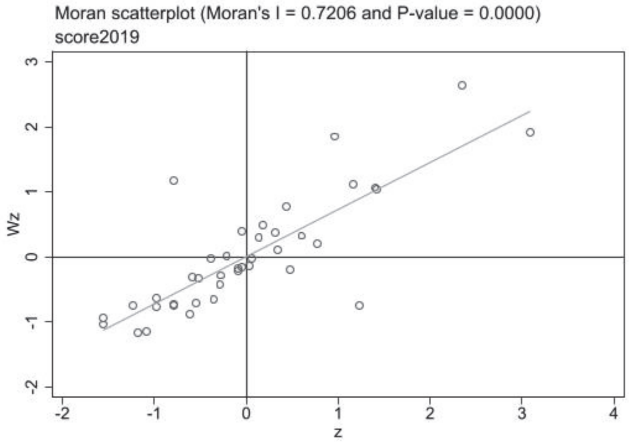

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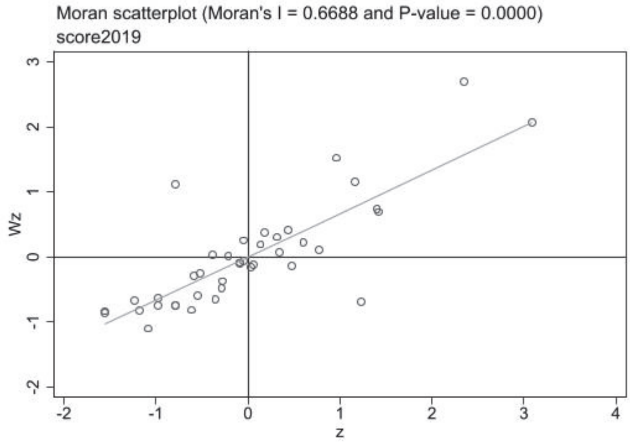

(**F**)

Figure 4. Spatial distribution of cities based on HSE using W1 and W2, 2009–2019. (**A**) Scatterplot distribution for W_1 2009. (**B**) Scatterplot distribution for W_2 2009. (**C**) Scatterplot distribution for W_1 2014. (**D**) Scatterplot distribution for W_2 2014. (**E**) Scatterplot distribution for W_1 2019. (**F**) Scatterplot distribution for W_2 2019.

Table 2. Global *Moran's I* index for the HSE in Jiangsu, Zhejiang, and Anhui (2009–2019).

Year	2009	2010	2011	2012	2013	2014
Moran's I	0.715 ***	0.757 ***	0.777 ***	0.77 ***	0.76 ***	0.77 ***
(W_1)	(0.101)	(0.103)	(0.102)	(0.101)	(0.1)	(0.101)
Moran's I	0.632 ***	0.684 ***	0.708 ***	0.696 ***	0.677 ***	0.699 ***
(W_2)	(0.092)	(0.094)	(0.093)	(0.092)	(0.092)	(0.092)
Year	**2015**	**2016**	**2017**	**2018**	**2019**	
Moran's I	0.725 ***	0.767 ***	0.714 ***	0.735 ***	0.721 ***	
(W_1)	(0.101)	(0.102)	(0.102)	(0.102)	(0.102)	
Moran's I	0.661 ***	0.703 ***	0.672 ***	0.684 ***	0.669 ***	
(W_2)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, t-statistics in parentheses.

Drawing upon the evidentiary base provided in Table 2, it emerges that both the economic–geographical weight matrix and the nested variant thereof yield positively valued *Moran's I* indices for the HSE. Importantly, these indices consistently surpassed the 1% significance threshold, affirming the robustness of our findings. This collectively underscores that the distribution of the HSE across the cities was not arbitrary; rather, it manifested a pronounced level of spatial dependence, implying that the HSE of a city is intricately tied to that of its spatial neighbors. Consequently, these results emphasize the pivotal role of spatial elements in shaping the HSE dynamics amidst the backdrop of urban renewal initiatives. It becomes imperative, therefore, to incorporate spatial correlation in assessments of urban renewal's repercussions on the human settlement environment, acknowledging that HSE outcomes are not solely a function of local factors but are also influenced by the broader spatial context. Inspection of the LISA scatterplots further illuminate this narrative, revealing a concentration of cities in the third quadrant, indicative of a scenario where cities with high (low) HSE scores tend to be surrounded by similarly high (low) scoring neighbors. This clustering pattern reinforces the notion that spatial contiguity significantly modulates HSE distributions and accentuates the necessity of adopting a spatially explicit analytical lens when deciphering the complexities of urban renewal's impact on the HSE.

4.2. The Impact of Urban Renewal on the HSE: Benchmark Findings

Based on Equation (1), we probed the relationship between urban renewal activities and their repercussions on the HSE, with the resultant findings tabulated in Table 3. In this structured analysis, Model 1 initiates the exploration by concentrating on the direct impacts of the primary explanatory variables on the HSE without additional controls. Expanding upon this, Model 2 integrates supplementary control measures such as population density and external investment into the mix, alongside the variables retained from Model 1, thereby enhancing the complexity and robustness of the model. Acknowledging the longitudinal nature of the dataset and to further refine our estimates, Model 3 adopts a two-way fixed-effects model, informed by the outcomes of the Hausman test and the inclusion of policy-specific dummy variables. This model rigorously assesses the temporal and cross-sectional dynamics influencing the connection between urban renewal and the HSE.

Notably, the reported R-squared statistics for the trio of models—0.763 for Model 1, 0.689 for Model 2, and 0.975 for Model 3—reveal the escalating explanatory power, with Model 3 demonstrating the highest capacity to account for the variance in HSE outcomes. These values signify the degree to which our models captured the variability in the HSE, with Model 3 achieving an especially high explanatory adequacy. Crucially, all three models attained statistical significance at the stringent 1% confidence level, attesting to the robust and credible nature of the observed associations between the explanatory variables and the HSE. This statistical significance reinforces our conviction in the reliability of the findings, underscoring that the dynamics of urban renewal indeed exert a quantifiable and substantial influence on shaping the human settlement environment.

Table 3. Benchmark results on the impact of urban renewal on HSE.

Variable	Model 1	Model 2	Model 3
Policy	0.256 *** (4.67)	0.25 *** (4.52)	0.004 (0.68)
Invest	0.01 * (1.92)	0.102 ** (2.02)	0.013 *** (2.91)
Pipe	0.005 (0.43)	0.003 (0.24)	−0.001 (−0.11)
Road	−0.005 (−1.07)	−0.005 (−1.07)	−0.007 (−1.52)
Second	0.038 *** (4.8)	0.035 *** (4.22)	0.025 *** (3.3)
Third	0.044 *** (5.15)	0.043 *** (4.84)	0.024 ** (2.49)
Income	0.025 *** (2.78)	0.028 *** (3.05)	0.021 ** (2.44)
Floor	−0.028 ** (−2.18)	−0.033 ** (−2.56)	−0.03 ** (−2.5)
Industrial	0.014 ** (2.03)	0.014 ** (2.11)	0.013 ** (2.19)
Pop		−0.005 (−0.8)	−0.003 (−0.68)
Foreign		0.000 (0.34)	0.000 (0.08)
Unemployed		0.000 (0.07)	0.002 (1.23)
Education		0.024 ** (2.2)	0.03 *** (3.03)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, t-statistics in parentheses.

The outcomes of the regression analyses for Models 1 and 2 affirmatively highlight a substantial, positive association between urban renewal endeavors and enhancements in the HSE. Progressing to Model 3, which employs a sophisticated two-way fixed-effects methodology, a more nuanced dissection of the underlying mechanisms was conducted. Specifically, this model delves into the roles of urban infrastructure advancements and shifts in industrial composition. Of note is the fact that Model 3 discloses that completed fixed asset investments channeled into urban municipal public facilities exert a profound, beneficial effect on the human settlement environment, evidenced by a statistically significant coefficient of 0.013 at the 0.01 significance level. This finding underscores the paramount importance of robust infrastructure development in fostering improved living environments. Furthermore, the coefficients pertaining to the contributions of the secondary (0.025) and tertiary (0.024) industries to the GDP, both statistically significant at the 5% level, attest to the transformative power of industrial restructuring and upgradation in augmenting the environmental quality for human habitation. This implies that urban renewal's facilitation of industrial transitions towards higher value-added and service sectors is instrumental in elevating the HSE.

Regarding the multifaceted impact of urban construction, the results are twofold. A positive contribution arises from enhancements in local general public budget revenue, reflected in a coefficient of 0.021, and an expansion in industrial land area, with a coefficient of 0.013, both of which significantly boost the human settlement environment. Conversely, an unexpected negative coefficient (−0.03) was attached to residential land area, intimating that while expanding residential areas might intuitively benefit the environment, it inadvertently introduces countervailing pressures. This paradox could stem from a complex interplay between residential expansion and its dual implications for economic development and ecological sustainability, necessitating careful calibration in urban planning.

Moreover, the control variables conformed to anticipated patterns. Higher human capital was positively correlated with better human settlement environments, as more educated urban residents typically see improved job prospects, heightened incomes, greater consumption, accelerated economic growth, and a more favorable living environment. Conversely, population density, foreign investment counts, and unemployment figures showed no substantial bearing on the urban HSE. This may be due to China's rapid urbanization, marked by uniformly high population densities across cities, especially in the Yangtze River Delta region of Jiangsu, Zhejiang, and Anhui. Hence, additional population density has marginal relevance to the HSE. Amidst the progress towards high-quality economic growth, foreign investments, though contributory, hold lesser sway than domestic investments, particularly from local firms. With minimal foreign capital involvement and a stable economic trajectory averaging a 7.8% annual GDP growth from 2009 to 2019, alongside low unemployment rates, the effect of unemployment on the HSE is negligible.

4.3. The Impact of Urban Renewal on the HSE: Mechanisms

The results from our GTWR analysis, summarized in Table 4, delve into the intricate web of relationships that exist between the dynamic changes in the HSE and a multitude of urban renewal indicators over space and time. This advanced modeling approach yielded notably high R-squared and adjusted R-squared values, both surpassing 0.95, which affirm the model's exceptional fitness and its prowess in accurately explicating the complex interplay between the independent variables and the HSE. These statistical measures assure us of the model's capability to provide a robust and nuanced understanding of the underlying mechanisms driving the impact of urban renewal on shaping and enhancing the human settlement environment across diverse spatial–temporal contexts.

Table 4. GTWR parameter estimates.

Parameter	Bandwidth	Residual Squares	Sigma	AICc	R^2	R^2 Adjusted	Spatio-Temporal Distance Ratio
Value	0.11006	0.346914	0.028079	−1485.41	0.9733	0.972526	2.2447

Figures 5–8 visually depict the geographic disparities in how various factors influence the HSE over distinct chronological intervals. Notably, the analysis accounts for a policy intervention—the State Council's 2013 directive on shantytown rehabilitation. Acknowledging a latency in policy execution, our study demarcates 2014 as the inception year of national policy enforcement, thereby defining 2009–2013 as the pre-policy epoch and 2015–2019 as the post-policy era.

Overall, the temporal dynamics reveal evolving HSE factor impacts. Post-2009, the urban renewal policies' HSE enhancement weakened, with local budgets and residential land dominating until 2013, joined by the tertiary sector's GDP share. However, post-2014, the tertiary and secondary sectors' GDP shares emerged as prime influencers, signaling industrial transformation's ascendancy in sculpting the human settlement environment. The key observations include the following:

(1) Policy Dimension (Figure 5): Local policy interventions are largely conducive to the HSE enhancement, with their potency escalating over time following their implementation. Pivoting around the 2014 national policy milestone, the 2009–2013 phase saw Jiangsu and Zhejiang provinces bask in the zenith of positive policy impact. Conversely, from 2015 to 2019, Anhui and Jiangsu emerged as new focal points, albeit with some southern Zhejiang cities, prominently Wenzhou, encountering adverse effects.

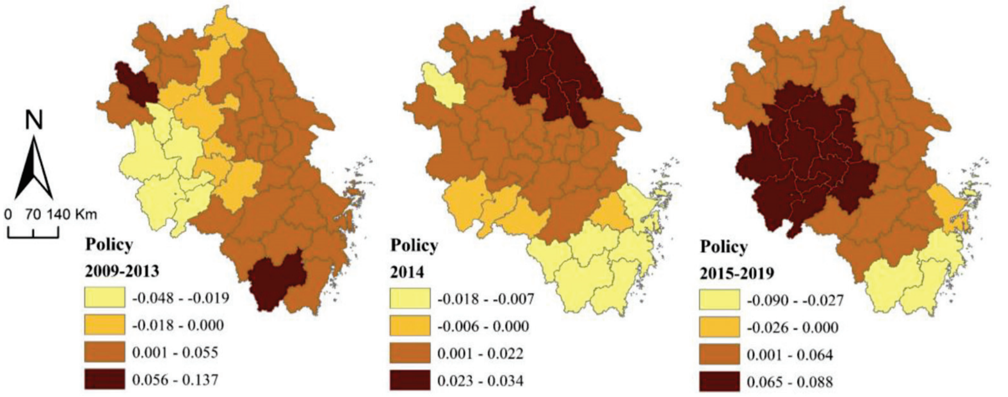

Figure 5. Spatio-temporal dynamics of policy effects in urban renewal's influence on the HSE.

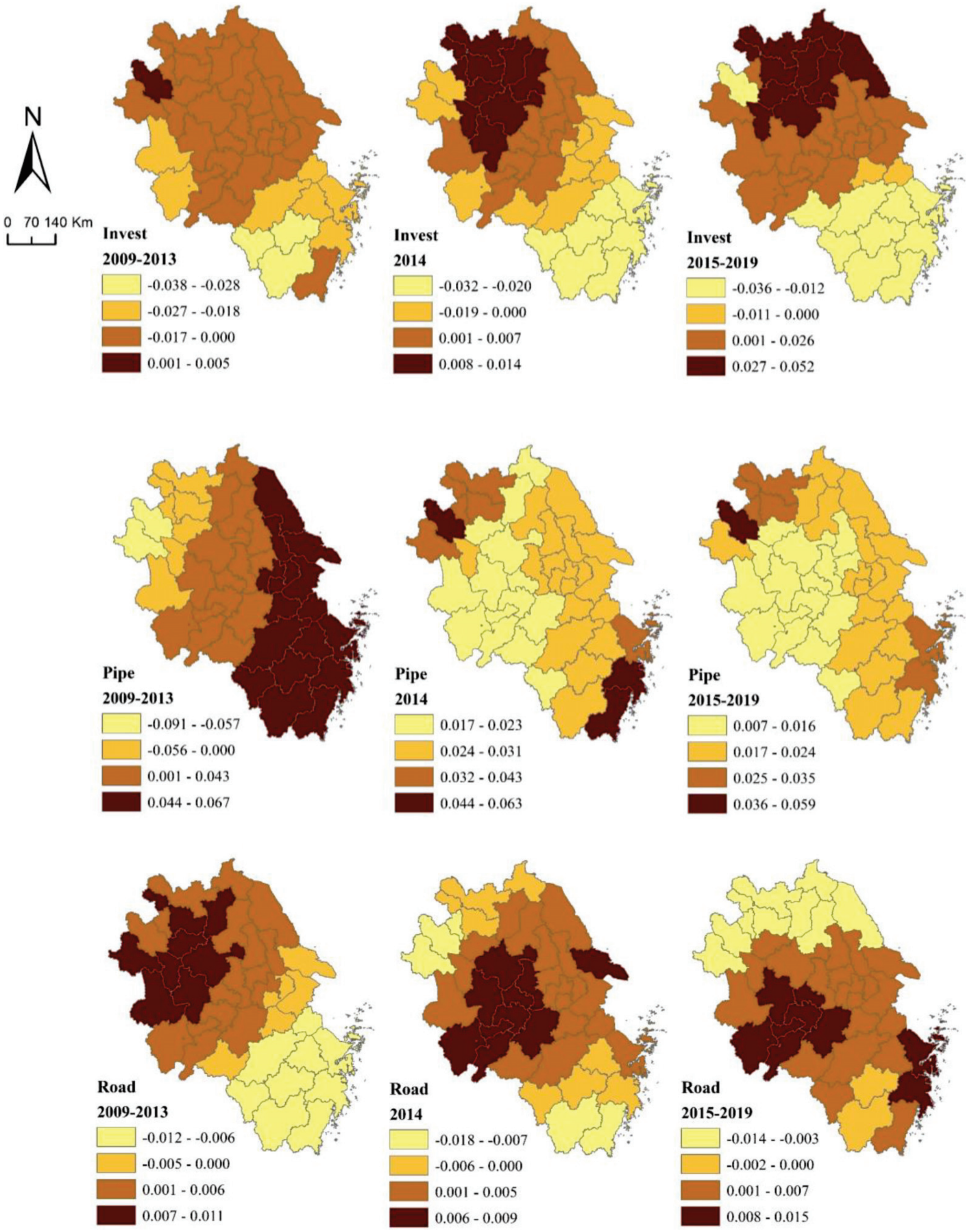

Figure 6. Spatio-temporal dynamics of infrastructure investment effects in urban renewal's influence on the HSE.

(2) Infrastructure Investment Dynamics (Figure 6): The trajectory of fixed asset investments in municipal public facilities' influence on HSE transitioned from adverse to favorable. Until 2013, all cities registered detrimental regression coefficients. Post-2014, however, a reversal in the coefficient polarity became prevalent across many cities, implying a strengthening constructive influence. This transformation aligns with the advent of the "Lucid Waters and Lush Mountains" green development philosophy, highlighting infrastructure investments' escalating role in bolstering the HSE. Meanwhile, the contribution of urban drainage pipeline length to HSE improvement was generally positive but stabilizing. Between 2009 and 2013, regions in Zhejiang and southern Jiangsu reaped the lion's share of benefits from extended drainage systems. Post-2014, the ameliorative effect dropped off, potentially due to rapid urbanization and mature infrastructure in these locales, diminishing the incremental advantage of further pipeline extensions on the HSE.

(3) Industrial Progress (Figure 7): The progress of industrial structure exerts a substantial effect on the HSE, with the secondary industry's GDP contribution displaying a stable, primarily positive impact. Between 2009 and 2013, the regression coefficients for 40 cities consistently hovered within a [0.04, 0.07] band. While Wenzhou and Taizhou momentarily showed a 2014 decline, the period from 2015 to 2019 witnessed a stronger, predominantly positive influence across the cities, particularly in Jiangsu and northern Anhui. The tertiary industry's GDP share had a more substantial bearing, with cities like Yancheng, Huai'an, Taizhou, Nanjing, Hangzhou, and Hefei consistently benefitting. Moreover, the Yangtze River cities registered significantly higher coefficients compared to their southern Zhejiang coastal counterparts, highlighting the tertiary sector's enhanced HSE impact in the Yangtze region.

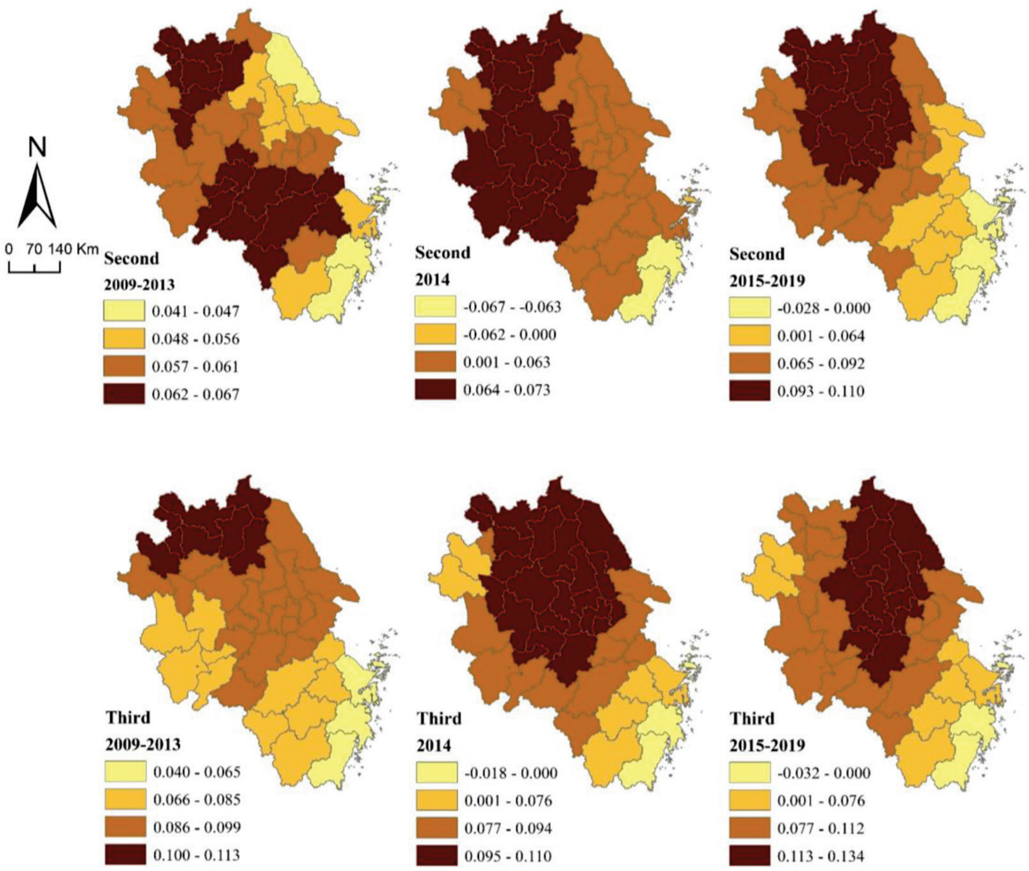

Figure 7. Spatio-temporal dynamics of industrial progress effects in urban renewal's influence on the HSE.

(4) Material Renewal (Figure 8): The physical revitalization of spaces significantly shapes the HSE landscape through multiple avenues. Local general public budget revenue, despite being generally positive, waned in influence over the timeline. The northern Anhui cities initially saw the most positive impact, yet post-2014 policy implementation, the southern Zhejiang cities exhibited a positive surge, except for Lianyungang's marginal negative coefficient. Residential land area generally fostered a positive HSE environment, yet with notable fluctuations, transitioning from negative dominance in northern Anhui and Jiangsu (2009–2013) to a positive swing favoring Zhejiang post-2014. Industrial land area mostly positively influenced the HSE, with initial mixed signals at provincial borders evolving into a more definitive positive trend concentrated in cities like Lu'an, Hefei, and Huai'an from 2015 to 2019, while southern Zhejiang cities experienced negative effects.

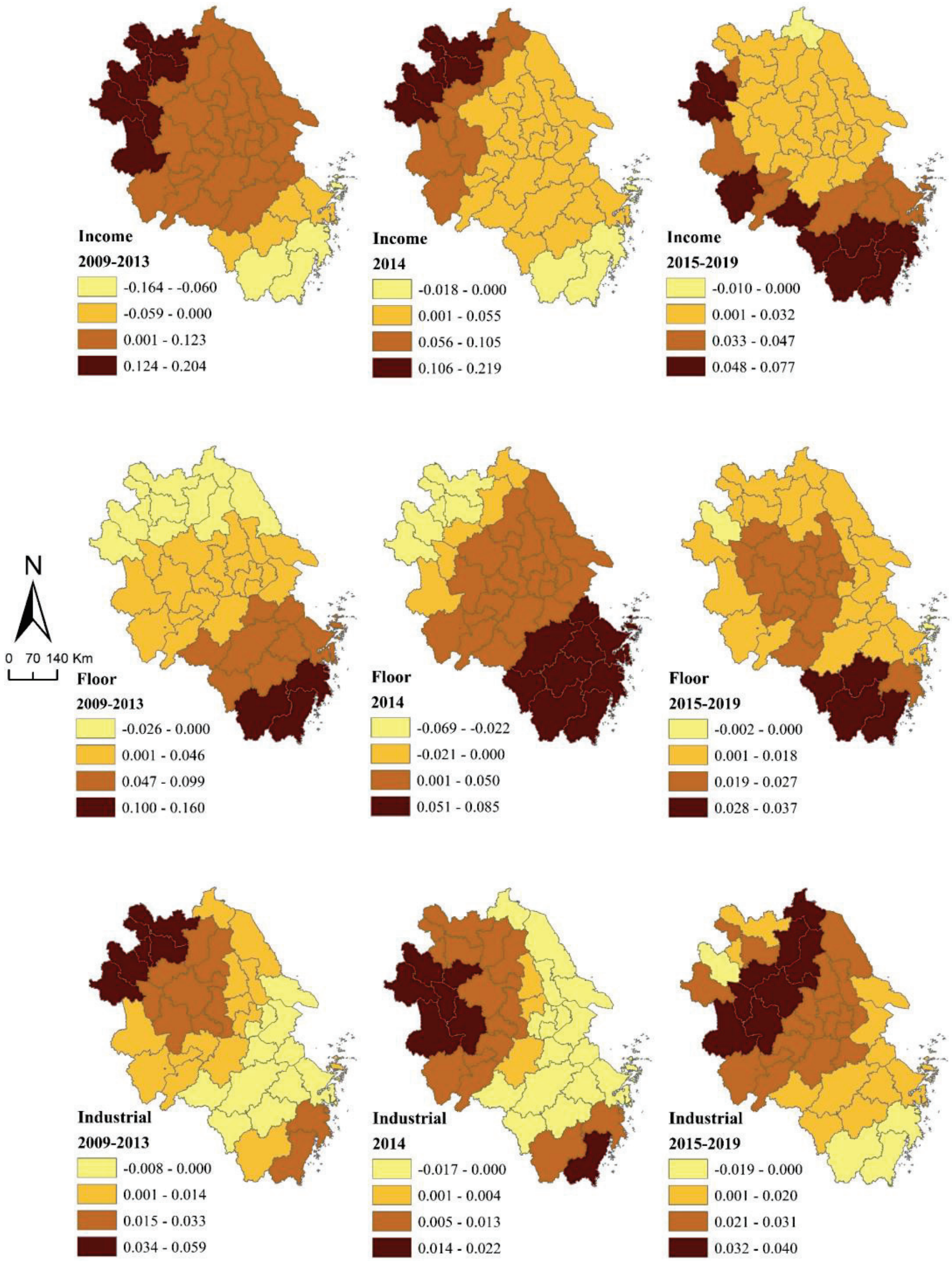

Figure 8. Spatio-temporal dynamics of material renewal effects in urban renewal's influence on the HSE.

5. Conclusions

This investigation employed an extensive analytical framework utilizing panel data spanning from 2009 to 2019, leveraging ordinary panel regression and fixed-effects models to scrutinize the determinants and pathways through which urban renewal shapes the HSE. To unravel the geographical and chronological nuances, a geographically and temporally weighted regression model was adopted, shedding light on the spatial–temporal heterogeneities in urban renewal's environmental impact. Our findings reveal a general upward trend in HSE quality across the cities since 2009, with progression rates diverging across various phases. Metropolises such as Nanjing, Hangzhou, Hefei, and Suzhou, characterized by advanced economies, have outpaced less prosperous zones in northern Jiangsu and Anhui in environmental quality. The spatial clustering analyses underscored the existence of high–high and low–low agglomerations, reflecting areas with consistently superior or inferior human settlement conditions, respectively.

A salient discovery entails the affirmation of a positive correlation between urban renewal endeavors and HSE improvement, suggesting that renewal projects yield favorable outcomes. Nonetheless, these enhancements exhibited spatial disparities, with Yangtze River Delta hubs and economically vibrant territories witnessing more dramatic enhancements. Moreover, our work underscores the multifaceted influence of urban renewal on the HSE through infrastructural enhancements, industrial stimulation, and construction activities. Initial potent policy effects have attenuated over time amidst intricate interplays among impacting variables, while the roles of population density, external investment, and urban unemployment remain inconclusive in our present study. The spatial–temporal dynamics also unveiled variable importance shifts among influencing factors, pivoting from an urban construction magnitude to an industrial development emphasis, underlining the centrality of industrial restructuring and modernization for HSE enhancement.

Our study innovatively contributes to the discourse by establishing an HSE assessment framework and deploying sophisticated modeling techniques to explore the causal mechanisms and spatio–temporal dynamics of urban renewal's HSE impact. We affirm the pivotal role of industrial evolution in shaping the HSE and advocate for urban renewal strategies harmonized with local industrial contexts, emphasizing tailored policies that prioritize structural adjustments in urban industries. Such an approach paves the way for human-centric urbanization and HSE augmentation.

While offering empirical insights into HSE uplift via urban renewal and bridging a research gap by integrating urban renewal with HSE considerations, we acknowledge limitations. Data constraints necessitated focusing on shantytown renovation as a proxy for broader urban renewal and limiting the scope to prefectural cities, bypassing granular analysis at the county level. Future inquiries should aspire to broaden the purview of urban renewal activities under examination and delve deeper into county-level impacts for a holistic comprehension of HSE transformations.

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References

1. Kang, Y.H.; Zhang, F.; Gao, S.; Peng, W.Z.; Ratti, C. Human settlement value assessment from a place perspective: Considering human dynamics and perceptions in house price modeling. *Cities* **2021**, *118*, 103333. [CrossRef]
2. Xia, C.; Yeh, A.G.-O.; 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]
3. Cao, K.; Deng, Y.; Wang, W.; Liu, S. The spatial heterogeneity and dynamics of land redevelopment: Evidence from 287 Chinese cities. *Land Use Policy* **2023**, *132*, 106760. [CrossRef]
4. Zhu, H.; Yu, W.; Li, J. The Spatial Injustice in Tourism-Led Historic Urban Area Renewal: An Analytical Framework from Stakeholder Analysis. *Curr. Issues Tour.* **2024**, *27*, 1229–1248. [CrossRef]
5. Li, H.; Dong, A.; Hu, X.; Fu, H. Innovative Research on Urban Renewal Operation Mechanism and Evolution: Based on Ecological Theory. *Fresenius Environ. Bull.* **2021**, *30*, 7933–7938.
6. Lee, C.; Liang, C.-M.; Chen, C.-Y. The Impact of Urban Renewal on Neighborhood Housing Prices in Taipei: An Application of the Difference-in-Difference Method. *J. Hous. Built Environ.* **2017**, *32*, 407–428. [CrossRef]
7. Ferrari, E. Competing Ideas of Social Justice and Space:Locating Critiques of Housing Renewal in Theory and in Practice. *Int. J. Hous. Policy* **2012**, *12*, 263–280.
8. Zhang, W.; Zhang, X.; Wu, G. The Network Governance of Urban Renewal: A Comparative Analysis of Two Cities in China. *Land Use Pol.* **2021**, *106*, 105448. [CrossRef]
9. Li, H.; Zhou, L.-A. Political turnover and economic performance: The incentive role of personnel control in China. *J. Public Econ.* **2005**, *89*, 1743–1762. [CrossRef]
10. Han, L.; Lu, M. Housing prices and investment: An assessment of China's inland-favoring land supply policies. *J. Asia Pac. Econ.* **2017**, *22*, 106–121. [CrossRef]
11. Li, J. Land sale venue and economic growth path: Evidence from China's urban land market. *Habitat Int.* **2014**, *41*, 307–313. [CrossRef]
12. Huang, Z.; Du, X. Strategic interaction in local governments' industrial land supply: Evidence from China. *Urban Stud.* **2017**, *54*, 1328–1346. [CrossRef]
13. Zhou, L.; Tian, L.; Cao, Y.; Yang, L. Industrial land supply at different technological intensities and its contribution to economic growth in China: A case study of the Beijing-Tianjin-Hebei region. *Land Use Policy* **2021**, *101*, 105087. [CrossRef]
14. Deng, F. Gated community and residential segregation in urban China. *GeoJournal* **2017**, *82*, 231–246. [CrossRef]
15. Chen, Q.X.; Zhang, K.W.; Zhang, G.Y.; Zhang, M.Y. Vulnerability assessment on human settlement environment of coastal towns with entire-array-polygon method: Evidence from Ninghai, China. *Environ. Dev. Sustain.* **2024**, 1–24. [CrossRef]
16. Li, J.B.; Huang, X.J.; Kwan, M.P.; Yang, H.; Chuai, X.W. The effect of urbanization on carbon dioxide emissions efficiency in the Yangtze River Delta, China. *J. Clean. Prod.* **2018**, *188*, 38–48. [CrossRef] [PubMed]
17. Wang, B.; Hu, D.; Hao, D.; Li, M.; Wang, Y. Influence of Government Information on Farmers' Participation in Rural Residential Environment Governance: Mediating Effect Analysis Based on Moderation. *Int. J. Environ. Res. Public Health* **2021**, *18*, 12607. [CrossRef] [PubMed]
18. Chen, L.; Tao, J. Will Model of Polycentric Synergetic Governance Be "The Good Road to Governance" of Rural Habitat Environment? *J. Northwest AF Univ. (Soc. Sci. Ed.)* **2024**, *24*, 10–21.
19. Lin, S.; Hou, L. SDGs-Oriented Evaluation of the Sustainability of Rural Human Settlement Environment in Zhejiang, China. *Heliyon* **2023**, *9*, e13492. [CrossRef] [PubMed]
20. Wang, Y.; Zhu, Y. Exploring the Effects of Rural Human Settlement on Rural Development: Evidence from Xianju County in Zhejiang Province, China. *Environ. Dev.* **2023**, *46*, 100845. [CrossRef]
21. Chen, J. Temporal-Spatial Assessment of the Vulnerability of Human settlement environment in Urban Agglomerations in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 3726–3742. [CrossRef] [PubMed]
22. Gao, J.; Cao, F.; Sun, D.; Bai, Z.; Lang, Z. Composite Characteristic and Mechanism Analysis of Human settlement environment in Jinan City Based on Demand Hierarchy Theory. *Buildings* **2023**, *13*, 1624. [CrossRef]
23. Zhou, X.; Ao, R.; Zhu, Y.; Chen, J.; Shen, X.; Aihemaitijiang, Y. Urban human settlements' resilience measurement and characteristics and their mechanism model in China. *PLoS ONE* **2023**, *18*, e0289754. [CrossRef] [PubMed]
24. Stal, G.Y.; Zuberi, D.M. Ending the Cycle of Poverty through Socio-Economic Integration: A Comparison of Moving to Opportunity (MTO) in the United States and the Bijlmermeer Revival Project in the Netherlands. *Cities* **2010**, *27*, 3–12. [CrossRef]
25. Wang, Y.; Li, J.; Zhang, G.; Li, Y.; Asare, M.H. Fuzzy Evaluation of Comprehensive Benefit in Urban Renewal Based on the Perspective of Core Stakeholders. *Habitat Int.* **2017**, *66*, 163–170. [CrossRef]
26. Yao, Z. The Design of Marine Architecture: A Renewal and Development of Coastal City Space Perspective. *J. Coast. Res.* **2020**, *106*, 347–350.
27. Tang, M.; Hong, J.; Wang, X.; He, R. Sustainability Accounting of Neighborhood Metabolism and Its Applications for Urban Renewal Based on Emergy Analysis and SBM-DEA. *J. Environ. Manag.* **2020**, *275*, 111177. [CrossRef] [PubMed]
28. Li, X.; Hui, E.C.M.; Chen, T.; Lang, W.; Guo, Y. From Habitat III to the New Urbanization Agenda in China: Seeing through the Practices of the "Three Old Renewals" in Guangzhou. *Land Use Pol.* **2019**, *81*, 513–522. [CrossRef]
29. Page, B.; Ross, E. Legacies of a Contested Campus: Urban Renewal, Community Resistance, and the Origins of Gentrification in Denver. *Urban Geogr.* **2017**, *38*, 1293–1328. [CrossRef]

30. Wallace, A. The Inbetweeners: Living with Abandonment, Gentrification and Endless Urban 'Renewal' in Salford, UK: A Cross-National Perspective. In *Social Housing and Urban Renewal*; Emerald Publishing Limited: Bingley, UK, 2017.
31. Yang, R.; Lin, Y. Rural Spatial Transformation and Governance from the Perspective of Land Development Rights: A Case Study of Fenghe Village in Guangzhou. *Growth Chang.* **2022**, *53*, 1102–1121. [CrossRef]
32. Konove, A. Making a Modern *Barrio*: Infrastructure and Progress in Mexico City, 1900–1903. *J. Urban Hist.* **2020**, *46*, 516–540. [CrossRef]
33. Dai, M.; Zhang, H. Luo Wanting. Theory and Practice of Urban Development Transformation--An Introduction to Shenzhen's Development Transformation. *Urban Probl.* **2013**, *12*, 84–88.
34. Chang, J.F.; Wang, W.; Liu, J.L. Industrial upgrading and its influence on green land use efficiency. *Sci. Rep.* **2023**, *13*, 2813. [CrossRef] [PubMed]
35. Ye, L.; Peng, X.; Aniche, L.Q.; Scholten, P.H.T.; Ensenado, E.M. Urban Renewal as Policy Innovation in China: From Growth Stimulation to Sustainable Development. *Public Adm. Dev.* **2021**, *41*, 23–33. [CrossRef]
36. Hsu, K.-W.; Chao, J.-C. Economic Valuation of Green Infrastructure Investments in Urban Renewal: The Case of the Station District in Taichung, Taiwan. *Environments* **2020**, *7*, 56. [CrossRef]
37. Deng, Y.; Fu, B.; Sun, C. Effects of Urban Planning in Guiding Urban Growth: Evidence from Shenzhen, China. *Cities* **2018**, *83*, 118–128. [CrossRef]
38. Wu, P.; Zhong, K.; Wang, L.; Xu, J.; Liang, Y.; Hu, H.; Wang, Y.; Le, J. Influence of Underlying Surface Change Caused by Urban Renewal on Land Surface Temperatures in Central Guangzhou. *Build. Environ.* **2022**, *215*, 108985. [CrossRef]
39. Shuai, S.; Xin, L.; Jianhua, C.; Lili, Y. China's Economic Policy Choices for Governing Smog Pollution Based on Spatial Spillover Effects. *Econ. Res. J.* **2016**, *51*, 73–88.
40. Li, W.; Cai, J.; Zhu, Y.; Li, J.; Li, Z. Can digital finance development drive green transformation in manufacturing? Evidence from China. *Environ. Sci. Pollut. Res.* **2024**, *31*, 23876–23895. [CrossRef]

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Article

Research on the Manifestation and Formation Mechanism of New Characteristics of Land Disputes: Evidence from the Yangtze River Economic Belt, China

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Abstract: Land disputes have significantly disrupted legal order, production, and social harmony, and has been regarded as a quintessential challenge in public governance, attracting worldwide attentions from scholars. As an emblematic feature of China's latest reform and opening-up strategy, the Yangtze River Economic Belt (YREB) in China has experienced rapid development after entering the new era (2012–2021) alongside substantial risks and challenges, particularly regarding land disputes. Better understanding of the manifestation and formation mechanism of new characteristics of land disputes is beneficial for contemporary public governance and for achieving a high-quality development of the YREB, whose Gross Domestic Product (GDP) accounted for 46.3% of the national GDP in 2023. A total of 325,105 land dispute cases in 11 provinces or municipalities of the YREB from 2012 to 2021 were collected and analyzed. On this basis, an evaluation index system of the new characteristics of land disputes, named the overall land dispute (OLD) index, was constructed according to measurement theory by coupling the interactions of quantity, claim amounts, duration periods, and the appeal rate of land dispute. Then, the OLD index was evaluated by descriptive statistical methods, a geographic information system (GIS) spatial analysis, a center of gravity model, kernel density estimation, and Theil index methods, to reveal the new characteristics and formation mechanisms of land disputes in the YREB from 2012 to 2021. The results indicated that: (1) The OLD index exhibited a trend of an initial increase followed by a decline, indicating that land disputes in the YREB showed signs of alleviation. (2) The government's capacity for resolving land disputes was significantly improved, as evidenced by the decline in the OLD index from 0.59 in 2018 to 0.51 in 2021. This improvement could be attributed to the effectiveness of enhanced governmental working mechanisms, regulatory standards, and the integration of digital technologies. (3) The analysis of the center of gravity model indicated that the focus of land disputes shifted westward, propelled by national policy support for upstream regions of the YREB and the need for land ecological protection. (4) The analysis of kernel density estimation indicated that regional disparities in land disputes within the YREB had declined, driven by a positive trend toward balanced regional development and rural governance. This study provides scientific insights into the new characteristics of land disputes in the YREB and guidance for policy decision making on effective land dispute management.

Keywords: land disputes; characteristics; manifestation; formation mechanism; Yangtze River Economic Belt

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1. Introduction

Land disputes have significantly disrupted legal order, production, and social harmony and was regarded as a quintessential challenge in public governance, attracting worldwide attention from scholars [1]. As an emblematic feature of China's latest reform and opening-up strategy, the Yangtze River Economic Belt (YREB) in China has experienced rapid development after entering the new era (2012–2021), but also alongside substantial risks and challenges, particularly regarding land disputes [2]. According to statistics from the Ministry of Land and Resources of the People's Republic of China, rural mass incidents caused by land have accounted for more than 65% of all rural mass incidents, and mass incidents of land disputes have become a prominent problem affecting social stability [3]. After 2012, China entered into a new era, as China was at the inflection point, shifting from high-speed development to high-quality development [4]. Such a new era typically accompanies intricate social structures and urbanization processes, the evolution of land use and environmental issues, the widespread application of digitization and technological advancements, shifting cultural and societal values, as well as adjustments in laws and policies. The Chinese government unveiled the "Outline of the Yangtze River Economic Belt Development" in October 2016, reflecting the region as possessing the greatest developmental potential within China [5]. A better understanding of the manifestation and formation mechanism of new characteristics of land disputes in this new era is beneficial for contemporary public governance and for achieving a high-quality development of the YREB, whose GDP accounted for 46.3% of the national GDP in 2023.

The land issue is one of the most controversial issues [6], which has attracted considerable worldwide attention. The concept of land disputes was a subject of considerable debate among scholars. Campbell et al. (2000) defined land disputes as conflicts that arise during the process of land resource utilization [7]. Alston et al. (2000) described land disputes as conflicts or property infringements occurring between farmers, the government, and other stakeholders over land ownership and usage rights [8]. Wehrmann (2008) believed that land dispute was a social fact involving at least two parties [9]. In fact, scholars have not established a clear conceptual distinction between land disputes and land conflicts. However, compared with land conflicts, which are often framed in socio-political terms, land disputes are typically characterized by more legalistic language [10]. Although there is no universally accepted definition of land disputes, the academic consensus is that they fundamentally involve the contestation of land-related interests [11]. Current studies on the characteristics of land disputes often involve theoretical discussions based on regional investigations. For example, Kansanga et al. (2019) examined three case studies in the Upper West Region of Ghana and found that customary land boundary conflicts between communities were intensifying [12]. Mugizi and Matsumoto (2021) conducted household surveys in post-war Northern Uganda and concluded that land conflicts negatively impacted agricultural productivity [13]. Bekele et al. (2022) used cross-sectional household surveys of 870 households in Ethiopia and discovered that land conflicts increased with land investment [14]. Recently, the widespread application of quantitative modeling methods has inspired academic research on the spatiotemporal evolution of land disputes. For instance, Lin et al. (2018) utilized exploratory spatial data analysis to reveal the spatiotemporal characteristics of land expropriation conflicts in China from 2006 to 2016 [15]. Tan et al. (2021) employed descriptive statistics, a GIS spatial analysis, and Markov chains to uncover the spatiotemporal evolution of land contract disputes in the YREB from 2016 to 2021 [16]. However, these studies typically summarized the characteristics of land disputes through theoretical discussions or quantitative analyses of the number of land disputes, neglecting the fact that land disputes are an abstract concept encompassing various attributes such as quantity, claim amounts, and duration periods. It is difficult to establish a comprehensive and objective overall understanding of the characteristics of land disputes and their underlying dynamics from a single dimension measure.

Currently, quantitative modeling of social conflict risk has become a standard approach in social conflict research [17], e.g., the Global Conflict Risk Index [18], the Financial Risk Culture Intensity Index [19], and the Internal Armed Conflict Risk Index [20]. These studies provided valuable insights for the quantitative modeling of land disputes, but few were devoted to constructing the quantity index for land disputes when considering multi-dimensional factors and applying the index for further study. In this study, a total of 325,105 land dispute cases in 11 provinces or municipalities of the YREB from 2012 to 2021 were collected and analyzed. The case numbers, claim amounts, and duration were extracted from the case repository to construct an extensive and substantial database of land dispute cases. On this basis, an evaluation index system of the new characteristics of land disputes, named the overall land dispute (OLD) index, was constructed according to measurement theory by coupling the interactions of quantity, claim amounts, duration periods, and appeal rate of land disputes. Then, the OLD index was evaluated by descriptive statistical methods, a GIS spatial analysis, a center of gravity model, kernel density estimation, and Theil index methods to reveal the new characteristics and formation mechanisms of land disputes in the YREB from 2012 to 2021. As an important branch of social conflict and dispute studies, the novel research approaches and methodologies proposed in this study on land dispute characteristics provide valuable reference paradigms and research experiences for the investigation of other social conflicts and disputes.

2. Study Area, Data, and Methods

2.1. Study Area

The Yangtze River, renowned as the third longest river globally and the lengthiest within China, holds historical significance as the cradle of Chinese civilization and is often referred to as the "golden waterway". The Yangtze River Economic Belt (YREB) is located alongside the Yangtze River, covering nine provinces—Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Sichuan, Yunnan, and Guizhou—and two cities—Shanghai and Chongqing—as shown in Figure 1. The YREB spans approximately 2.05 million square kilometers, constituting 21% of China's territory [21]. In 2022, the YREB's GDP surged to CNY 56 trillion, contributing to 46.5% of the national economy, with a per capita GDP exceeding the national average by CNY 7541, totaling CNY 93,239. Moreover, the YREB is home to approximately 599 million inhabitants, representing 42.9% of China's total population [22].

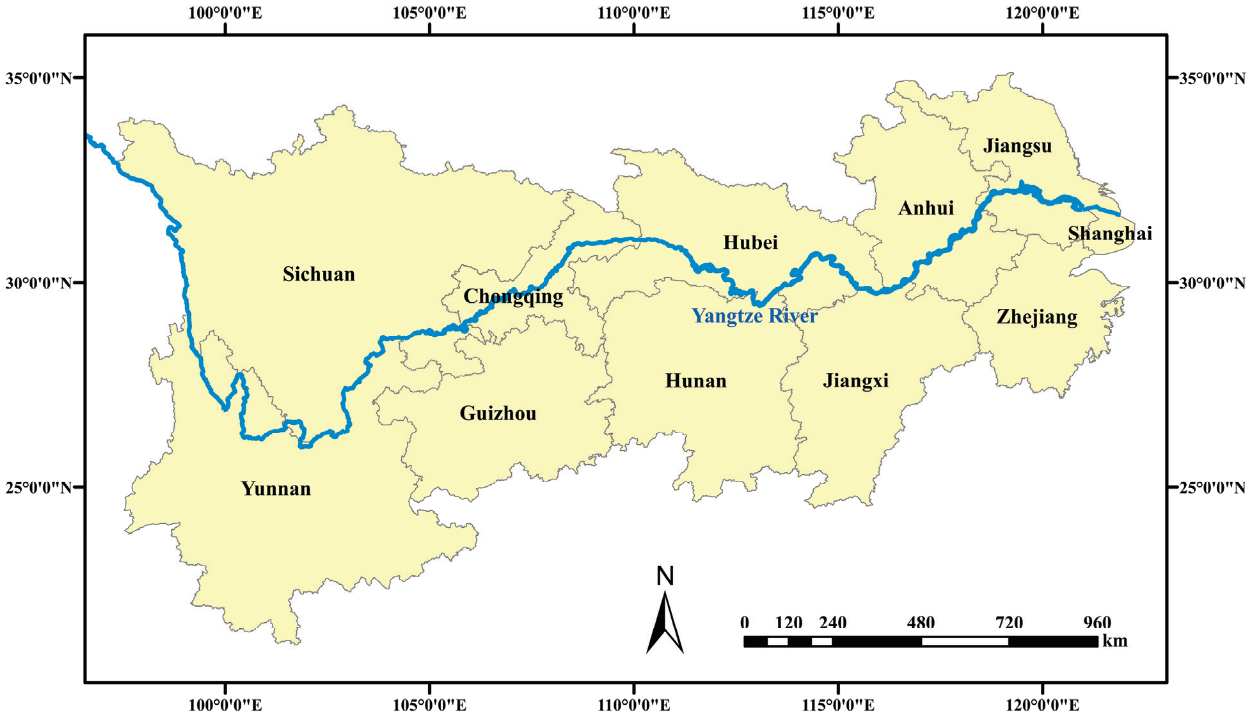

Figure 1. *Cont.*

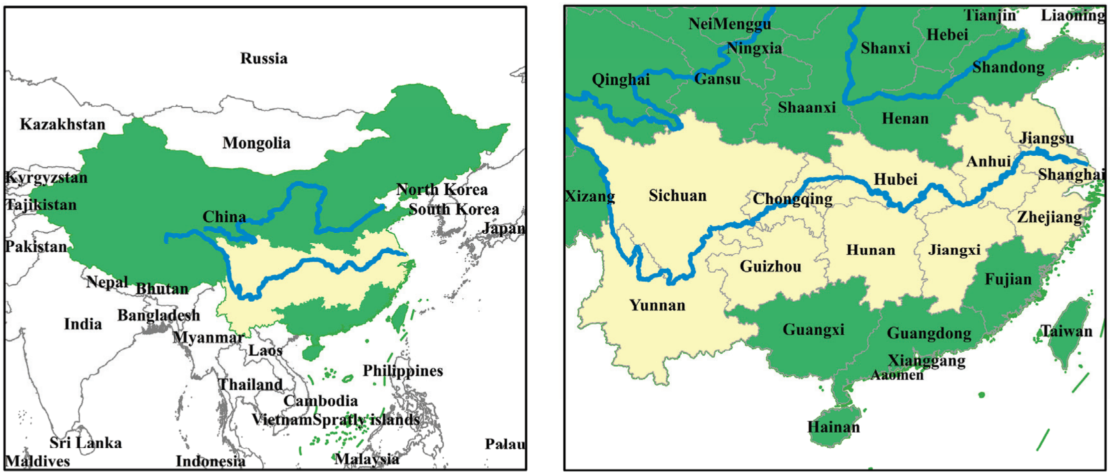

Figure 1. Study area.

In recent years, China has promulgated a series of policy directives to propel the development of the YREB, including the "Guiding Opinions on Leveraging the Golden Waterway to Promote the Development of the Yangtze River Economic Belt" (2014) and the "Outline of the Development Plan for the Yangtze River Economic Belt" (2016). As part of China's new wave of reform and opening up, coupled with the high-quality development strategies, the YREB has been treated as a pivotal area for national strategic development. Nevertheless, with the rapid economic growth in the accelerated urbanization process, the prominence of land disputes has arisen with the appreciating land values. Thus, a better understanding of the manifestation and formation mechanism of new characteristics of land disputes is beneficial for contemporary public governance and for achieving high-quality development of the YREB.

2.2. Data

The land dispute case dataset utilized in this paper was obtained from China Judgment Online (https://wenshu.court.gov.cn, accessed on 1 March 2023). The data acquisition process involved keyword searches for essential case documents using terms such as "land dispute", "land contract management", "land contract agreement", "land transfer", "land expropriation", and "distribution of land expropriation compensation". Subsequently, regular expressions were employed to parse and extract requisite information for the study, including case causes, trial periods, judicial reasoning, and verdicts. This paper adopted the provincial level within the Yangtze River Economic Belt (YREB) as its research scale, encompassing a total of 11 provinces or municipalities. The temporal scope was restricted to the years 2012 to 2021, resulting in the accumulation of 325,105 land dispute cases.

The socio-economic data utilized in this paper of formation mechanisms were sourced from a variety of official statistical publications, including the *China Rural Operation and Management Statistical Yearbook* (2012–2018), *China Rural Policy Reform Statistical Yearbook* (2019–2021), *China Statistical Yearbook* (2013–2022), *China Environmental Statistical Yearbook* (2013–2022), *China Natural Resources Statistical Yearbook* (2013–2022), *China Population and Employment Statistical Yearbook* (2013–2022), *China Urban Statistical Yearbook* (2013–2022), *China Urban Construction Statistical Yearbook* (2013–2022), and *China Science and Technology Statistical Yearbook* (2013–2022). Additionally, data from the official statistical yearbooks of the 11 provinces (or cities) within the Yangtze River Economic Belt (YREB), as well as publicly available data from the judicial department websites of the corresponding years, were incorporated. Due to discrepancies in statistical methodologies and data availability, obtaining complete datasets for certain provinces and municipalities posed challenges. In such instances, interpolation methods were employed to address missing data points.

2.3. Methods

2.3.1. Calculation of the Land Dispute Index

To evaluate the new characteristics of land disputes in the YREB comprehensively and quantitively, this paper utilizes the comprehensive index method to establish a new characteristic evaluation index system based on the textual information from the constructed land dispute case database and the current status of the YREB [23]. Four indicators, including the land dispute quantity, claim amounts, duration, and appeal rate, are coupled for the calculation of the land dispute index as follows:

$$LDL_{ij} = \int \left(LDC_{ij}, LDM_{ij}, LDT_{ij}, LDR_{ij}\right) \tag{1}$$

where LDL_{ij} represents the land dispute index for province (or city) j in year i. LDC_{ij}, LDM_{ij}, LDT_{ij}, and LDR_{ij} denote the quantity and claim amounts, duration, and plaintiff's appeal rate in province (or city) j in year i, respectively.

As the quantity of land disputes, claim amounts, duration, and appeal rate increase, the magnitude of land disputes also grows. Following the principle of multiplying similar factors and adding dissimilar ones, this study defines the expression for the land dispute index as:

$$LDL_{ij} = \lambda * \alpha \ln LDC_{ij} * \beta \ln LDM_{ij} * \gamma LDT_{ij} * \delta LDR_{ij} \tag{2}$$

where α, β, γ, and δ represent the weights of the quantity, claim amounts, duration, and plaintiff's appeal rate, respectively. Adopting the analytic hierarchy process (AHP) method [24], the weights of the aforementioned four indicators are calculated as 50.54%, 39.29%, 4.35%, and 5.82%, respectively. λ serves as the standardized adjustment coefficient. The variable LDL_{ij} ranges between 0 and 1.

This paper calculated the land dispute index of various provinces (or cities) in the YREB from 2012 to 2021 based on Equation (2). Subsequently, the spatiotemporal evolution of the land dispute index was calculated for analyzing the new characteristics of land disputes in the YREB.

2.3.2. The Center of Gravity Model

The center of gravity model was employed for the examination of the spatial movement and evolutionary processes of the specific elements within a defined geographical area [25]. This paper employed ArcGIS10.2 software to achieve a spatial visualization and quantitative analysis of the evolution patterns of land dispute centroids in the YREB. Assuming each province (or city) within the YREB constitutes a uniformly textured plane, geographic positions of provinces (or cities) were represented by latitude and longitude. Utilizing the center of gravity model, the centroids of land dispute indices for various provinces (or cities) within the YREB were computed over the years, thereby deriving the spatiotemporal evolution of land dispute centroids. The center of gravity model is calculated by:

$$X_t = \sum P_{ti} x_i / \sum P_{ti} \tag{3}$$

$$Y_t = \sum P_{ti} y_i / \sum P_{ti} \tag{4}$$

where X_t and Y_t represent the longitude and latitude coordinates, respectively, of the centroid of land disputes in the tth year; P_{ti} denotes the land dispute index of province (or city) i. x_i and y_i denote the longitude and latitude coordinates of the geometric center of province (or city) i, respectively.

2.3.3. Kernel Density Estimation

Kernel density estimation (KDE) is a non-parametric method used for estimating probability density curves, and it is capable of describing the distributional shape of random variables with continuous density curves [26]. It is widely employed in studying the dynamic evolution characteristics of sample data [27,28]. The equation of the kernel density function for the land dispute index is:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{5}$$

where $f(x)$ represents the density function of the land dispute index. x denotes the mean and N represents the number of observations; X_i signifies independently and identically distributed observations; $K(\cdot)$ stands for the kernel function, and h denotes the bandwidth. Additionally, the kernel function must satisfy conditions $\lim_{x\to\infty} K(x)\cdot x = 0$, $K(x) \geq 0$, $\int_{-\infty}^{+\infty} K(x)dx = 1$, $K(x) < +\infty$. The Gaussian kernel function, adopting a random variable x following a normal distribution, was employed in this study. The expression for the Gaussian kernel function is:

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \tag{6}$$

In this paper, the regional disparities in land disputes in the YREB was evaluated based on the distribution analysis of the kernel density curve of the land dispute index. Within the overall shape of the variable distribution, the height and width of peaks indicate the magnitude of disparities, while the number of peaks reflects polarization phenomena [29].

2.3.4. Theil Index

The Theil index, proposed by the economist Theil in the 1960s, is an important metric for measuring income disparities among individuals or regions [30]. It is widely used in various fields, such as land use efficiency or the distribution of social resources [31,32]. This paper calculated the Theil index for economic development, rural governance level, and land dispute index by

$$T = \frac{1}{n} \sum_{q=1}^{n} \left(\frac{S_q}{\overline{S}} \times ln \frac{S_q}{\overline{S}}\right) \tag{7}$$

where T represents the overall Theil index for the economic development level, rural governance level, and land dispute index within the YREB, $T \in [0, 1]$. A higher value of T indicates greater overall disparity, while a lower value suggests lesser disparity. S_q denotes the specific values of these indicators for each province or municipality, $\overline{S}$ signifies the average value of these indicators, and n represents the number of provinces (or cities) within the YREB.

3. Results

3.1. Spatiotemporal Evolution of the Land Dispute Index

3.1.1. Temporal Evolution

The overall land dispute (OLD) was classified into three categories in this study, including disputes of requisited land remuneration (DRLR), disputes of land ownership (DLO), and disputes of land contract (DLC) [11]. The temporal evolution of the land dispute index (LDI) for the YREB from 2012 to 2021 is presented in Figure 2, including the indicators of the overall land dispute and the categorical indicators of DRLR, DLO, and DLC. The results indicated that the OLD index of the YREB increased from 0.198 in 2012 to 0.590 in 2018, which was also the peak value during the research period, and then decreased to 0.510 at the end of 2021. The value of the OLD index increased by 2.58 times, which increased from 2012 to 2018 at the beginning and then decreased from 2018 to 2021. The polynomial relationship model for the OLD index was fitted as follows:

$$y = -0.011x^2 + 0.151x + 0.055 \tag{8}$$

where y is the OLD index and x refers to the year. The R^2 of the fitted equation is 0.992, showing a reliable matching. It is worth noting that although the OLD index has begun to decline in the new era; its absolute value was still above 0.510 and remained relatively high.

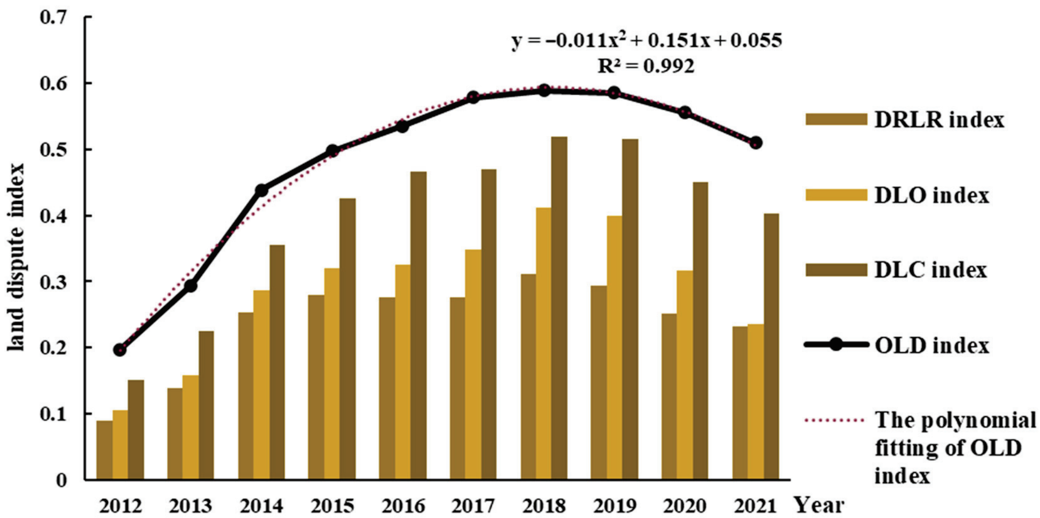

Figure 2. The indices of OLD, DRLR, DLO, and DLC in the Yangtze River Economic Belt from 2012 to 2021.

Specifically, the DRLR index fluctuated upward from 0.090 in 2012 to 0.311 in 2018 and then downward to 0.233 in 2021; the DLO index increased from 0.105 in 2012 to 0.412 in 2018 and then decreased to 0.235 in 2021; the DLC index increased from 0.152 in 2012 to 0.519 in 2018 and then decreased to 0.403 in 2021. The index value of DLCs was the largest, followed by that of DRLR and DLO, all of which show the same tendency as the OLD index from 2012 to 2021. However, it should be noted that the conflicts caused by the DLCs were more serious and, which suggests that they require more attention.

3.1.2. Spatial Evolution

The focus of the OLD index in the YREB from 2012 to 2021 was evaluated by a center of gravity approach and illustrated on the provincial (city) map, as shown in Figure 3. And the focus evolution of longitude and latitude was presented in Figure 4. The results indicated that the focus of the OLD index in the YREB moved from Jiangxia district, Wuhan, Hubei Province, in 2012 to Gong'an County, Jingzhou, Hubei Province, China, in 2016. The moving trajectory covered a distance of 167.4 km along the southwest direction during this period, and the largest moving distance per year occurred in 2013–2014. From 2016 to 2018, the focus of the OLD index in the YREB moved from Gong'an County, Jingzhou, Hubei Province, to Linli County, Changde, Hunan Province. Since then, the focus of the OLD index in the YREB moved back to Gong'an County, Jingzhou, Hubei Province, China. The moving trajectory covered a distance of 24.18 km along the northwest direction initially and then the southwest direction during this period. The moving trajectory initially covered a distance of 41.63 km along the northeast direction and then the southeast direction during this period. Generally speaking, during the period from 2012 to 2021, the focus of the OLD index in the YREB moved westward significantly with a slightly southward tendency.

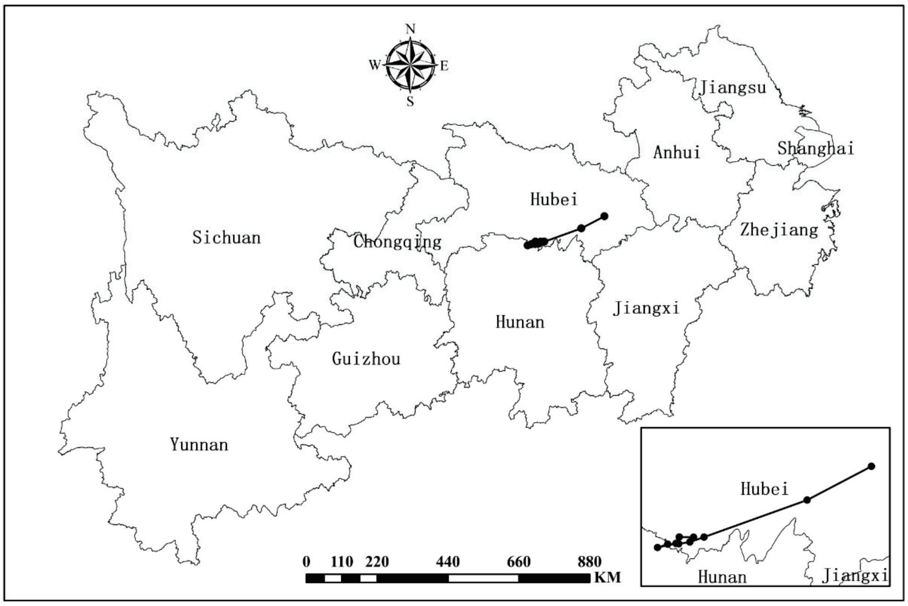

Figure 3. The migration trajectory of the focus of the OLD index in the Yangtze River Economic Belt from 2012 to 2021.

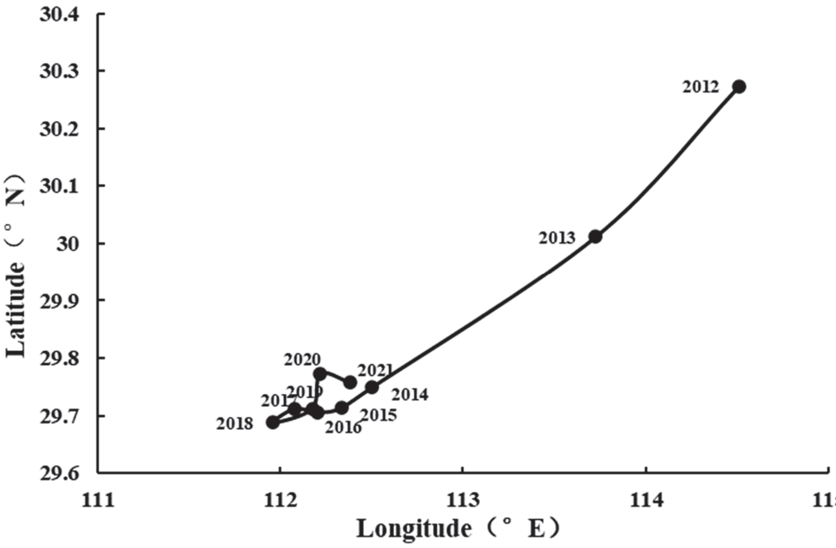

Figure 4. Details of the migration trajectory of the focal point of land disputes in the Yangtze River Economic Belt from 2012 to 2021.

The kernel density estimation of the OLD index in the YREB from 2012 to 2021 was calculated and presented in Figure 5. The center of the kernel density distribution moved to the right over time during 2012–2018, and then to the left during 2018–2021, indicating that the OLD index initially increased and then decreased during the research period. Overall, the peak value of the kernel density estimation showed a fluctuating upward tendency, which rapidly increased during 2012–2018 and gradually decreased during 2018–2021, rebounding during 2020–2021. The fluctuating tendency indicated that the regional disparity of the OLD index initially decreased, then increased, and then decreased again. In addition, only one peak was presented in the curve of the kernel density estimation in the early stage of the research period, but there were two peaks, including one main peak and one secondary peak, after 2017. During the research period, there was an unclear polarization phenomenon in land disputes within the YREB. Generally speaking, during the period from 2012 to 2021, there was an unclear polarization phenomenon in land disputes within the YREB, but regional disparities have been generally decreased.

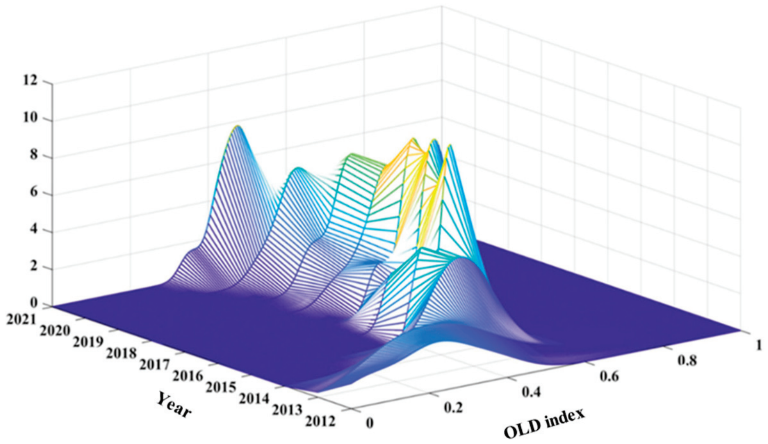

Figure 5. Kernel density estimation of the OLD index in the YREB from 2012 to 2021.

3.2. Analysis of New Characteristics and Formation Mechanisms

3.2.1. Land Disputes Have Been Alleviated

For a long time, land disputes have shown an increasing trend in terms of quantity, scale, and degree, exerting increasingly significant impacts on social and political stability [33], which were prone to incite collective events, posing as the foremost challenge to rural social stability and development [34]. However, the temporal evolution analysis on the spatiotemporal evolution of the land dispute index of the YREB showed a significant decline in the land dispute index in the new era. The results could be concluded as a new characteristic that the land disputes have been alleviated in the new era. The formation of this new characteristic is attributed to the coupled effects of the continuous optimization of land utilization structure, gradual improvement of land utilization systems, and ongoing enhancement of public legal awareness in the transition of the YREB towards high-quality development.

(1) The optimization of land utilization structure has led to the alleviation of conflicts arising from land disputes. The stakeholder theory posited that the fundamental reason of conflicts lays in the divergent interests of various parties and the local government's need to balance the needs of all stakeholders through rational resource allocation and management [35]. The strategically planned land use and optimizing land utilization structure were beneficial for balancing the land utilization needs of all stakeholders, including local governments, residents, developers, farmers, and so on [36], thereby reducing potential risks of land disputes. In the new era, various local governments of the YREB continuously optimized the land structure within administrative boundaries through new policy implementation including, adjusting land use planning, activating idle land, and addressing land pollution. For example, the Government of Zaoyang City in Hubei Province issued the "Management Measures for the Change of Use of State-Owned Construction Land in Zaoyang City"; the Natural Resources and Planning Bureau of Huai'an City in Jiangsu Province exceeded its targets for revitalizing and disposing of idle land, and fifteen departments in Mianyang City, Sichuan Province, jointly released the "14th Five-Year Plan for Soil Pollution Prevention and Control in Mianyang City" [37]. According to the index system proposed by Zhu et al. (2021) [38], the average efficiency of land utilization structure in the YREB during the period of 2018–2021, when the land dispute index declined, is calculated and presented in Figure 6. It was evident that the average efficiency values of land utilization structure in the YREB increased with time and was negatively correlated with the OLD index. The results indicated that the land utilization structure in the YREB

was becoming more reasonable and the land use demands of various industries were better balanced, thereby alleviating land disputes.

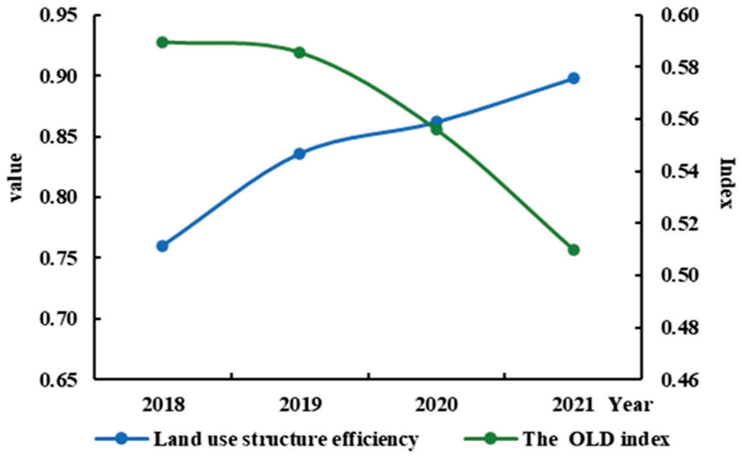

Figure 6. Land use structure efficiency and OLD index in the YREB from 2018 to 2021.

(2) The improvement of land utilization systems led to the alleviation of land disputes. According to institutional change theory, institutional change begins with society's perception of problems. When existing institutional frameworks fail to effectively address or adapt to new social issues, the reduction of social conflicts can be achieved through adjustments and improvements to the institutions [39]. The continuous adaptation of land utilization systems to the changes in social economy, technology, and culture can effectively advance the smooth operation of the land market and thereby lead to the alleviation of land disputes. Previous studies have pointed out that the deficiencies in land regulations, e.g., the deficiencies in the land acquisition system, the ambiguity in agricultural land ownership, the incomplete contracting rights of agricultural land, the ambiguous delineation of collective member entitlements, the deficiencies in land conflict mediation systems, etc., were important causes of land disputes in the past [40]. After entering the new era, the utilization system in China was improved continuously, including establishing the separation system of ownership, contracting rights, and management rights for rural land; extending the second round of land contracting for another thirty years upon expiration; promoting the market entry of collectively owned commercial construction land and reforming the homestead system; improving the rural land property rights transfer and transaction system; and so on [41]. Furthermore, the percentage of villages in the YREB that have completed property rights system reforms was adopted in this study as a measuring index of perfection in land utilization systems, which is calculated and presented in Figure 7. The perfection of land utilization systems in the YREB has been significantly improved, with an increase of 187.7% over the four-year period, while the land dispute index was continuously decreased by about 13.50%. The results indicate that as the land utilization systems in the YREB was improved contentiously, more flexible, fair, and sustainable solutions to land utilization have been achieved, thereby alleviating land disputes in the YREB.

(3) Enhancing public legal awareness facilitated the alleviation of land disputes. The legal sociology theory by Max Weber posited that enhancing public legal awareness allowed individuals to a deeper understanding that the law was not merely a transcendent set of rules but rather a product of collective social organization. This awareness was helpful for understanding the legitimacy and authority of law, thereby urging them to abide by regulations and restrain their own unlawful behaviors [42]. In land utilization activities, enhancing public legal awareness could assist individuals in better understanding the societal background and purposes of the land regulations, which could strengthen the normative cognition of lawful land utilization activities, thus alleviating land disputes. Inspired by the new era's rural revitalization strategy, various local governments in the YREB were eager to enhance farmers' legal awareness. For instance, in Pengxi County, Sichuan Province,

the "Rule of Law Services for Rural Revitalization" tour has been launched to provide a common show on a popularization performance with vivid and simple language. Additionally, six departments in Yunnan Province jointly formulated the "Three-Year Action Plan for Legal Propaganda and Education to Support Rural Revitalization", providing legal guarantees for rural revitalization. Meanwhile, the Department of Agriculture and Rural Affairs of Jiangxi Province has launched the "Rural Revitalization, Legal Primacy" for popularizing law, which ignited the public enthusiasm of legal learning throughout the province's rural areas. According to Silbey (2005) [43], the number of practicing lawyers was adopted as the index of public legal awareness and was calculated. As shown in Figure 8, the public legal awareness in the YREB increased with time in 2018–2021, showing a negative correlation with the OLD index. The results indicated that as public legal awareness improved, the land utilization activities of the farmers were further regulated, which significantly alleviated land disputes.

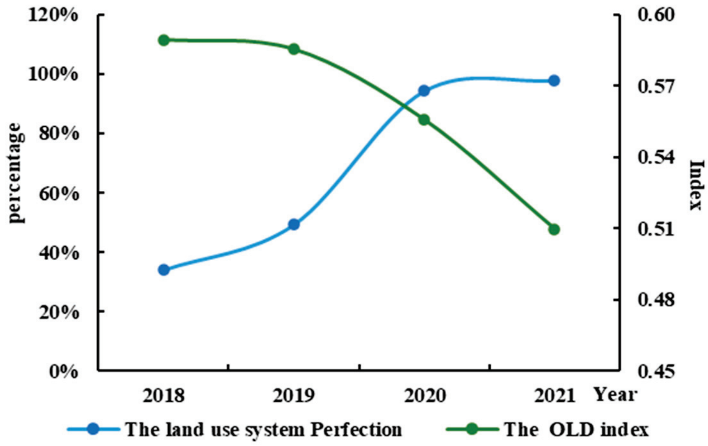

Figure 7. Land use system perfection and OLD index in the YREB from 2018 to 2021.

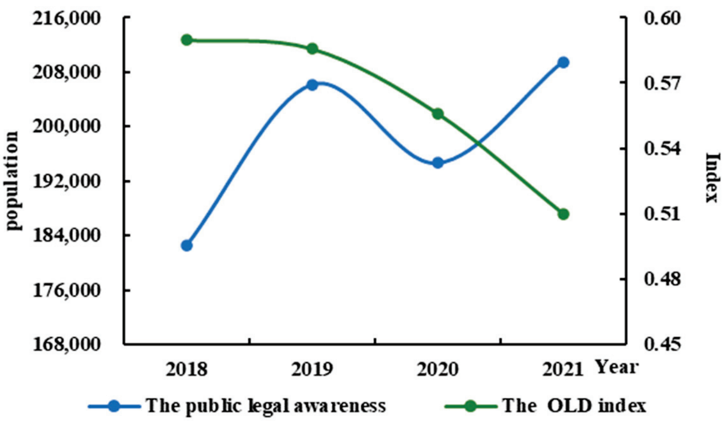

Figure 8. The public legal awareness and OLD index in the YREB from 2018 to 2021.

3.2.2. The Capacity for Resolving Land Disputes Has Been Enhanced

The temporal evolution of the land dispute index from 2012 to 2021 in Section 3.1.1 showed a significant decline during the new era, which could be concluded as the governmental capacity for resolving land disputes having been enhanced. The reason for this new characteristic in the new era lay in the continuous refinement of governmental operation, the gradual application of digital technologies into governance practices, and the enhancement of governmental regulatory standards.

(1) Strengthening institutional development enhanced the capacity for resolving land disputes. The new institutionalism theory holds that institutions play a normative role.

Through the reinforcement of institutional development, governments could improve their internal structures and operations to enhance governance efficacy and better fulfill their responsibilities [44]. In the operation of the land market, the governments could establish clearer and more comprehensive rules and procedures for dispute resolution in order to resolve or prevent land disputes by diversified approaches. It was helpful in the prompt and accurate coordination among relevant departments in resolving land disputes [45], resulting in the promotion of the governmental efficiency of land affairs governance and facilitating the fulfillment of its responsibilities in social governance. Entering the new era, General Secretary Xi Jinping has repeatedly emphasized the importance of adhering to and developing the "Fengqiao Experience", providing guidance for the construction of the diversified prevention and resolution mechanism for land disputes for local governments in the YREB. This study adopted the number of arbitration committee members as the intensity measure of the dispute resolution institutional development, according to Tan and Zou (2022) [46]. As shown in Figure 9, the overall intensity of dispute resolution institutional development among provinces (or cities) in the YREB exhibited an upward trend. The results indicate that with the enhancement of the dispute resolution institutional development in the YREB, as well as the diversified mechanisms for the prevention and resolution of land dispute, the government's capacity for resolving land disputes was enhanced.

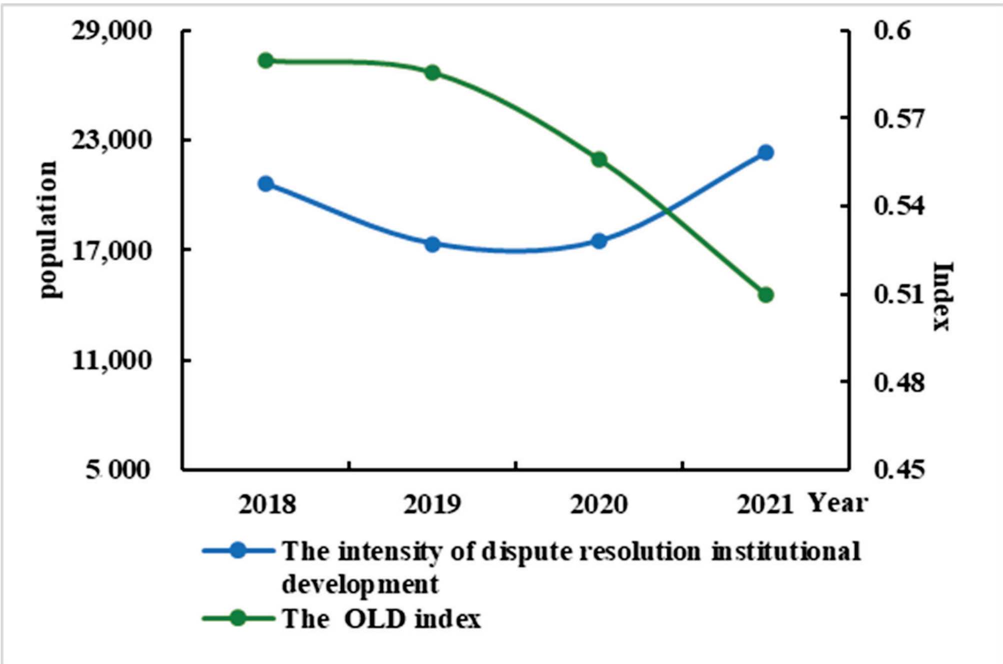

Figure 9. The intensity of dispute resolution institutional development and OLD index in the YREB from 2018 to 2021.

(2) Utilizing digital technology enhanced land dispute resolution capability. The theory of new public services posited that public service providers were supposed to continuously enhance the quality and efficiency of services using new technologies. The application of digital technology was believed to offer a more intelligent, efficient, and service-oriented governance approach, which contributed to the improvement of public service capabilities [43]. In contemporary society, governments serve as public service providers. By integrating digital technologies such as artificial intelligence and big data analytics into land management, governments could not only facilitate the efficient management and sharing of land information [47] but also provide intelligent decision support systems for resolving land disputes [48], which prompted the governmental capacities in land dispute resolution. Entering the new era, General Secretary Xi Jinping proposed that "We must

utilize big data to enhance the modernization of national governance, and establish sound operations for big data-assisted scientific decision-making and social governance". Various local governments in the YREB have acted on the national call. For instance, Xiaoshan District in Zhejiang Province has implemented a new digitalized grassroots social governance model. The Shanghai courts have embedded "digital court" applications into case handling systems to provide decision-making references for judicial trials. Additionally, Xuzhou in Jiangsu Province has embraced a new model of social governance, combining big data analytics and artificial intelligence applications. This paper adopted the annual counts of patent applications in high-tech industries as a metric for measuring the innovative output of digital technology. As in Figure 10, there was a significant increase in the innovation output of digital technology in the YREB during the periods when the land dispute index declined. The results indicated that the application of digital technology was beneficial in resolving conflicts and disputes, with land disputes serving as a representative example.

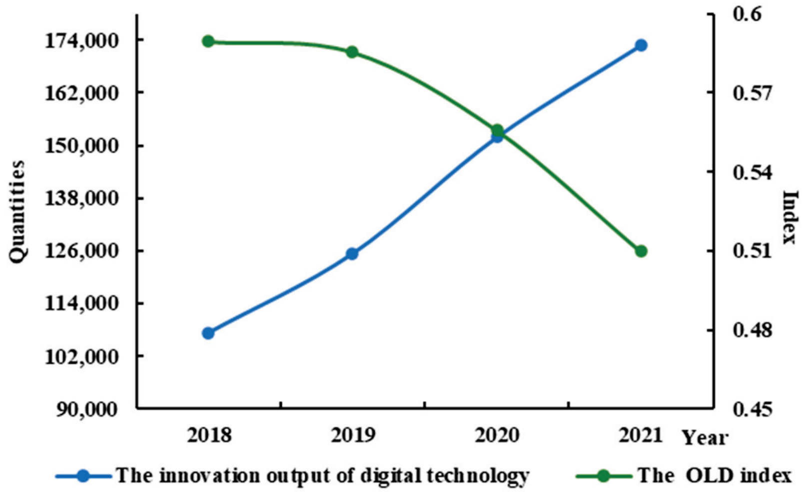

Figure 10. The innovation output of digital technology and OLD index in the YREB from 2018 to 2021.

(3) Strengthening government oversight enhanced the land dispute resolution capability. According to the theory of agency, agents might not always act in accordance with the rule of maximizing the principal's interests, which require government oversight or incentive operations to address agency problems [49]. In the governance of land disputes specifically, agents (the government) might not fully fulfill the expectations of the principal (the public) due to their own interests. In this case, government oversight could be considered an effective supervisory mechanism, which enables the public to effectively access, assess, and rectify the information asymmetries in government behaviors [50]. This was helpful in enhancing the government's capability to resolve land disputes. Entering the new era, local governments in the YREB were continuously strengthening government oversight and vigorously combating land-related illegal activities in order to promote the modernization of the land dispute governance system and governance capabilities. In this study, the annual quantity of land violation disposals was used as a measure of the intensity of government oversight. As in Figure 11, the intensity of the government oversight in land management in the YREB was continuously strengthened during the periods when the land dispute index declined, resulting in a significant enhancement in land dispute resolution capability.

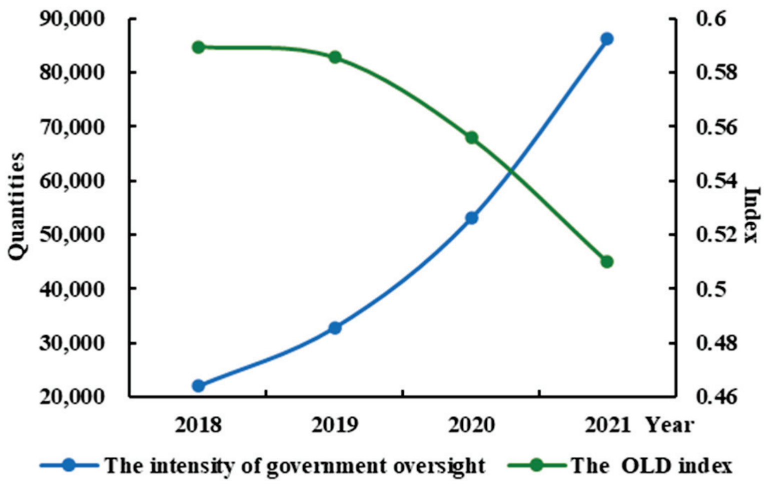

Figure 11. The intensity of government oversight and OLD index in the YREB from 2018 to 2021.

3.2.3. The Focus of Land Disputes Moved to the West in the YREB

Previous studies indicated that the land disputes were severe in the developed coastal areas in the east during periods of rapid economic development in China [51]. However, the spatial analysis of land dispute index in the YREB from 2012 to 2021 highlighted a new characteristic of land disputes where the focus of land disputes in the YREB moved to the west. This new characteristic was attributed to the influence of national policies supporting the upstream regions of the YREB. These regions were entrusted with more significant tasks related to land ecological protection as the economic developed rapidly, which resulted in more conflicts when compromising the balance between economic development and land ecological conservation compared with other regions.

(1) Urgent requirements for the increased demand for land led to the focus of land disputes towards the west. According to the theory of supply and demand, land was one of the factors of production under market economy conditions, which was influenced by supply and demand dynamics [52]. When the increasing demand for land resources in the market exceeded its supply, land prices increased and competition for land and its associated benefits intensified accordingly [53]. In the new era, the center of the regional development in the YREB exhibited accelerated westward migration characteristics [54]. Economic development served as the primary driver of urban expansion. Local governments in the upstream regions of the YREB were eager to promote urban expansion to accelerate regional economic development. In this study, the annual area of the requisitioned collective land was used as a metric for land demand. As in Figure 12, the focus of the land demand in the YREB showed a trajectory of “northeast-southwest-northeast-southwest”. Overall, there was a westward trend, consistent with the OLD index. The results indicate that as urban expansion accelerated in the upstream regions of the YREB, the focus of land demand moved westward, leading to an increase in land disputes and a westward shift in the focus of land disputes.

(2) Urgent requirements for land ecological protection caused the focus and disputes to move to the west. Spatial conflict theory suggested that spatial conflicts arise from the opposition and competition among stakeholders for resources (assets) [55] or from the overlapping of spatial utilization in an irrational manner [56]. The limited land space and the increasing diverse land demands led to conflicts. In the new era, General Secretary Xi Jinping emphasized the development principle of the YREB as “pursuing green development and rejecting large-scale unsustainable development”. Located in Western China, the upstream area of the YREB serves as a crucial ecological barrier zone for the Yangtze River basin and even the whole nation, where the restricted ecological area by the government is 804.3 km^2, accounting for 67.7% of the total restricted ecological area of the YREB [57]. While promoting economic development, local governments in the upstream YREB have also strengthened the protection and restoration of land resources. In this study,

the annual area of forestland converted from cropland in 2012–2021 was treated as a metric to measure the intensity of land ecological protection, and that of the upstream, midstream, and downstream areas of the YREB is calculated and presented in Figure 13. The intensity of land ecological protection in the upstream area of the YREB has consistently remained the highest in 2012–2020 with an average of 80%, followed by the midstream area at 18% and the downstream area at 1%. Consequently, with the implementation of measures such as restricting land use, restoring polluted land, and converting cropland to forest, more land space was required for land ecological protection, resulting in land utilization conflicts and a tendency of the focus of land disputes to move westward.

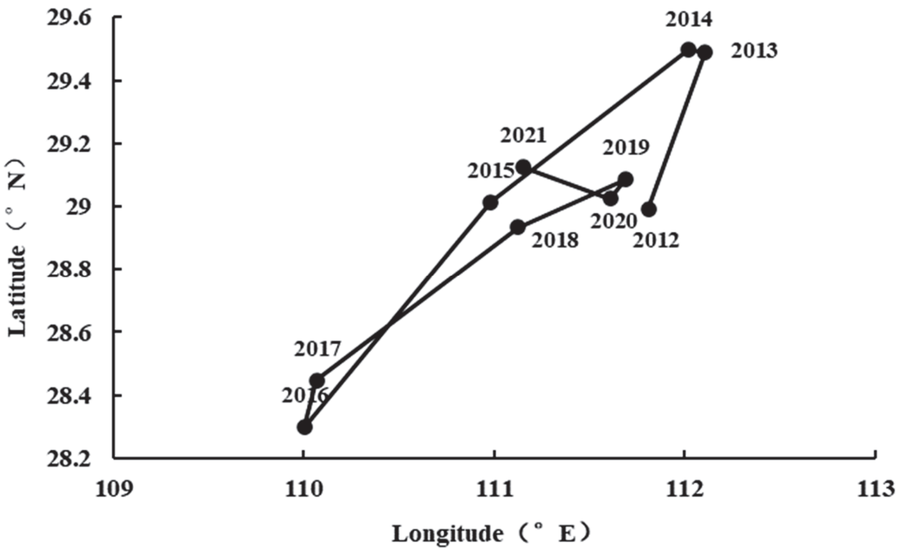

Figure 12. The migration trajectory of the focus of land demand in the Yangtze River Economic Belt from 2012 to 2021.

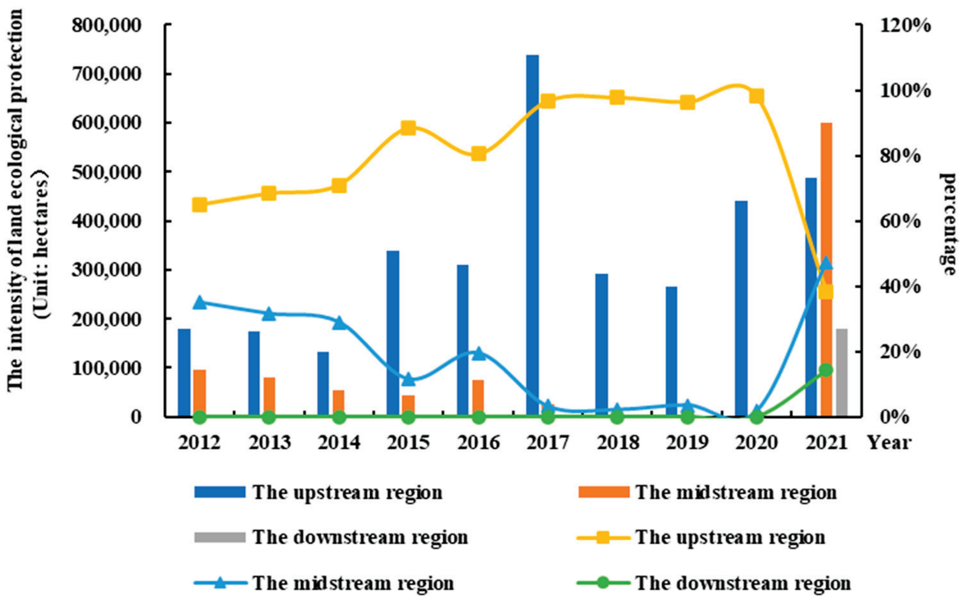

Figure 13. The land ecological protection intensity and its proportion in the upstream, midstream, and downstream regions of the YREB from 2012 to 2021.

3.2.4. Regional Disparities in Land Disputes Have Declined

According to research conducted by the groups at the Chinese Academy of Agricultural Sciences, the land dispute occurrence rates across different regions in China have shown significant disparities since 2005 [58]. However, the spatial evolution analysis of the OLD index in the YREB revealed a new characteristic: the regional disparity in land disputes has declined. This new characteristic was attributed to the regional disparity of both land disputes and the governance level being decreased as a result of reduced regional disparities in economic development and inputs into rural governance in the accelerated pace of integrated development in the YREB in the new era.

(1) The decline in the regional disparity of the economic development led to a decrease in the regional disparity of land disputes. The theory of growth poles posits that as the initial growth pole regions developed, their diffusion effects in economic activities, including technology diffusion, talent migration, and the expansion of industrial chains, would reduce regional development disparities [59]. Many research studies have revealed the significant correlation between economic growth and land disputes [60,61]. As economic activities in growth pole regions spread, the reduction in regional development disparities also led to a decrease in regional disparities in land disputes and their spread. A previous study indicated that the disparities in high-quality economic development in the YREB have been continuously diminishing and the imbalances within urban agglomerations gradually decreased, and the disparities in the development capabilities among cities decreased as well [62]. In this study, the per capita GDP was employed as a measure of economic development level, while its Theil index calculation was used for the measure of the internal economic development disparities within the YREB, both of which showed a declining trend from 2012 to 2021, as in Figure 14. The Theil index of the YREB decreased from 0.119 in 2012 to 0.075 in 2021. The results indicated that the internal economic development disparities within the YREB decreased consistently, aligning with the trend observed in the Theil index of OLD index. Thus, the decline in the regional disparity of the economic development led to a decrease in the regional disparity of land disputes.

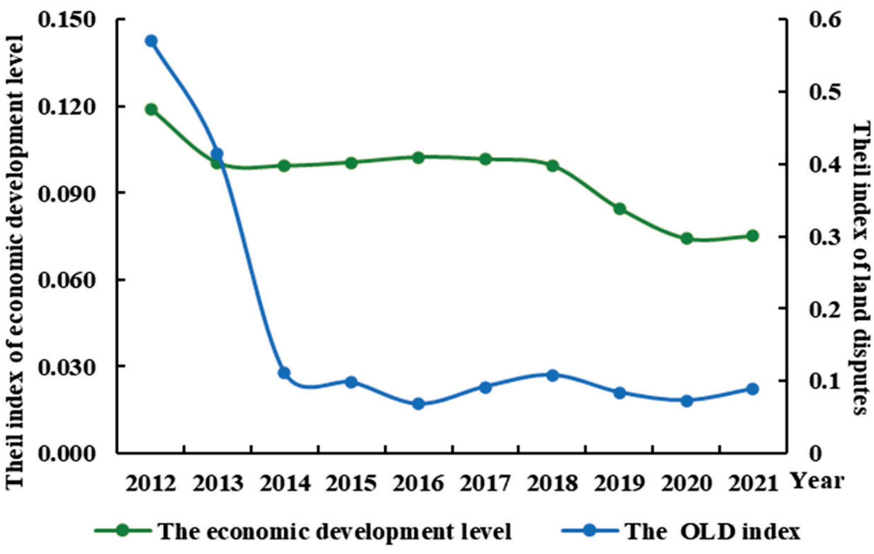

Figure 14. The Theil index of economic development level and land disputes within the YREB from 2012 to 2021.

(2) The decline in the regional disparity of the rural governance level led to a decrease in the regional disparity of land disputes. The theory of public governance suggests that improving the government public services could promote the governance capacity and reduce the uncertainty and probability of conflicts [63]. Previous studies have stated that the modernization level of rural governance in East China was higher than that in West China. However, the regional disparities in governance level have been gradually

diminishing [64], which consequently led to a reduction in the regional disparity of land conflicts. In the new era, local governments in the YREB are continuously enhancing governance capacity, especially rural governance capacity. This study adopted the success rate of dispute mediation in the rural governance capacity evaluation index, proposed by Gao et al. (2024) [65], as a quantitative indicator of the rural governance level. The Theil index of the rural governance level within the YREB from 2012 to 2021 is calculated and shown in Figure 15, as well as the Theil index of land disputes. The Theil index of rural governance level within the YREB decreased from 0.212 in 2012 to 0.076 in 2021, showing a downward trend on the whole, which was consistent with the trend in the Theil index of the OLD index. Thus, the decline in the regional disparity of the rural governance level led to a decrease in the regional disparity of land disputes.

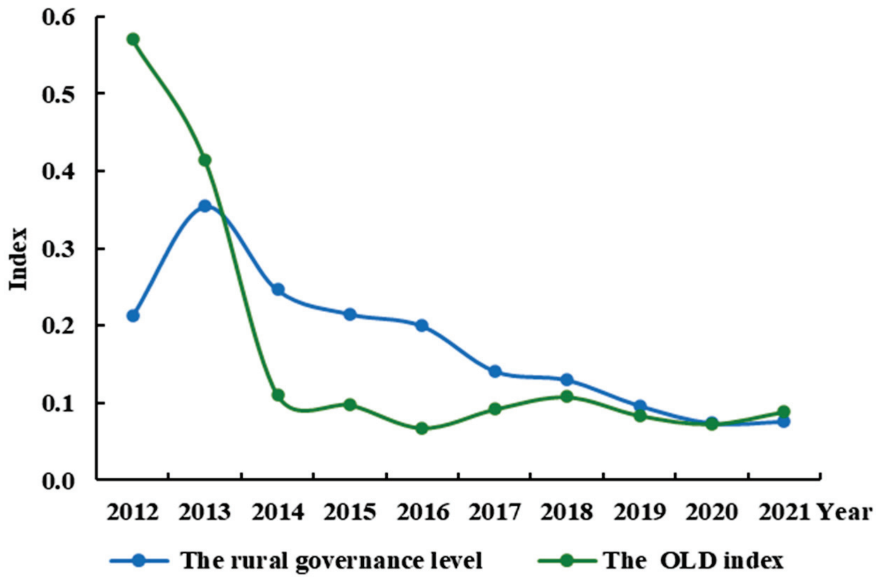

Figure 15. The Theil index of the rural governance level and land disputes in the YREB from 2012 to 2021.

4. Discussion

This study aims to provide a tool for characterizing and analyzing land disputes in the YREB in China, which is beneficial for contemporary public governance and for achieving a high-quality development of the YREB. Some meaningful and new achievements have been acquired. For example, this study found that the number of land acquisition conflicts in the YREB first increased and then decreased over time, which was similar to the result in previous studies [15,46]. Meanwhile, a previous study also revealed that the number of land disputes in western regions surpassed that in eastern regions [16], which also corroborated the observation that the focus of land disputes has shifted westward in this study, as evidenced in our research from one aspect. However, this study also indicated that these disparities declined over time, although there were significant regional disparities in current land disputes. This positive progress indicated an overall improvement in land disputes in the YREB. Furthermore, an evaluation index system of the new characteristics of land disputes, named the overall land dispute (OLD) index, was constructed according to measurement theory by coupling the interactions of quantity, claim amounts, duration periods, and the appeal rate of land disputes. The OLD index was evaluated by descriptive statistical methods, a GIS spatial analysis, a center of gravity model, kernel density estimation, and Theil index methods. Then, the new characteristics of the land disputes in the YREB were acquired through quantitative analysis.

Faced with land disputes accompanying economic growth in the new era, government intervention played an important role in land dispute resolution [66]. A set of land dispute resolution mechanisms including legislation, propaganda, negotiations, mediation, litigation, arbitration, administrative reconsideration, and petitions have been established [44,45]. These mechanisms have led to the emergence of new characteristics in the YREB, such as the alleviation of land disputes and the enhancement of dispute resolution capabilities, indicating that the overall situation regarding land disputes in the YREB shows improvement. However, due to the increasing cross-border, interconnected, and complex nature of land dispute issues [67], the absolute level of land disputes in the YREB remains relatively high, and the focus of land disputes has shifted westward. Thus, some policy implications are recommended in the prevention and resolution of land disputes, as follows:

(1) The land disputes remain at a high level in both complexity and quantity, which requires the government to construct a multi-level and multi-faceted dispute resolution mechanism, not just solve cases using the judicial system. Considering that the judicial system was overwhelmed by a high volume of cases and small-scale disputes [68], the optimized dispute resolution system should offer multiple remedies for the parties, fully utilize various dispute resolution methods, and strive to resolve disputes quickly and properly.

(2) The government should pay attention to the shifting focus of land disputes towards the west in recent years. The western region of the YREB was at a relatively low economic development level, where the government heavily relied on land-based fiscal income due to a lack of diversified revenue sources, and it had also been assigned a crucial role in national ecological protection [69]. The local governments are suggested to vigorously support the development of innovative economies in this region and reduce reliance on land finance. At the same time, the land protection and governance should be strengthened to promote the sustainable development of land resources and reduce the possibility of potential land disputes as well.

(3) Currently, as a positive tendency, the regional disparities in land disputes are declining. The establishment of a unified information sharing platform is essential for further decreasing the regional disparities [70]. In this case, the platform not only enables the effective sharing of resources relevant to land dispute governance but also facilitates the expeditious resolution of inter-provincial and inter-municipal land dispute cases. It is instrumental in proactively preventing and mitigating the adverse consequences that may arise from land disputes.

(4) The overall capacity for resolving land disputes has been constantly improved. Nowadays, artificial intelligence and big data provide new tools for local governments in the YREB to monitor and manage the land dispute information [71]. It would facilitate the integration and management of collected land dispute information, enabling real-time updates and queries. And the assisted decision-making system using AI and big data would be recommended for highlighting and solving the higher levels of dispute and prominent issues noted by public feedback.

It should be noted that more details, such as the number of individuals involved in the disputes, the area of disputed land, whether legal representation was sought, or whether the disputes constituted collective events, were difficult to extract from court judgments, which were omitted by the current technologies. Furthermore, future research should focus on enhancing the evaluation system of land disputes comprehensively by coupling augmented discussions on relevant land dispute cases in representative regions.

5. Conclusions

A better understanding of the manifestation and formation mechanism of new characteristics of land disputes is beneficial for contemporary public governance and for achieving a high-quality development of the YREB. A total of 325,105 land dispute cases in 11 provinces or municipalities of the YREB from 2012 to 2021 were collected and analyzed. On this basis, an evaluation index system of the new characteristics of land disputes, named the overall land dispute (OLD) index, was constructed according to measurement theory by coupling the interactions of quantity, claim amounts, duration periods, and the appeal rate of land disputes. Then, the OLD index was evaluated by descriptive statistical methods, a

GIS spatial analysis, a center of gravity model, a kernel density estimation, and Theil index methods, to reveal the new characteristics and formation mechanisms of land disputes in the YREB from 2012 to 2021. The main conclusions of this study are as follows:

(1) **Land disputes have been alleviated**, as evidenced by the trends of the OLD, DRLR, DLO, and DLC indices, all of which initially increased but have subsequently declined in the new era. However, the OLD index remained above 0.510, indicating a relatively high level, with conflicts stemming from DLCs appearing to be more severe compared with other types of disputes. The alleviation of land disputes in the YREB could be attributed to the collective effects of the region transitioning into a phase of high-quality development, characterized by the continuous optimization of land utilization structure, gradual improvement of land utilization systems, and the ongoing enhancement of public legal awareness.

(2) **The capacity for resolving land disputes has been enhanced.** The OLD index exhibited a significant decline, decreasing from 0.59 in 2018 to 0.51 in 2021, reflecting a notable promotion in the government's land dispute resolution capabilities. This promotion was attributed to the continuous improvement of governmental working mechanisms, the gradual integration of digital technologies into governance, and the steady enhancement of governmental regulatory standards.

(3) **The focus of land disputes moved to the west in the YREB.** Based on the analysis of the spatial evolution of the OLD index from 2012 to 2021, the focus of the index in the YREB exhibited a significant westward shift along with a slight southward tendency. Urgent requirements for land ecological protection led to more severe conflicts between economic development and land ecological preservation compared with other regions due to the national policy support for the upstream regions of the YREB.

(4) **Regional disparities in land disputes have declined.** According to the kernel density estimation of the OLD index, the overall rise in the peak of the kernel density curve indicated the new characteristic of reduced regional disparities in land disputes within the YREB. This characteristic was attributed to the reduction in regional disparities in both land disputes and governance levels. The reduction was a result of the decreased regional disparities in economic development and investments in rural governance, driven by the accelerated pace of integrated development in the YREB in the new era.

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References

1. Gong, X. Non-traditional security cooperation between China and south-east Asia: Implications for Indo-Pacific geopolitics. *Int. Aff.* **2020**, *96*, 29–48. [CrossRef]
2. Rose, L. *The Politics of Harmony: Land Dispute Strategies in Swaziland*; Cambridge University Press: Cambridge, UK, 1992.
3. Yang, S.; Wen, T. The Economic Fluctuations, the Change in Taxation Institution, and the Capitalization of Land Resources: A Case Study on the Problems with "The Three Times of Enclosing Land" since China's Reform. *Manag. World* **2010**, *4*, 32–41+187.
4. Pan, W.; Wang, J.; Lu, Z.; Liu, Y.; Li, Y. High-quality development in China: Measurement system, spatial pattern, and improvement paths. *Habitat Int.* **2021**, *118*, 102458. [CrossRef]
5. Sun, C.; Chen, L.; Tian, Y. Study on the urban state carrying capacity for unbalanced sustainable development regions: Evidence from the Yangtze River Economic Belt. *Ecol. Indic.* **2018**, *89*, 150–158. [CrossRef]
6. Platteau, J. The evolutionary theory of land rights as applied to sub-Saharan Africa: A critical assessment. *Dev. Change* **1996**, *27*, 29–86. [CrossRef]

7. Campbell, D.; Gichohi, H.; Mwangi, A.; Chege, L. Land use conflict in Kajiado district, Kenya. *Land Use Policy* **2000**, *17*, 337–348. [CrossRef]
8. Alston, L.; Libecap, G.; Mueller, B. Land reform policies, the sources of violent conflict, and implications for deforestation in the Brazilian Amazon. *J. Environ. Econ. Manag.* **2000**, *39*, 162–188. [CrossRef]
9. Wehrmann, B. *Land Conflicts: A Practical Guide to Dealing with Land Disputes*; GTZ: Eschborn, Germany, 2008.
10. Zhao, X. *Power and Justice: Dispute Resolution and Pluralistic Authority in Rural Society*; Tianjin Ancient Books Publishing House: Tianjin, China, 2003.
11. Zhou, Y. Types, causes and solutions of rural land disputes. *Academics* **2008**, *1*, 171–176.
12. Kansanga, M.; Arku, G.; Luginaah, I. Powers of exclusion and counter-exclusion: The political ecology of ethno-territorial customary land boundary conflicts in Ghana. *Land Use Policy* **2019**, *86*, 12–22. [CrossRef]
13. Mugizi, F.M.; Matsumoto, T. From conflict to conflicts: War-induced displacement, land conflicts, and agricultural productivity in post-war Northern Uganda. *Land Use Policy* **2021**, *101*, 105149. [CrossRef]
14. Bekele, A.E.; Drabik, D.; Dries, L.; Heijman, W. Large-scale land investments and land-use conflicts in the agro-pastoral areas of Ethiopia. *Land Use Policy* **2022**, *119*, 106166. [CrossRef]
15. Lin, Q.; Tan, S.; Zhang, L.; Wang, S.; Wei, C.; Li, Y. Conflicts of land expropriation in China during 2006–2016: An overview and its spatio-temporal characteristics. *Land Use Policy* **2018**, *76*, 246–251. [CrossRef]
16. Tan, S.; Tong, B.; Zhang, J. How Did the Land Contract Disputes Evolve? Evidence from the Yangtze River Economic Belt, China. *Land* **2023**, *12*, 1334. [CrossRef]
17. Halkia, M.; Ferri, S.; Schellens, M.; Papazoglou, M.; Thomakos, D. The Global Conflict Risk Index: A quantitative tool for policy support on conflict prevention. *Prog. Disaster Sci.* **2020**, *6*, 100069. [CrossRef]
18. Zhao, J.; Cao, Y.; Yu, L.; Liu, X.; Yang, R.; Gong, P. Future global conflict risk hotspots between biodiversity conservation and food security: 10 countries and 7 Biodiversity Hotspots. *Glob. Ecol. Conserv.* **2022**, *34*, e02036. [CrossRef]
19. Richter, C. Development of a risk culture intensity index to evaluate the financial market in Germany. In Proceedings of the FIKUSZ'14 Symposium for Young Researcher, Budapest, Hungary, 2014; pp. 237–248.
20. Burnley, C.; Buda, D.; Kayitakire, F. Quantifying the Risk of Armed Conflict at Country Level—A Way Forward. In Proceedings of the 3 Treaty Monitoring Based on Geographic Information Systems and Remote Sensing, Bonn, Germany, 2008; p. 38.
21. Gong, G.; Zhao, Y. Ecology versus economic development: Effects of China's Yangtze River Economic Belt strategy. *Int. Stud. Econ.* **2024**. [CrossRef]
22. Feng, Y.; Sun, M.; Pan, Y.; Zhang, C. Fostering inclusive green growth in China: Identifying the impact of the regional integration strategy of Yangtze River Economic Belt. *J. Environ. Manag.* **2024**, *358*, 120952. [CrossRef] [PubMed]
23. Ting, H.; Liangen, Z.; Yan, Z.; Chuanying, Z.; Jing, L. Water quality comprehensive index method of Eltrix River in Xin Jiang Province using SPSS. *Procedia Earth Planet. Sci.* **2012**, *5*, 314–321. [CrossRef]
24. Sutadian, A.; Muttil, N.; Yilmaz, A.; Perera, B. Using the Analytic Hierarchy Process to identify parameter weights for developing a water quality index. *Ecol. Indic.* **2017**, *75*, 220–233. [CrossRef]
25. Zhang, Y.; Zhang, J.; Yang, Z.; Li, J. Analysis of the distribution and evolution of energy supply and demand centers of gravity in China. *Energy Policy* **2012**, *49*, 695–706. [CrossRef]
26. Luo, X.; Ao, X.; Zhang, Z.; Wan, Q.; Liu, X. Spatiotemporal variations of cultivated land use efficiency in the Yangtze River Economic Belt based on carbon emission constraints. *J. Geogr. Sci.* **2020**, *30*, 535–552. [CrossRef]
27. Zhang, S.; Liu, J.; Song, C.; Chan, C.-S.; Pei, T.; Wenting, Y.; Xin, Z. Spatial-temporal distribution characteristics and evolution mechanism of urban parks in Beijing, China. *Urban For. Urban Green.* **2021**, *64*, 127265. [CrossRef]
28. Flores, J.; Calvo, B.; Perez, A. Supervised non-parametric discretization based on Kernel density estimation. *Pattern Recognit. Lett.* **2019**, *128*, 496–504. [CrossRef]
29. 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]
30. Miśkiewicz, J. Globalization—Entropy unification through the Theil index. *Phys. A Stat. Mech. Its Appl.* **2008**, *387*, 6595–6604. [CrossRef]
31. Duro, J.; Lauk, C.; Kastner, T.; Erb, K.; Haberl, H. Global inequalities in food consumption, cropland demand, and land-use efficiency: A decomposition analysis. *Glob. Environ. Change* **2020**, *64*, 102124. [CrossRef]
32. Li, M.; Ao, Y.; Peng, P.; Bahmani, H.; Han, L.; Zhou, Z.; Li, Q. Resource allocation of rural institutional elderly care in China's new era: Spatial-temporal differences and adaptation development. *Public Health* **2023**, *223*, 7–14. [CrossRef] [PubMed]
33. Liu, Z.; Chen, M. From "Land Conflict" to "Land Risks": Theoretical Prospect on Land Issues in Rural China. *China Land Sci.* **2012**, *26*, 23–28+35.
34. Yu, J. The land issue has become the focus of the peasants' struggle to protect their rights—A special research on the current social situation in rural China. *World Surv. Res.* **2005**, *03*, 22–23.
35. Bridges, S.; Harrison, J.K. Employee perceptions of stakeholder focus and commitment to the organization. *J. Manag. Issues* **2003**, *15*, 498–509.
36. Yue, W.; Wang, T. Logical Problems on the Evaluation of Resources and Environment Carrying Capacity for Territorial Spatial Planning. *China Land Sci.* **2019**, *33*, 1–8.

37. Liu, K.; Qiao, Y.; Zhou, Q. Analysis of China's industrial green development efficiency and driving factors: Research based on MGWR. *Int. J. Environ. Res. Public Health* **2021**, *18*, 3960. [CrossRef] [PubMed]
38. Zhu, Q.; Tu, T.; Chen, Y.; Chen, K.; Mei, Y.; Zhang, Y.; Li, Y.; Liu, M. Spatio-temporal pattern for the coordination degree between industrial structure and land use efficiency of Yangtze River Economic Zone. *Trans. Chin. Soc. Agric. Eng.* **2021**, *37*, 235–246.
39. North, D. *Institutions, Institutional Change and Economic Performance*; Cambridge University Press: Cambridge, UK, 1990.
40. Li, H.; Tan, S.; Peng, K. Analysis on the defects of land laws and regulations that induce rural land conflicts. *Reform Econ. Syst.* **2007**, *01*, 90–95.
41. Han, C. The Reform of China's Rural Land System. *Issues in Agricultural Economy* **2019**, *1*, 001.
42. Turner, S.; Factor, R. *Max Weber: The Lawyer as Social Thinker*; Routledge: London, UK, 2003.
43. Silbey, S. After legal consciousness. *Annu. Rev. Law Soc. Sci.* **2005**, *1*, 323–368. [CrossRef]
44. Immergut, E. The theoretical core of the new institutionalism. *Politics Soc.* **1998**, *26*, 5–34. [CrossRef]
45. Li, H.; Li, B.; Li, S. Governance Mechanism on Land-expropriation Conflicts in the Minorities Areas of Western China. *China Land Sci.* **2013**, *36*, 008.
46. Tan, S.; Zou, S. Study on the Evolution Characteristics and Influencing Factors of Land Disputes in the Yangtze River Economic Belt. *China Land Sci.* **2022**, *36*, 22–31.
47. Zheng, X.; Hu, Y.; Zhang, C.; Ai, G.; Yuan, Z. Research on the Development of China Land Information Science from 1980 to 2017. *China Land Sci.* **2018**, *32*, 90–96.
48. Zheng, C. Big Data Empowering the Governance of Multiple Contradictions and Disputes in China's New Era: Practice-Driven, Problem Challenges and Mechanism Optimization. *Chin. Public Adm.* **2023**, *3*, 54–59.
49. Wiseman, R.; Cuevas-Rodríguez, G.; Gomez-Mejia, L. Towards a social theory of agency. *J. Manag. Stud.* **2012**, *49*, 202–222. [CrossRef]
50. Pierce, J. The Role of the Judiciary in Implementing an Agency Theory of Government. *NYUL Rev.* **1989**, *64*, 1239.
51. Mei, D. Analysis of Rural Land Conflicts in China during the Period of Social Transformation: Status, Types, and Trends. *Southeast Acad. Res.* **2008**, *6*, 36–41.
52. Benson, B. Land Use Regulation: A Supply and Demand Analysis of Changing Property Rights. *J. Libert. Stud.* **1981**, *5*, 435–451.
53. Wu, M.; Yan, J.; Chen, H. Risk Management Research on Rural Homestead Transfer Based on Supply and Demand Theory. *Mod. Manag. Sci.* **2017**, *5*, 30–32.
54. Liu, C.; Wang, X.; Li, H. County-Level Land Use Carbon Budget in the Yangtze River Economic Belt, China: Spatiotemporal Differentiation and Coordination Zoning. *Land* **2024**, *13*, 215. [CrossRef]
55. Zhou, D.; Lin, Z.; Lim, S. Spatial characteristics and risk factor identification for land use spatial conflicts in a rapid urbanization region in China. *Environ. Monit. Assess.* **2019**, *191*, 677. [CrossRef]
56. Chen, L.; Zhang, A. Identification of land use conflicts and dynamic response analysis of Natural-Social factors in rapidly urbanizing areas−a case study of urban agglomeration in the middle reaches of Yangtze River. *Ecol. Indic.* **2024**, *161*, 112009. [CrossRef]
57. Chen, D.; Duan, Y.; Jiang, P.; Li, M. Spatial zoning to enhance ecosystem service co-benefits for sustainable land-use management in the Yangtze River economic Belt, China. *Ecol. Indic.* **2024**, *159*, 111753. [CrossRef]
58. DNRC. Why do rural land disputes occur frequently? *Land Resour.* **2016**, *09*, 36–37.
59. Wang, C.; Shen, J.; Liu, Y.; Lin, L. Border effect on migrants' settlement pattern: Evidence from China. *Habitat Int.* **2023**, *136*, 102813. [CrossRef]
60. Tesfaye, B.; Lengoiboni, M.; Zevenbergen, J.; Simane, B. Rethinking the Impact of Land Certification on Tenure Security, Land Disputes, Land Management, and Agricultural Production: Insights from South Wello, Ethiopia. *Land* **2023**, *12*, 1713. [CrossRef]
61. Han, B.; Jin, X.; Zhao, Q.; Chen, H. Spatiotemporal patterns and mechanisms of land-use conflicts affecting high-quality development in China. *Appl. Geogr.* **2023**, *155*, 102972. [CrossRef]
62. Wang, Y.; Yang, N. Differences in High-Quality Development and Its Influencing Factors between Yellow River Basin and Yangtze River Economic Belt. *Land* **2023**, *12*, 1461. [CrossRef]
63. Farazmand, A. *Global Encyclopedia of Public Administration, Public Policy, and Governance*; Springer Nature: Berlin/Heidelberg, Germany, 2023.
64. Cai, X.; Pang, Z. Measurement and Spatial Convergence of Chinese Modernization of Rural Governance. *Chin. J. Agric. Resour. Reg. Plan.* **2023**, *9*, 1–17.
65. Gao, D.; Zhao, Y.; Pan, B. Research on China Rural Governance Evaluation and Its Influence Mechanism. *J. Agrotech. Econ.* **2024**, *3*, 94–113.
66. Pritchard, M. Contesting land rights in a post-conflict environment: Tenure reform and dispute resolution in the centre-West region of Côte d'Ivoire. *Land Use Policy* **2016**, *54*, 264–275. [CrossRef]
67. Li, A. Challenges and Opportunities of Chinese International Arbitral Institutions and Courts in a New Era of Cross-Border Dispute Resolution. *BU Int'l LJ* **2020**, *38*, 352.
68. He, X. Pressures on Chinese judges under Xi. *China J.* **2021**, *85*, 49–74. [CrossRef]
69. Jiang, Y.; Guan, D.; He, X.; Yin, B.; Zhou, L.; Sun, L.; Zhang, Y. Quantification of the coupling relationship between ecological compensation and ecosystem services in the Yangtze River Economic Belt, China. *Land Use Policy* **2022**, *114*, 105995. [CrossRef]

70. Ma, S.; Ren, F.; Wan, F. Sharing benefits? The disparate impact of home-sharing platform on industrial and social development. *Electron. Commer. Res. Appl.* **2022**, *53*, 101152. [CrossRef]
71. Allam, Z.; Dhunny, Z. On big data, artificial intelligence and smart cities. *Cities* **2019**, *89*, 80–91. [CrossRef]

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Article

Temporal and Spatial Effects of Heavy Metal-Contaminated Cultivated Land Treatment on Agricultural Development Resilience

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Abstract: Heavy metal-contaminated cultivated land treatment (HMCLT) plays an essential role in the realization of sustainable utilization of cultivated land resources and sustainable agricultural development. Evaluating this policy's impact on agricultural development resilience (ADR) has great practical significance. This paper reveals the impact HMCLT has on ADR from the perspectives of time and space, utilizing data from Hunan province between 2007 and 2019. The synthetic control method (SCM) and spatial Durbin model (SDM) are employed for investigating the temporal and spatial effects HMCLT has on ADR. The results demonstrate that the HMCLT policy has effectively improved the pilot cities' ADR and can enhance ADR in adjacent areas from a spatial perspective. In addition to HMCLT policy, financial support for agriculture, farmers' per capita disposable income, and rural population density are key factors affecting ADR. However, they all have a crowding-out effect on the ADR in neighboring areas. Due to these circumstances, while the governments make efforts in promoting the policy design and improvement of HMCLT, increasing the disposable income of farmers, narrowing regional differences in government financial support and human capital, and promoting regional interactions are essential to enhance ADR. This study formulates valuable insights for policymakers and researchers in the field of sustainable agricultural development.

Keywords: cultivated land use; agricultural high-quality development; impact mechanism; spatio-temporal effect

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1. Introduction

Agricultural development resilience (ADR) refers to the ability of the agricultural system to maintain its original structure, essential functions, and basic services following the absorption and resolution of external interference [1]. ADR improvement can result in many benefits, such as tackling inevitable shocks, ensuring food security, cultivating the endogenous forces that drive agricultural economic growth, and creating a modernized agricultural system [2,3]. In 2022, the Chinese "Central No.1" document noted the importance of actively responding to a variety of risks and challenges both domestically and abroad, stabilizing the essential agricultural market, maintaining and promoting agricultural production, and enhancing the stable and sustainable development of both the economy and society, thereby affirming the state and position of agriculture and the importance of ADR enhancement. Cultivated land is the fundamental resource of social and economic activities and can be regarded as the agricultural "input-output" system, in addition to playing a crucial role in ADR enhancement. However, as urbanization and industrialization progress rapidly, the ecological costs resulting from population growth and food production will keep increasing significantly. Agriculture faces imminent challenges, including heavy metal-contaminated cultivated land and groundwater over-extraction [4–6]. As reported, more than one-fifth of cultivated land has been polluted by heavy metals in China, resulting in the problems of grain production reduction and food pollutants exceeding limits [7]. This has become an issue of great concern for both central and local governments.

To promote the circulation of cultivated land while also alleviating the negative impact environmental pollution has on regional agricultural production and sustainable agricultural development, China implemented the pilot policy of heavy metal-contaminated cultivated land treatment (HMCLT) in 2014. For example, promoting collaboration to the enhancement of technological innovation and conducting research on the restoration of cultivated land. Meanwhile, much investment has been put into this field. Around 150 billion to 200 billion yuan can be invested annually; moreover, as predicted, the total investment is expected to exceed 5.7 trillion yuan in the long run. In practice, 1.7 million mu (a Chinese unit of area, equal to around 1133 km^2) area of cultivated land in the Changsha-Zhuzhou-Xiangtan urban agglomeration of Hunan province was chosen as the pilot area, which is a significant pilot project in eliminating the heavy metal-contaminated pollution. Numerous measures were taken according to the condition of the heavy metal-contaminated cultivated land. Alternative crop planting or fallow methods were employed for cultivated land with less pollution. Meanwhile, advanced agricultural technologies (e.g., removing chemical materials) were utilized for cultivated land with more pollution to achieve HMCLT. Anticipated outcomes were achieved after the implementation of HMCLT, with the average cadmium reduction rate of the pilot area reaching approximately 60%, as this triggered the additional policy design and practice. In addition, along with the improvement of top-down policy design and bottom-up practice exploration of HMCLT, the implementation of HMCLT has gradually been expanded. Some reports have revealed that the coordination between agricultural production and ecology in the pilot areas has exhibited gradual improvement because of the adoption of this policy. At the same time, agricultural production is becoming increasingly stable because it can cope with the negative impacts of natural disasters and cumulative energy shortages [8]. HMCLT has long been seen as a driving force for green agricultural development that can continuously optimize the agriculture system through resource reallocation and spillover effects, thereby enhancing ADR. In practice, since Hunan province was chosen as the pilot area, the ecological and economic effects of HMCLT have arisen; however, its output growth and structural changes in agriculture have remained rigid, and agricultural production, distribution, and consumption continue to be relatively low. Therefore, further optimizing the policymaking of HMCLT is necessary as a means of enhancing its sustained role in agricultural development.

Relatively few studies have investigated the relationship between heavy metal-contaminated cultivated land management strategies and ADR. Previous literature has mainly focused on the role played by heavy metal-contaminated cultivated land technologies in the sustainable use of cultivated land and ecological restoration, including improving sustainable agricultural development potential through the green chemical material of soil [9], utilizing the biological methods to remove heavy metals in soil [10], and planting wind-proof, sand-fixing, water-conservation plants [11]. With an increasing number of insights into cultivated land loss, degradation, and ecological pollution, numerous scholars have focused on the impact management strategies have on agricultural financing [12], agricultural productivity stability [13], and sustainable agricultural development [14]. Meanwhile, they focused on agricultural production, ecological changes, and the farmers' income after the implementation of HMCLT policies [15–18]. In addition, a small number of scholars have explored the green development effects of HMCLT [19], reflecting the indirect influence HMCLT has on ADR.

These studies provided great practical value for enhancing the effects of HMCLT on ADR. However, they could not reveal the influencing mechanism of the effects HMCLT has on ADR. Previous research has mainly employed qualitative analysis, biochemical experiments, or detection, but ignored the characteristics and effects of HMCLT policy at the macro level. At the same time, heavy metal-contaminated cultivated land has the characteristics of peripheral aggregation, meaning that heavy metal-contaminated cultivated land close to the pilot area may have a higher risk of being polluted [20]. However, a small number of papers have comprehensively studied the spatial effects of HMCLT on ADR, providing tailor-made policy advice for the regional joint prevention and treatment of heavy metal-contaminated cultivated land. Therefore, this paper theoretically reveals the internal mechanism of the effects HMCLT has on ADR. This study uses the HMCLT pilot policy in Hunan province in a quasi-natural experiment. Synthetic control method (SCM) and spatial econometric models are employed for empirically testing and analyzing the temporal and spatial effects HMCLT has on ADR. This paper also makes several contributions, providing tailor-made suggestions for the promotion of HMCLT and the achievement of green and sustainable agricultural development, while providing policy references for HMCLT policy enhancement in similar regions.

2. Analysis of the Spatio-Temporal Mechanism

HMCLT is a complex issue that aims to adjust interactions between ecological environment services and human activities to realize sustainable agricultural production. With the dynamics of HMCLT, a series of policy changes, capital support, and technological innovation took place that can impact ADR. Specifically, HMCLT can positively affect ADR from both temporal and spatial perspectives (Figure 1).

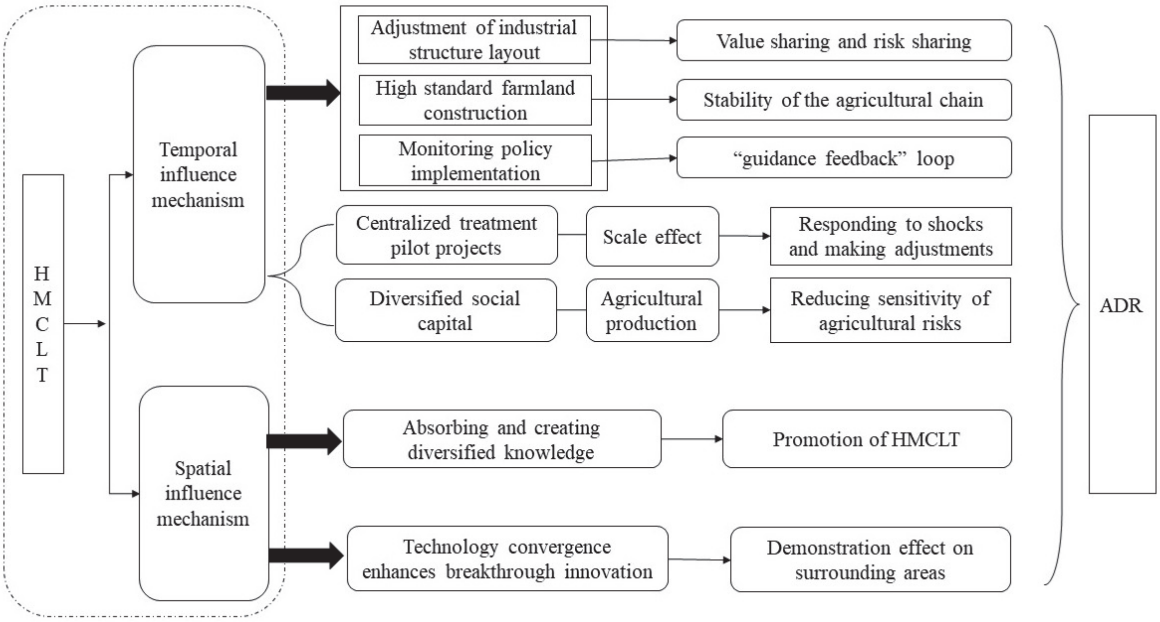

Figure 1. Temporal and spatial influence mechanism of HMCLT on ADR.

2.1. Temporal Mechanism of HMCLT on ADR

Firstly, central and local governments and their departments continuously issue policies and regulations as a means of effectively intervening and regulating the scale and impact of HMCLT policy. In the case of adjusting the industrial structure and layout of HMCLT, stakeholders (including governments, enterprises, and farmers) are able to realize the sharing of interests and risks with their involvement in HMCLT [19], thereby helping the farmers recover from the external shock and improve the overall ADR. At the same time, implementing policies, such as the vigorous promotion of high-standard farmland construction and comprehensively transforming agricultural land in key areas, can effectively improve cultivated land quality and productivity in pilot areas, optimize the production, storage, and transportation of agricultural products, and assist the regions in responding to the potential risks in the agricultural production chain [21,22]. In addition, the bottom-up policy supervision provides feedback on farmers' actual expectations and attitudes towards HMCLT from a demand perspective, which contributes to forming a production elasticity "guidance-feedback" loop [23–25]. This serves to balance the relationship between agricultural production and consumption while improving ADR.

Secondly, massive investment in special funds for HMCLT, in addition to exploring and establishing diversified fund-raising channels, provides a solid foundation for ADR enhancement in HMCLT [26]. This massive investment will swiftly promote the HMCLT to become comprehensive and centralized, which forms a scale effect and accumulation effect that can help the agricultural system tackle the changing issues [27,28], thereby affecting ADR. Meanwhile, the farmers can promote the labor resources in agricultural development [22], and higher labor productivity is conducive to ADR enhancement. In addition, diversified social capital into HMCLT can help stabilize and ensure sufficient fund resources, stimulating agricultural production and output, and reducing the sensitivity of agricultural risks [26].

2.2. Spatial Mechanism of HMCLT on ADR

HMCLT is an effective tool for promoting the sustainable utilization of cultivated land resources, in addition to the penetration and sharing of new-generation information technology into agriculture (e.g., the Internet of Things, cloud computing, and big data), which will inevitably result in spatial spillover effects. The effects are mainly manifested in the following aspects. Firstly, the cultivated land system must adapt to the dynamic changes and changing environment, advanced technologies, and novel products that are commonly used for achieving HMCLT. The combination of technologies, knowledge, and information can be regarded as a "technology pool" that can promote the absorption of diversified knowledge in agriculture [29,30]. In this regard, a regional knowledge network of agricultural production can be formed to promote HMCLT and enhance ADR spillover effects. Secondly, the cross-fusion of HMCLT technologies can generate breakthrough innovations, which can change resource allocation and reduce the dependency on agricultural production on labor [19]. At the same time, the effects can have an impact on the surrounding areas while mutually promoting ADR between regions. Finally, the pilot area of HMCLT in a specific region can result in the enhancement of the ADR level of the surrounding regions through information sharing and resource transfer. Ultimately, the endogenous momentum of coordinated ADR promotion can be strengthened from economic, production, and ecological perspectives.

3. Material and Methods

This paper adopts the synthetic control method (SCM) and spatial econometrics model for studying the spatio-temporal effects of ADR affected by HMCLT for the following two considerations. Firstly, as a non-parametric estimation method, SCM can be used for evaluating the treatment effects in comparative studies. The basic principle of the approach is to assign a total weight of 1 to a non-negative weighted synthesis of an optimal control group that is consistent with the trend of treatment group unit changes. On this basis, policy effects can be evaluated by calculating the difference between the treatment group and the synthetic group before and after policy implementation. In comparison to the difference-in-differences (DID) method, this method eliminates endogenous and control group selection bias and can be applied for assessing policy effects in small samples [31]. Therefore, this method performs an HMCLT experiment and constructs a "synthetic group" of a "counterfactual state" using data weighting and linear fitting for other regions. This means that differences in ADR between the implementation (treatment group) and the non-implementation (synthetic group) can be compared as a means of evaluating the net effect of the policy from a temporal dimension. Secondly, based on the theoretical framework of the impact HMCLT has on ADR, the existence of spatial spillover effects of HMCLT can be confirmed. If such effects are neglected, the effects and mechanisms obtained will be biased. Therefore, spatial econometrics models are used for studying the effects of HMCLT on ADR.

3.1. Measurement and Index Selection of ADR

ADR is the ability of the agricultural system to resist external shocks, recover from shocks, and transform to other paths as a means of achieving adaptive development, which is composed of the three interrelated capabilities of resistance, recovery, and regeneration. The pressure-state-response (PSR) model is commonly used for assessing environmental quality [32–36]. Due to its advantages in revealing the interactions of multiple factors, the PSR model is widely used in the field of eco-environmental quality [32], regional ecological change [33], and ecosystem health [34]. With this model, the pressure (P) represents the damage and disturbance of external pressure to the system, the state (S) is the current state of the system under pressure, and the response (R) is the response measures that are taken in situations where the system faces external pressure.

ADR is a complex process that involves the "input-transformation-output" cycle [37,38], where the output is heavily reliant on the adaptation and adjustment of the input. From this perspective, the PSR model is adequately used for mapping the realization of ADR. Therefore, based on existing conclusions regarding the definition and connotation of resilience, together with the PSR model, the comprehensive measurement index system of ADR is constructed from the three dimensions of resistance (P), recovery (S), and regeneration (R). More specifically, resistance is the ability of the agricultural system to reduce external shocks under uncertainty, which has a close relationship with the state of cultivated land, its water conservancy infrastructure conditions, and machinery input density. Therefore, the proportion of the effective irrigation area of cultivated land (the area of effective irrigation/the area of cultivated land), agricultural machinery usage intensity (total power of agricultural machinery/the area of cultivated land), and the proportion of the disaster area of cultivated land to the total area of cultivated land are chosen as indicators for measuring resistance. In addition, recovery is the ability of the agricultural system to recover from the impact of pressure, as reflected in terms of the agricultural economy, society, and stakeholders before and after the external shocks. Therefore, the average agricultural output value (agricultural output value/agricultural population), rural road network accessibility, and the expenditure of farmers are chosen as indicators for measuring recovery. Finally, regeneration emphasizes the agricultural system's self-adjustment and adaptation before and after the external shocks, including remedial measures that the government takes or farmers for repairing and enhancing the agricultural system. Therefore, investment in agricultural infrastructure, the pure amount of agricultural fertilizer application per unit sown area, the amount of agricultural plastic film use per unit sown area, and rural electricity consumption are chosen as regeneration indicators. On this basis, the entropy weight method [39,40] is used for calculating ADR following the standardization of each indicator.

3.2. Research Object and Model Specification

The majority of heavy metal-contaminated cultivated land in China is distributed in 14 provinces (municipalities and autonomous regions), including Hebei, Jiangsu, Guangdong, Shanxi, Hunan, and Henan, which accounts for approximately one-fifth of the total cultivated land area, thus the implementation of HMCLT is of great importance. The Chinese government started piloting and promoting the HMCLT policy in 2014 in several regions. Compared to other pilot areas, Hunan province is an area that is rich in nonferrous metals and non-metallic minerals, and its cultivated land has been contaminated, and it is in a severe condition. However, the planting area and yield of Changsha ranked first in China. As a result, governments and scholars have given extensive attention to the pilot policy of HMCLT. Investigating the effects of HMCLT on ADR in Hunan province is conducive to the promotion of HMCLT and has significant value for sustainable agricultural development in other regions of China and even the world.

The SCM was used in this study for investigating the time effect of HMCLT on ADR in Hunan province. It is assumed that the total sample is the relevant data of $J + 1$ regions in $t \in [1, T]$, and only the first region ($i = 1$) implements the HMCLT policy during the period $t = T_0$, so that the region is the treatment group, and the dependable variable is $\text{Resilience}_{i,t}$.

The remaining J regions are the control city groups without the implementation of the pilot policy. Under the SCM, $\text{Resilience}_{i,t} = \text{Resilience}'_{i,t} + D_{it}\eta_{it}$ (where $\text{Resilience}_{i,t}$ and $\text{Resilience}'_{i,t}$ represent ADR in one city in the treatment group and the control group, D_{it} indicates whether it is a dummy variable of the HMCLT pilot, while η_{it} represents the net effect of the policy). As it is possible to directly observe $\text{Resilience}_{i,t}$, but not $\text{Resilience}'_{i,t}$, in order to obtain the estimated parameter value η_{it}, the "counterfactual" method must be used to construct the variable $\text{Resilience}'_{i,t}$ as follows:

$$\text{Resilience}'_{i,t} = \alpha_i + \delta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \quad (1)$$

Z_i is the control variable of this paper; δ_t is the estimation coefficient vector; λ_t is the unobservable factor vector; μ_i is the individual fixed effect; and ε is the random error term. This study fitted the characteristics of the cities in the treatment group where no policies have been implemented by weighting the cities in the alternative control group. Therefore, Formula (1) is converted into:

$$\sum_{j=2}^{J+1} v_j w_{it} = \alpha_t + \beta_t \sum_{j=2}^{J+1} v_j Z_j + \lambda_t \sum_{j=2}^{J+1} v_j \mu_i + \sum_{j=2}^{J+1} v_j \varepsilon_{it} \quad (2)$$

$v_j(j = 2, 3, \cdots, J+1)$ can constitute $J+1$-dimensional multiple vector group $V = (v, \cdots, v_{J+1})$. For those $\forall J$ that meet the conditions of $V_J \geq 0$ and $v_2 + \cdots + v_{J+1} = 1$, it is further assumed that there is a vector group $V^* = \left(v_2^*, \cdots, v_{J+1}^*\right)'$, which meets the conditions of $\sum_{j=2}^{J+1} v_j^* w_{jt} = w_{11}, \cdots, \sum_{j=2}^{J+1} v_j^* w_{jT0} = w_{1T0}$ and $\sum_{j=2}^{J+1} v_j^* Z_j = Z_1$. If $\sum_{i=1}^{T_0} \lambda'_t \lambda_t$ is full rank, it can be concluded that:

$$\text{Resilience}'_{i,t} - \sum_{j=2}^{J+1} v_j^* w_{jt} = \sum_{j=2}^{j+1} v_j^* \sum_{s=1}^{T_0} \lambda_t \left(\sum_{i=1}^{T_0} \lambda'_t \lambda_t \right)^{-1} \lambda'_s \left(\varepsilon_{js} - \varepsilon_{is}\right) - \sum_{j=2}^{J+1} v_j^* \left(\varepsilon_{js} - \varepsilon_{is}\right) \quad (3)$$

According to Abadie et al. [41], $T_0 < t \leq T$, $\sum_{j=2}^{J+1} v_j^* w_{jt}$ is regarded as an unbiased estimation of $\text{Resilience}'_{i,t}$. At this timepoint, the core parameter estimator is obtained via regression analysis using Formula (1) $\eta_{1t} = w_{it} - \sum_{j=2}^{J+1} v_j^* w_{jt}$.

The pilot policy of HMCLT in Hunan province was implemented in 2014, thus 2014 is the time point of policy impact for this study. The three aforementioned cities (i.e., Changsha, Zhuzhou, and Xiangtan) are taken as the treatment group for the empirical study, while the remaining cities in Hunan province (excluding Tujia and Miao Autonomous Prefecture in Xiangxi) are taken as the control group. The research period for this paper is 2007–2019.

In addition, the theoretical analysis framework of this paper indicates an apparent spatial dependence between HMCLT and ADR. Spatial econometric models have been employed in numerous fields, such as eco-environmental quality [42], cultivated land protection policy [43], cultivated land use efficiency [44], and land supply [45], indicating that these spatial models are suitable for this paper. Therefore, the following spatial Durbin model (SDM) is constructed in this paper for investigating the spatial effects of HMCLT on ADR in Hunan province, and the spatial autoregressive model (SAR) results are compared.

$$\text{Resilience}_{it} = c_0 + \rho \sum_{j=1}^{n} W\text{Resilience}_{it} + c_1 Policy_{it} + c_2 Policy_{it} + \kappa_1 X_{it} + \kappa_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

$$\text{Resilience}_{it} = h + \rho \sum_{j}^{n} W\text{Resilience}_{it} + h_1 Policy_{it} + \rho \sum_{j}^{n} W Policy_{it} + X_{it}\theta_3 + \varphi_i + p_i + \varsigma_{it} \quad (5)$$

Formula (4) is the SDM model, Formula (5) is the SAR model, i and t represent year and city, and $Policy$ is the core explanatory variable. X_{it} refers to control variables. W is the nested spatial weight matrix, μ_i and φ_i represent the individual effect, λ_t and p represent the time effect, and ε_{it} and ς_{it} represent the random error term.

3.3. Data Sources

The original data used in this paper is obtained from the Hunan Provincial Statistical Yearbook, Hunan Rural Statistical Yearbook, Cities and Prefectures Local Statistical Yearbook in Hunan province, and the national economic and social development statistical bulletin for each city. Missing values for some years or regions are filled using neighboring values or the linear fitting method. However, due to the data unavailability in Xiangxi Tujia and Miao Autonomous Prefecture, this region was not included in this paper. Table 1 provides descriptions of variables and indicators used in this analysis.

Table 1. Summary statistics of the variables.

Variables	Unit	Descriptions
Nature	Hectare	The area of cropland [46,47]
Modernization	%	The ratio of the added value of the service industry to that of agriculture, forestry, animal husbandry, and fishery [48]
Finance	%	The proportion of agricultural and forestry financial expenditure in total financial expenditure [49]
Income	Yuan	Per capita disposable income of farmers [50]
Information	Person	The total workload of all full-time employees and the number of full-time equivalent part-time employees [51]
Labor	Person/km^2	Rural population density [52]
Intensive	_	Location quotient [53]

4. Results

4.1. Temporal Effect of HMCLT on ADR

4.1.1. Descriptive Analysis of ADR

The ADR values of all cities in Hunan province from 2007 to 2019 were calculated based on the entropy weight method. The natural fracture point method was then applied to map the spatial pattern of ADR in Hunan province (Figure 2). From a time dimension, the evolution of ADR in Hunan province is divided into two stages: slow rise (2007–2013) and steady rise (2014–2019), with significant phased characteristics. In 2007, the ADR value in Hunan province was 0.128, and it fluctuated to 0.238 in 2013 before proliferating to 0.520 in 2019. Shaoyang, Yueyang, Yongzhou, and Changde first experienced falling and then rising, the ADR level of Zhangjiajie, Yiyang, Hengyang, and Chenzhou showed a feature of first rising and then fluctuating, while Huaihua demonstrated a downward trend. At the same time, the ADR level of Changsha, Zhuzhou, and Xiangtan fluctuated and rose. From a spatial dimension, the intra-provincial differentiation of ADR in Hunan province exhibited a widening trend, with higher-value cities moving from the initial concentration in Yueyang, Changde, and Yiyang to Changsha-Zhuzhou-Xiangtan, while the range of lower-value cities decreased in circles. The spatial pattern shows “ridge” distribution characteristics along the southwest line, with Changsha-Zhuzhou-Xiangtan urban agglomeration at the core and extending toward the northeast.

4.1.2. Weight Setting of Synthetic Pilot Cities

This study used data from 2007 to 2019 and employed Stata 15 software for fitting and synthesizing virtual control cities in 10 control city groups. Table 2 shows a comparison of dependent variables between pilot cities and synthetic pilot cities and demonstrates that ADR levels in Changsha, Zhuzhou, and Xiangtan were similar prior to HMCLT policy implementation. Regarding the difference in independent variables, the difference between *Informatization* in Changsha and *Nature* in Zhuzhou and Xiangtan was relatively high.

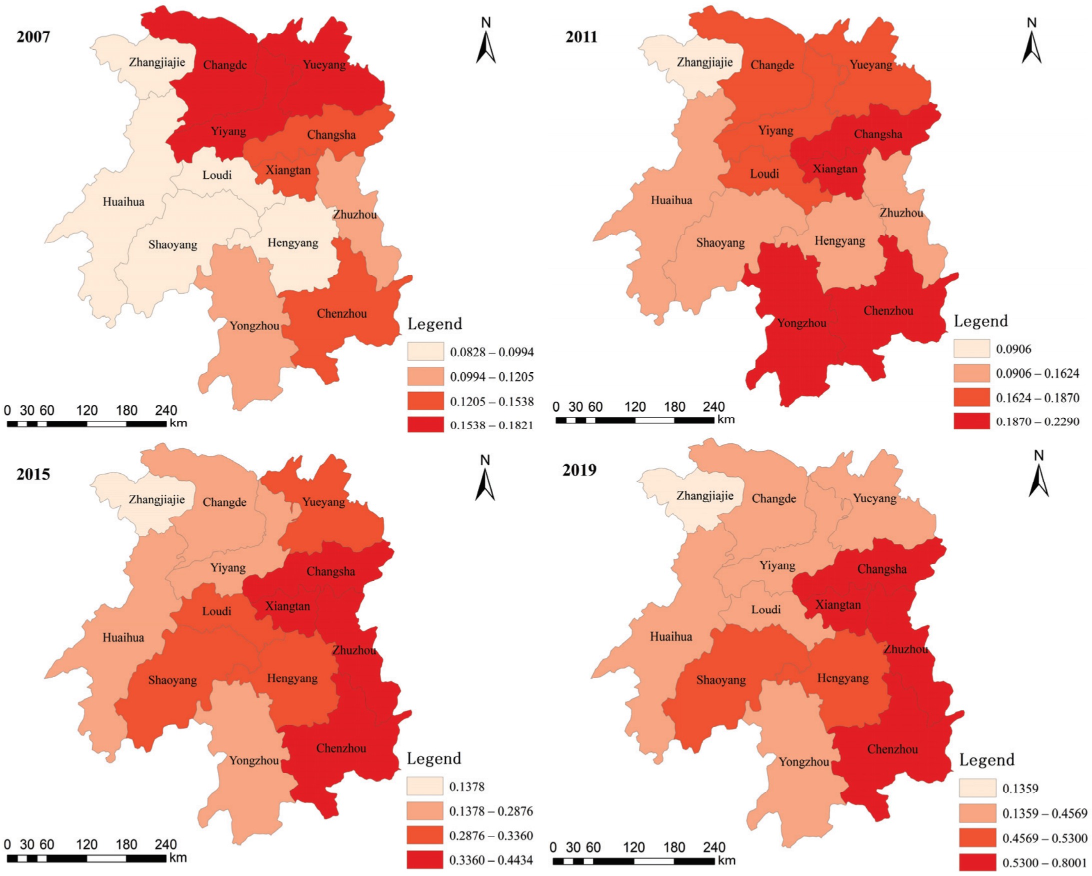

Figure 2. Evolution of ADR in Hunan province from 2007 to 2019.

Table 2. Independent variables of pilot cities and synthetic pilot cities.

Independent Variables	Changsha			Zhuzhou			Xiangtan		
	Synthetic	Real	Difference	Synthetic	Real	Difference	Synthetic	Real	Difference
Nature	6.772	6.450	0.323	6.759	5.919	0.840	6.643	5.716	0.927
Modernization	0.072	0.023	0.050	0.108	−0.091	0.199	0.184	0.040	0.144
Finance	0.122	0.250	0.128	0.150	0.301	0.151	0.120	0.009	0.111
Income	8.568	9.331	0.763	8.739	8.976	0.237	8.586	9.000	0.414
Information	2.634	5.496	2.861	2.571	2.076	0.495	2.414	2.193	0.221
Labor	7.000	7.256	0.256	7.896	8.148	0.253	7.032	7.776	0.744
Intensive	0.771	0.977	0.206	1.109	1.124	0.015	0.837	1.328	0.491

The weight combinations selected when three HMCLT pilot sites in Changsha, Zhuzhou, and Xiangtan were chosen as the composite areas can be seen in Table 3. Yongzhou is the city that constructed and synthesized Changsha, and its weight is 1. At the same time, cities with positive contributions to Zhuzhou are Hengyang, Yongzhou, Chenzhou, and Changde. Yongzhou and Chenzhou can be forged to synthesize Xiangtan, and the ADR level of these two cities can be summed up by the respective weights of 0.683 and 0.317 for ADR level simulation.

Table 3. Weights of control groups in each synthetic control area.

Region	Synthetic Area (Weight)	RMSPE
Changsha	Yongzhou (1), Others (0)	0.0285
Zhuzhou	Hengyang (0.467), Yongzhou (0.331), Chenzhou (0.118), Changde (0.084), Others (0)	0.0114
Xiangtan	Yongzhou (0.683), Chenzhou (0.317), Others (0)	0.0211

4.1.3. SCM Results

The evolution of the ADR of pilot cities and their synthetic cities for HMCLT can be seen in Figure 3, which shows that prior to HMCLT policy implementation, the ADR levels of Zhuzhou and Xiangtan were closer to their synthetic ADR level, which indicates that the synthetic pilot can fit the real pilot. It is notable that some differences in ADR exist between Changsha and its synthetic pilot area because Changsha is the economic and political center of the Changsha-Zhuzhou-Tanzhou urban agglomeration. Green agricultural technology, modern agricultural development, and agricultural labor input are at leading levels, thus the independent variables of other cities cannot fit the trends of ADR in Changsha.

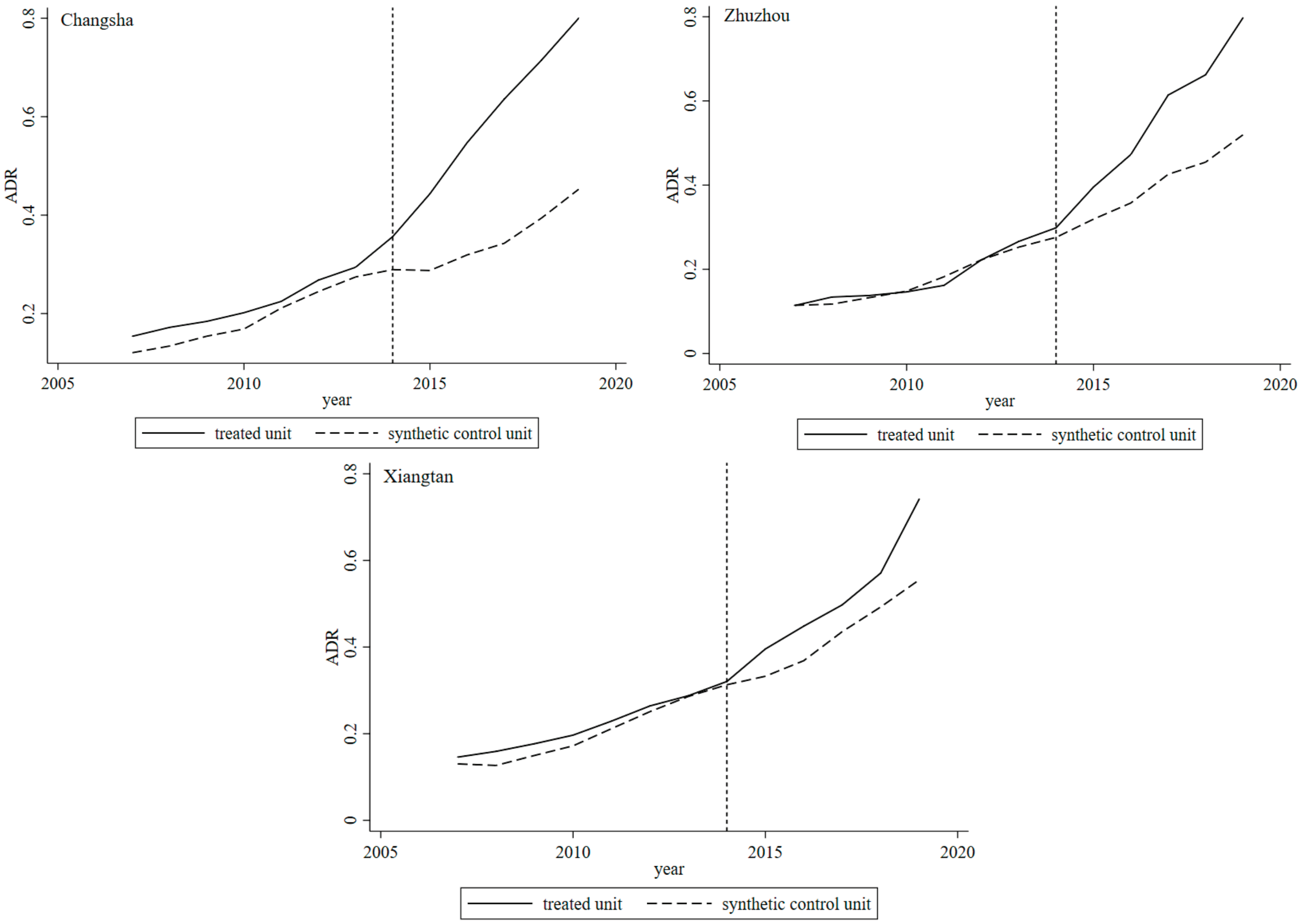

Figure 3. ADR trends in real and synthetic pilot cities.

According to the fitting degree after the implementation of the HMCLT policy, ADR levels in Changsha, Zhuzhou, and Xiangtan improved. Among them, the standards of Changsha improved most significantly, followed by Zhuzhou and Xiangtan. In addition, the impact of the HMCLT pilot policy on ADR was found not to be significant in 2014. One possible reason is that R&D activities can be delayed due to the inducement of the HMCLT policy, thereby inhibiting the policy's effects on ADR that year. The pilot policy of HMCLT should be further explored in this stage. The policy effect will be weakened by the constraints of social capital, the ineffectiveness of management strategies, and the imperfect guidance from the government.

4.2. Spatial Effect of HMCLT on ADR

The effects the pilot policy has on ADR have been investigated. Does the HMCLT policy also lead to ADR improvement in neighboring cities through spillover effects? This section investigates the spatial impact of HMCLT on ADR.

4.2.1. Spatial Correlation Analysis

Before spatial regression, the spatial autocorrelation of ADR was tested using Moran's I index (shown in Table 4). ADR was significant in the research period, with the exception of 2010, which indicates an obvious spatial dependence between ADR in various regions, and the SDM is a reasonable means for analyzing spatial effects.

Table 4. Moran's I test results.

Year	Moran's I	Z	Year	Moran's I	Z
2007	0.017 **	2.120	2014	0.025 ***	2.484
2008	0.004 **	1.910	2015	0.045 ***	2.848
2009	0.000 **	1.855	2016	0.054 ***	3.005
2010	−0.075	1.255	2017	0.054 ***	2.971
2011	−0.021 *	1.398	2018	0.048 ***	2.838
2012	−0.003 **	1.980	2019	0.054 ***	2.977
2013	0.040 ***	2.781			

Note: *, **, and *** represent 10%, 5%, and 1% statistical levels, respectively.

4.2.2. Spatial Effect Estimation Results

In order to avoid the bias and error of the model setting on the model estimation, the maximum likelihood estimation method was used in this study, and the Wald test and LR test were employed to verify the effectiveness of the SDM model. The results found that the Wald test and LR test rejected the original hypothesis at the 5% confidence level, while the results of the Hausman test showed the effectiveness of the fixed effect model. Therefore, the SDM model based on individual fixed effects was chosen for studying the spatial effects of HMCLT on ADR. The results of the SAR model were also provided for comparison. The coefficient of *Policy* was found to be significantly positive at the 1% level in these two models, which indicates that HMCLT can improve ADR, further verifying the results' robustness, as shown in Table 5. The W * Policy coefficient was 0.093 and it was significant, which suggests that HMCLT has spillover effects on ADR in neighboring areas. Under the dual pressure of local government performance improvement and agricultural economic growth, a "bottom-by-bottom competition" phenomenon exists in HMCLT policy, thus the spatial effects of the policy were significantly enhanced. At the same time, to realize high-quality agricultural development, HMCLT can further promote agricultural production development and technological innovation in the pilot areas. Specifically, the ADR in neighboring cities can be affected through economic interaction, industrial cooperation, and technological communication. Therefore, establishing the policy governance system and information-sharing mechanism based on regional cooperation, and realizing the exchange and sharing of agricultural resources between regions are effective means for improving the future policymaking of HMCLT.

4.2.3. Decomposition and Estimation Results of Spatial Effects

Based on the work of LeSage and Pace [54], the spatial effects of HMCLT on ADR were further characterized into direct, indirect, and total effects to avoid estimation result bias. As Table 6 demonstrates, the coefficient of direct effects of HMCLT on ADR is 0.138, which indicates ADR can be significantly improved by the HMCLT policy. The coefficient of indirect effects of HMCLT on ADR is 0.106, which suggests that the HMCLT policy had significant spatial effects on ADR in adjacent areas. This is consistent with the estimated results in Section 4.2. In addition, it should be noted that although HMCLT promotes the formation of an inter-regional governance network, it also produces various transaction costs, thereby weakening the spillover effects HMCLT has on ADR. From the perspective of control variables, the direct and indirect effects of *Finance*, *Income*, and *Labor* were significant at the 5% level, and the direct and indirect effects of Finance and Labor were significantly negative. It can be inferred that the financial support from the local government for agriculture and the scale of human capital in agriculture is currently relatively low, which inhibits ADR improvement in the local region and surrounding areas.

Table 5. The results of the spatial effect of the driving forces on the ADR.

	SDM	SAR
Policy	0.137 *** (7.41)	0.151 *** (7.72)
Nature	0.002 (0.02)	−0.084 (1.24)
Modernization	−0.001 (0.22)	−0.002 (0.44)
Finance	−0.402 ** (2.43)	−0.061 (0.38)
Income	0.118 * (1.80)	0.061 ** (2.42)
Information	−0.012 (1.44)	−0.009 (1.06)
Labor	−0.142 *** (3.85)	−0.091 ** (2.53)
Intensive	−0.0001 (0.21)	0.0004 (0.58)
*W * Policy*	0.093 * (1.83)	
*W * Nature*	−0.251 * (1.74)	
*W * Modernization*	0.002 (0.12)	
*W * Finance*	−3.370 *** (3.77)	
*W * Income*	−0.223 *** (2.79)	
*W * Information*	−0.039 ** (2.06)	
*W * Labor*	−0.684 *** (4.73)	
*W * Intensive*	−0.007 ** (2.19)	
ρ	0.027 (0.14)	0.464 *** (5.30)
σ^2	0.002 *** (9.19)	0.003 *** (9.13)
R-squared	0.257	0.423
Log-L	286.095	257.971
N	169	169

Note: *, **, and *** represent 10%, 5%, and 1% statistical levels, respectively. The numbers in the brackets are the standard error of the coefficients. The same is true for the table below.

Table 6. Decomposition results of spatial effects.

	Direct Effects	Indirect Effects	Total Effects
Policy	0.138 *** (7.17)	0.106 ** (2.21)	0.244 *** (4.99)
Nature	−0.003 (0.03)	−0.250 * (1.78)	−0.252 *** (2.58)
Modernization	−0.0004 (0.11)	0.002 (0.14)	0.002 (0.11)
Finance	−0.427 ** (2.28)	−3.591 *** (2.60)	−4.018 *** (2.68)
Income	0.118 * (1.84)	−0.236 *** (2.70)	−0.118 * (1.81)
Information	−0.011 (1.41)	−0.040* (1.95)	−0.051 ** (2.49)
Labor	−0.144 *** (3.95)	−0.717 *** (6.39)	−0.860 *** (6.98)
Intensive	−0.0002 (0.34)	−0.008 * (1.88)	−0.008 * (1.82)

Note: *, **, and *** represent 10%, 5%, and 1% statistical levels, respectively.

5. Discussion

5.1. Direct Associations

An increasing amount of attention is paid to environmental protection and agricultural production. The central government has made numerous efforts to improve the agricultural environment, especially in the field of heavy metal-contaminated cultivated land. To investigate the effectiveness of the HMCLT policy issued in 2014, SCM was employed to explore this effect, which can provide implications for the central and local governments to take tailor-made actions to address similar issues. The outcomes of this paper demonstrate that the HMCLT can significantly improve ADR in the pilot areas (i.e., Changsha, Zhuzhou, and Xiangtan). Therefore, it can be inferred that the top-down policies are conducive to enhancing ADR to serve agricultural production and protect the environment. Governments need to design additional policies to tackle similar challenges. Moreover, the results of SCM in Changsha show a different trend compared to other cities before the pilot policy. A possible reason for this situation is that the research was conducted in Hunan province, and Changsha maintains a leading and unique role in the research area [55]. The situation in Changsha was hard to synthesize in other Hunan province cities. Therefore, as an increasing number of policies are implemented in different regions, more studies can be conducted to verify the outcomes obtained in this research.

5.2. Spillover Effects

According to the influence mechanism of this paper and Moran' I index, spatial dependence exists in Hunan province's ADR. To explore the spatial effects of the HMCLT policy on ADR, SDM and SAR models were utilized. The results showed that the direct effects and spatial effects of the HMCLT policy on ADR were significant at the 5% level, indicating that the pilot policy cannot only affect its local region but also impact the ADR of its neighboring regions. This contributes to the overall improvement of ADR in all regions. The region's financial expenditure and population density were also significant in the relationship between HMCLT and ADR, but the coefficients were negative. On the one hand, "urban-biased" development causes the proportion of rural and agricultural spending sourced from central finance revenue to decrease. Moreover, there is no strictly spatial match between financial spending and agricultural and rural development needs. On the other hand, a larger number of rural populations commonly make the local government focus on addressing the problem of insufficient agricultural production capacity, and ignore the environmental benefits, thus inhibiting the enhancement of ADR.

In addition, following Liu et al. [56], the policy of HMCLT can be promoted due to its positive and significant effect. However, spatial heterogeneity should be paid special attention to. On the one hand, the market-based mechanism can play a crucial role in improving ADR, leading to competition with governments and weakening the policy effects [56–58]. On the other hand, the economic, environmental, and social conditions can vary significantly in different regions, thus requiring tailor-made actions and policies in various regions [59].

5.3. Theoretical Implications

This paper generated several contributions to the literature on the effects of HMCLT on ADR. Firstly, this paper constructed the ADR index system, enriching the agricultural development literature. This index system can provide references for researchers and policymakers to consider numerous aspects of agriculture to achieve sustainable development. Secondly, this paper integrated the SCM and spatial models into a holistic framework and investigated the HMCLT policy effects on ADR from the time and space perspectives, as this generates fresh insights into enhancing ADR. To our knowledge, this is the first paper to explore the impact of HMCLT policy on ADR, which can extend the boundaries of policy studies and provide implications for the central and local governments.

5.4. Policy Implications

HMCLT has the potential to drive rural revitalization and agricultural high-quality development. Moreover, this policy can result in ADR improvement in terms of economic, social, and ecological aspects through policy support, capital investment, and spillover effects. It is suggested that further strengthening the support of HMCLT on ADR and achieving agricultural modernization and rural revitalization are possible in the following aspects.

On the one hand, considering the practical role HMCLT policy plays in ADR improvement, it is essential to strengthen the policy design and framework from a top-down approach, advance agricultural technologies, and establish a green agricultural system in China. These measures will facilitate the adjustment of the agricultural production supply chain and improve the governance of agricultural ecology, which are conducive to HMCLT achievement. At the same time, strengthening the role of the government and introducing new business entities through the market-based mechanism will ensure policy implementation and its effectiveness.

On the other hand, due to the practical need for strengthening the spillover effects the HMCLT policy has on ADR, focusing on areas with strict resource constraints and heavy ecological pressure, and addressing imminent issues (e.g., water consumption, soil pollution, land degradation, and supply and demand imbalance) are essential. In addition, the priority of the policy implementation areas should be determined based on their situation. In addition, an information-sharing mechanism should also be built to facilitate collaboration among governments to improve ADR. These measures can enable the full utilization of the spillover effects of HMCLT.

6. Conclusions

The literature on agricultural development and sustainability has been extensive. However, the means to realize agricultural development and promote the resilience of agricultural development has been unclear. This paper has investigated the impact HMCLT has on ADR from the dimensions of time and space, using sample data from Hunan province between 2007 and 2019. The SCM and spatial Durbin model were comprehensively employed for studying the spatio-temporal effects of HMCLT on ADR. It was found that the HMCLT policy has effectively improved ADR in the pilot cities, while also enhancing ADR in the neighboring cities. In addition, financial support for agriculture, agricultural disposable income, and rural population density are also essential factors for ADR. However, these factors will have a crowding-out effect on the ADR of neighboring cities. This paper enriches the literature on the agricultural system and agricultural development theoretically and provides important implications for the central and local governments to improve ADR.

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References

1. Huang, X.; Li, H.; Zhang, X.; Zhang, X. Land use policy as an instrument of rural resilience—The case of land withdrawal mechanism for rural homesteads in China. *Ecol. Indic.* **2018**, *87*, 47–55. [CrossRef]
2. Lipper, L.; Thornton, P.; Campbell, B.M.; Baedeker, T.; Braimoh, A.; Bwalya, M.; Caron, P.; Cattaneo, A.; Garrity, D.; Henry, K.; et al. Climate-smart agriculture for food security. *Nat. Clim. Chang.* **2014**, *4*, 1068–1072. [CrossRef]
3. Glaze-Corcoran, S.; Hashemi, M.; Sadeghpour, A.; Jahanzad, E.; Keshavarz Afshar, R.; Liu, X.; Herbert, S.J. Understanding intercropping to improve agricultural resiliency and environmental sustainability. *Adv. Agron.* **2020**, *162*, 199–256.
4. Huang, M.; Zhu, Y.; Li, Z.; Huang, B.; Luo, N.; Liu, C.; Zeng, G. Compost as a Soil Amendment to Remediate Heavy Metal-Contaminated Agricultural Soil: Mechanisms, Efficacy, Problems, and Strategies. *Water Air Soil Pollut.* **2016**, *227*, 359. [CrossRef]
5. Hellegers, P.; Zilberman, D.; van Ierland, E. Dynamics of agricultural groundwater extraction. *Ecol. Econ.* **2001**, *37*, 303–311. [CrossRef]
6. Bommarco, R.; Vico, G.; Hallin, S. Exploiting ecosystem services in agriculture for increased food security. *Glob. Food Sec.* **2018**, *17*, 57–63. [CrossRef]
7. Jennifer, D. One Fifth of China's Farmland Polluted. Available online: https://www.theguardian.com/environment/chinas-choice/2014/apr/18/china-one-fifth-farmland-soil-pollution (accessed on 20 March 2023).
8. Saxena, G.; Purchase, D.; Mulla, S.I.; Saratale, G.D.; Bharagava, R.N. Phytoremediation of Heavy Metal-Contaminated Sites: Eco-environmental Concerns, Field Studies, Sustainability Issues, and Future Prospects. *Rev. Environ. Contam. Toxicol.* **2019**, *249*, 71–131.
9. Hoang, S.A.; Lamb, D.; Seshadri, B.; Sarkar, B.; Choppala, G.; Kirkham, M.B.; Bolan, N.S. Rhizoremediation as a green technology for the remediation of petroleum hydrocarbon-contaminated soils. *J. Hazard. Mater.* **2021**, *401*, 123282. [CrossRef] [PubMed]
10. Jacob, J.M.; Karthik, C.; Saratale, R.G.; Kumar, S.S.; Prabakar, D.; Kadirvelu, K.; Pugazhendhi, A. Biological approaches to tackle heavy metal pollution: A survey of literature. *J. Environ. Manag.* **2018**, *217*, 56–70. [CrossRef] [PubMed]
11. Lyu, Y.; Su, S.; Wang, B.; Zhu, X.; Wang, X.; Zeng, E.Y.; Xing, B.; Tao, S. Seasonal and spatial variations in the chemical components and the cellular effects of particulate matter collected in Northern China. *Sci. Total Environ.* **2018**, *627*, 1627–1637. [CrossRef] [PubMed]
12. Onyiriuba, L.; Okoro, E.U.O.; Ibe, G.I. Strategic government policies on agricultural financing in African emerging markets. *Agric. Financ. Rev.* **2020**, *80*, 563–588. [CrossRef]
13. Kaur, G.; Singh, G.; Motavalli, P.P.; Nelson, K.A.; Orlowski, J.M.; Golden, B.R. Impacts and management strategies for crop production in waterlogged or flooded soils: A review. *Agron. J.* **2020**, *112*, 1475–1501. [CrossRef]
14. Rong, Y.; Du, P.; Sun, F.; Zeng, S. Quantitative analysis of economic and environmental benefits for land fallowing policy in the Beijing-Tianjin-Hebei region. *J. Environ. Manag.* **2021**, *286*, 112234. [CrossRef] [PubMed]
15. Xie, X.; Cui, Y.; Yao, L.; Ni, Q.; Khan, S.U.; Zhao, M. Does fallow policy affect rural household income in poor areas? A quasi-experimental evidence from fallow pilot area in Northwest China. *Land Use Policy* **2022**, *120*, 106220. [CrossRef]
16. Yu, Z.; Yao, L.; Wu, M. Farmers' attitude towards the policy of remediation during fallow in soil fertility declining and heavy metal polluted area of China. *Land Use Policy* **2020**, *97*, 104741. [CrossRef]
17. Yu, Z.; Tan, Y.; Wu, C.; Zheng, H. Progress Review on Land Fallow. *China Land Sci.* **2018**, *32*, 82–89. [CrossRef]
18. Qing, W.; Hualin, X. A Review and Implication of Land Fallow System Research. *J. Resour. Ecol.* **2017**, *8*, 223–231. [CrossRef]
19. Fan, X.; Kuang, B.; Lu, X. Green Development Effect of Treatment of Heavy Metal-Contaminated Cultivated Land in Chang-Zhu-Tan Region. *Resour. Environ. Yangtze Basin* **2021**, *30*, 2277–2286.
20. Wu, P.; Wang, Y. Establishing System of Ecological Compensation for Farmland Rotation. *Theory Reform* **2017**, *216*, 20–27.
21. Zhong, Y.; Zhang, X. The Problems and Countermeasures of Fallow Policy. *Issues Agric. Econ.* **2018**, *465*, 76–84.
22. Jia, X. Digital Economy, Factor Allocation, and Sustainable Agricultural Development: The Perspective of Labor and Capital Misallocation. *Sustainability* **2023**, *15*, 4418. [CrossRef]
23. Zhang, L.; Lin, X.; Qiu, B.; Ou, G.; Zhang, Z.; Han, S. Impact of Value Perception on Farmers' Willingness to Participate in Farmland Fallow: A Case-Study in Major Grain-Producing Areas of Hubei and Hunan, China. *Sustainability* **2022**, *14*, 724. [CrossRef]
24. 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]
25. Yu, Z.; Tan, Y.; Wu, C.; Mao, M.; Zhang, X. Alternatives or status quo? Improving fallow compensation policy in heavy metal polluted regions in Chaling County, China. *J. Clean. Prod.* **2019**, *210*, 287–297. [CrossRef]
26. Yu, Z.; Tan, Y.; Mao, M.; Wu, C.; Zhao, Y. The subsidy policies on fallow of farmland contaminated with heavy metals: A farmers' choice experiment and influencing factors analysis. *China Rural Econ.* **2018**, *2*, 109–125.
27. Urruty, N.; Tailliez-Lefebvre, D.; Huyghe, C. Stability, robustness, vulnerability and resilience of agricultural systems. A review. *Agron. Sustain. Dev.* **2016**, *36*, 15. [CrossRef]
28. Aryal, J.P.; Sapkota, T.B.; Khurana, R.; Khatri-Chhetri, A.; Rahut, D.B.; Jat, M.L. Climate change and agriculture in South Asia: Adaptation options in smallholder production systems. *Environ. Dev. Sustain.* **2020**, *22*, 5045–5075. [CrossRef]
29. de Roest, K.; Ferrari, P.; Knickel, K. Specialisation and economies of scale or diversification and economies of scope? Assessing different agricultural development pathways. *J. Rural Stud.* **2018**, *59*, 222–231. [CrossRef]

30. Micheels, E.T.; Nolan, J.F. Examining the effects of absorptive capacity and social capital on the adoption of agricultural innovations: A Canadian Prairie case study. *Agric. Syst.* **2016**, *145*, 127–138. [CrossRef]
31. Dong, F.; Li, Y.; Li, K.; Zhu, J.; Zheng, L. Can smart city construction improve urban ecological total factor energy efficiency in China? Fresh evidence from generalized synthetic control method. *Energy* **2022**, *241*, 122909. [CrossRef]
32. Boori, M.S.; Choudhary, K.; Paringer, R.; Kupriyanov, A. Eco-environmental quality assessment based on pressure-state-response framework by remote sensing and GIS. *Remote Sens. Appl. Soc. Environ.* **2021**, *23*, 100530. [CrossRef]
33. Hu, X.; Xu, H. A new remote sensing index based on the pressure-state-response framework to assess regional ecological change. *Environ. Sci. Pollut. Res.* **2019**, *26*, 5381–5393. [CrossRef]
34. Liu, D.; Hao, S. Ecosystem Health Assessment at County-Scale Using the Pressure-State-Response Framework on the Loess Plateau, China. *Int. J. Environ. Res. Public Health* **2016**, *14*, 2. [CrossRef]
35. Li, W.; Qi, J.; Huang, S.; Fu, W.; Zhong, L.; He, B. A pressure-state-response framework for the sustainability analysis of water national parks in China. *Ecol. Indic.* **2021**, *131*, 108127. [CrossRef]
36. Chen, D.; Lu, X.; Liu, X.; Wang, X. Measurement of the eco-environmental effects of urban sprawl: Theoretical mechanism and spatiotemporal differentiation. *Ecol. Indic.* **2019**, *105*, 6–15. [CrossRef]
37. Heijman, W.; Hagelaar, G.; van der Heide, M. Rural Resilience as a New Development Concept. *EU Bio Econecon. Policies* **2019**, *II*, 195–211.
38. Li, Y. A systematic review of rural resilience. *China Agric. Econ. Rev.* **2023**, *15*, 66–77. [CrossRef]
39. Zhao, J.; Ji, G.; Tian, Y.; Chen, Y.; Wang, Z. Environmental vulnerability assessment for mainland China based on entropy method. *Ecol. Indic.* **2018**, *91*, 410–422. [CrossRef]
40. Cunha-Zeri, G.; Guidolini, J.F.; Branco, E.A.; Ometto, J.P. How sustainable is the nitrogen management in Brazil? A sustainability assessment using the Entropy Weight Method. *J. Environ. Manag.* **2022**, *316*, 115330. [CrossRef]
41. Abadie, A.; Gardeazabal, J. The Economic Costs of Conflict: A Case Study of the Basque Country. *Am. Econ. Rev.* **2003**, *93*, 113–132. [CrossRef]
42. 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]
43. Zhang, X.; Chen, D.; Lu, X.; Tang, Y.; Jiang, B. Interaction between Land Financing Strategy and the Implementation Deviation of Local Governments' Cultivated Land Protection Policy in China. *Land* **2021**, *10*, 803. [CrossRef]
44. Lu, X.; Hou, J.; Tang, Y.; Wang, T.; Li, T.; Zhang, X. Evaluating the Impact of the Highway Infrastructure Construction and the Threshold Effect on Cultivated Land Use Efficiency: Evidence from Chinese Provincial Panel Data. *Land* **2022**, *11*, 1044. [CrossRef]
45. Yang, L.; Wang, J.; Feng, Y.; Wu, Q. The Impact of the Regional Differentiation of Land Supply on Total Factor Productivity in China: From the Perspective of Total Factor Productivity Decomposition. *Land* **2022**, *11*, 1859. [CrossRef]
46. Peng, W.; Zheng, H.; Robinson, B.E.; Li, C.; Li, R. Comparing the importance of farming resource endowments and agricultural livelihood diversification for agricultural sustainability from the perspective of the food–energy–water nexus. *J. Clean. Prod.* **2022**, *380*, 135193. [CrossRef]
47. Yang, C.; Li, W. A Study on the Measurement of Farmer Household Credit Efficiency and Its Influencing Factors: An Empirical Analysis Based on Hunan Province. *Wuhan Financ.* **2021**, *261*, 33–40.
48. Liu, Y.; Jin, L.; Zhan, Y.; Zhu, Q.; Huang, Z.; Xiao, J. Evaluation on Development Level of Agricultural and Rural Modernization in Hunan Province. *Hunan Agric. Sci.* **2021**, *427*, 116–120.
49. Yan, X.; Song, M.; Xiang, H.; Chen, N. Analysis of Influencing Factors of Rural Planning in Hunan Provincce based on Sustainable Development of Agriculture. *Chin. J. Agric. Resour. Reg. Plan.* **2020**, *41*, 204–311.
50. Tang, K.; Xiong, Q.; Zhang, F. Can the E-commercialization improve residents' income?—Evidence from "Taobao Counties" in China. *Int. Rev. Econ. Financ.* **2022**, *78*, 540–553. [CrossRef]
51. Xu, Y.; Ren, M. The Development of Modern Agriculture in Hunan Province Level Evaluation. *Econ. Geogr.* **2009**, *29*, 1166–1171.
52. Yin, C.; Yao, X.; Sun, B. Population density and obesity in rural China: Mediation effects of car ownership. *Transp. Res. Part D Transp. Environ.* **2022**, *105*, 103228. [CrossRef]
53. Huang, Y.; Chen, L.; Li, X. Productivism and Post-Productivism: An Analysis of Functional Mixtures in Rural China. *Land* **2022**, *11*, 1490. [CrossRef]
54. LeSage, J.P.; Pace, R.K. Spatial Econometric Models. In *Handbook of Applied Spatial Analysis*; Springer: Berlin/Heidelberg, Germany, 2010; pp. 355–376.
55. Cai, H.; Yu, Z.; Amanze, C.; Wang, S.; Yu, R.; Zeng, W.; Wu, X.; Shen, L.; Li, J. Variations of airborne bacterial community with seasons and environmental factors in Changsha, China. *Air Qual. Atmos. Health* **2022**, *15*, 773–783. [CrossRef]
56. Liu, Y.; Liu, S.; Shao, X.; He, Y. Policy spillover effect and action mechanism for environmental rights trading on green innovation: Evidence from China's carbon emissions trading policy. *Renew. Sustain. Energy Rev.* **2022**, *153*, 111779. [CrossRef]
57. Warner, M.E. Market-based Governance and the Challenge for Rural Governments: US Trends. *Soc. Policy Adm.* **2006**, *40*, 612–631. [CrossRef]

58. Ji, X.; Wu, G.; Lin, J.; Zhang, J.; Su, P. Reconsider policy allocation strategies: A review of environmental policy instruments and application of the CGE model. *J. Environ. Manag.* **2022**, *323*, 116176. [CrossRef]
59. Chen, S.; Shi, A.; Wang, X. Carbon emission curbing effects and influencing mechanisms of China's Emission Trading Scheme: The mediating roles of technique effect, composition effect and allocation effect. *J. Clean. Prod.* **2020**, *264*, 121700. [CrossRef]

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Impacts of Rural–Urban Labour Transfer and Land Transfer on Land Efficiency in China: A Analysis of Mediating Effects

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Abstract: In the midst of China's ongoing rural–urban integration and development, a pivotal transformation involving the realignment of labour dynamics and land utilisation is underway. This paradigm shift has substantial implications for rural land use and agricultural productivity. Drawing from the field survey conducted in Zhejiang Province in 2019, this study puts non-agricultural employment, land transfer, and land efficiency into one econometric model and establishes a comprehensive framework to explain the mechanisms. Unlike existing research, this paper delves into the impact of different land-transfer behaviours, namely inflow and outflow, on land efficiency. The findings indicate that non-agricultural employment has no significant impact on land efficiency. Rural households acquiring land significantly enhance land efficiency, whereas relinquishing land shows no significance, thus addressing the gap in existing literature regarding the study of different transfer behaviours. Furthermore, to explore the underlying mechanisms, we investigate the mediating effect of land inflows on land efficiency, finding that it operates through plot size. In light of this, we propose that, in guiding land inflows, more emphasis should be placed on the integration and reorganisation of fragmented land rather than simply expanding the total land area, aiming to create large, well-managed areas of arable land by achieving concentrated and contiguous transferable land parcels.

Keywords: land transfer; mediating effect; land efficiency; heterogeneity

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1. Introduction

In the late 1970s, China initiated the implementation of the household rural system (HRS), which aims at enhancing farmers' motivation, has yielded significant results. Nevertheless, critical issues, including land fragmentation and irrational land use, have surfaced as the reform evolves and the situation changes. Consequently, the land efficiency and agricultural productivity face declining challenges. At the same time, the rapid urbanisation which accelerates China's rural hollowing worsened the situation. Developing countries like Ethiopia share similar situations and perceptions with China, particularly rural–urban labour transfer. Ethiopia and China have experienced significant rural–urban migration due to economic pressures and land-management issues, although the specific historical and policy contexts differ. For example, China's economic reforms and rapid urbanisation have led to a massive rural labour movement to urban centres, driven by industrialisation and the search for better living standards. In Ethiopia, similar migration patterns have been observed, though often within different policy frameworks and economic contexts, such as the need for agricultural reforms and addressing landlessness (Central Statistical Authority, 2003 [1]; Zewdu and Malek, 2010 [2]). It is noteworthy that the migration of rural labour to urban areas and non-agricultural employment has brought opportunities for the transfer of rural land, with the area of land-use rights transfers reaching approximately 532 million mu (equivalent to about 35 million hectares) in 2022 (Xu et al., 2022) [3] in China. Land transfer is expected to significantly impact agricultural production methods and land-use efficiency, while the mechanisms explaining this process remain a subject of debate and controversy in the academic community. Therefore, there is an urgent need for further research and analysis to uncover the complex dynamics of this crucial aspect of rural development.

2. Literature Review

Numerous studies have investigated the intricate relationship between non-agricultural employment and regional development. A prevailing perspective, characterised by optimism, asserts that rural–urban migration catalyses local development. This assertion is primarily based on the premise that migrant workers contribute to local economies through remittances, which are seen as sources of enhanced productive investments, ultimately fostering economic development within these rural areas. Furthermore, this positive perspective highlights the transfer of expertise and the introduction of technological advancements by returning migrants as additional drivers of local economic progress (Penninx, 1982) [4]. Complementing this view, Wang et al. (2020) [5] utilised data from the Chinese Household Income Project 2013 to analyse how non-agricultural employment impacts rural land circulation in China. Their findings indicate that stability in non-agricultural employment, primarily through non-agricultural assets, significantly influences land-transfer decisions, with notable variations between China's Central and Western regions. This suggests a nuanced need for region-specific policies to promote efficient land use and support rural economic development.

Conversely, a more pessimistic viewpoint suggests that migration exacerbates labour shortages in rural villages, triggering adverse social and cultural consequences within these communities. Furthermore, this perspective argues that remittances often serve as short-term coping mechanisms rather than as investments in agricultural production. Instead, these financial resources are frequently allocated towards immediate consumption needs such as constructing new houses, supporting elderly family members, and covering educational expenses. Empirical evidence from Ethiopia and Nepal indicates that out-migration has led to shifts towards less labour-intensive agriculture and altered land-use patterns without necessarily enhancing local development (Kharel et al., 2023) [6]. Moreover, studies in sparsely populated areas reveal that urban-centric growth often fails to produce beneficial spillovers for rural hinterlands, instead exacerbating disconnects and deepening regional inequalities (Cristina, 2012 [7]; Chen and Hanori, 2009 [8]; Carson et al., 2022 [9]).

This ongoing debate within scholarly literature underscores the multifaceted nature of rural–urban migration's impact on regional development. The divergence in viewpoints highlights the need for comprehensive empirical analyses and nuanced investigations to better understand the complex dynamics involved in the interplay between migration, remittances, and their consequences for rural communities. Such research endeavours are essential for crafting effective policies that can harness the potential benefits of migration while addressing its challenges in the context of regional development.

Much research has explored the intricate correlation between non-agricultural employment and land efficiency. However, there has yet to be a consensus regarding this relationship's outcomes, with findings exhibiting considerable variation. Some empirical investigations suggest that non-agricultural employment negatively influences land productivity. For instance, Li et al. (2020) [10], drawing on survey data from the Loess Plateau in China, identified a significant increase in household income attributable to non-agricultural employment but also observed a notable decrease in agricultural labour productivity and land output associated with this form of employment. Similarly, Jiang et al. (2022) [11] corroborated these findings by demonstrating that non-agricultural employment poses constraints on agricultural production, particularly for smallholder households with fewer than three labourers, thereby hindering improvements in production efficiency.

In contrast, some studies posit a positive correlation between non-agricultural employment and the enhancement of land productivity. For example, Seoge and Zahonogo (2023) [12], analysing nationally representative data from Burkina Faso, identified non-agricultural activities as a significant determinant in elevating land production efficiency. Additionally, Nguyen et al. (2019) [13], examining non-agricultural employment behaviours in Vietnamese rural households, reported increased land productivity among rural households engaged in non-agricultural employment and receiving remittances.

Moreover, certain studies indicate that non-agricultural employment may not necessarily induce significant changes in land productivity. For instance, Sun's study (2021) [14] on land efficiency at the county level in China revealed that non-agricultural employment did not have a discernible impact on land efficiency in western Chinese counties.

The existing body of research presents conflicting views regarding land transfer and its relationship with land efficiency. Land transfer can contribute to improvements in land productivity. For instance, Ricker-Gilbert (2018) [15] identified significant positive effects of land transfer on household land productivity. Similarly, based on data from Ethiopia, Gottlieb and Grobovsek (2019) [16] found that land transfer could release surplus labour from agriculture, leading to increased rural–urban migration and ultimately resulting in improved agricultural productivity. Additionally, Kijima and Tabetando (2020) [17] found that land rental markets in Uganda and Kenya exhibited high efficiency, transitioning land from lower-capacity farming households to higher agricultural productivity, thereby enhancing overall agricultural production efficiency.

However, various pieces of literature have demonstrated negative relationships between land transfer and productivity. For instance, Pender and Fafchamps (2006) [18] compared land productivity between Africa's self-owned and rented land, revealing that the latter was less productive than the former. Chen et al. (2011) [19] used the DEA method to calculate the impact of land transfer on household productivity in Beijing, Shanghai, and Guangdong provinces. The results showed that land transfer could decrease land productivity.

In addition, there are also findings suggesting that land transfer does not necessarily lead to increased land efficiency (Gollin & Udry, 2021) [20]. Gai et al. (2020) [21], drawing upon data collected from established observation points in rural China, conducted a study illuminating how land transfers from households to corporations and cooperatives often find application in 'non-agricultural' and 'non-grain' ventures. Even with the overall rise in farmers' income after the transfer, there may be an equal enhancement in agricultural productivity. Similarly, Zhang et al. (2017) [22], utilising data from four counties in Jiangsu Province, ascertained that autonomously instigated household land transfers typically encompass relatively modest land scales and abbreviated transfer durations. This prevailing scenario militates against the facilitation of economies of scale and the realisation of enduring investments in production.

Consequently, impromptu land transfers might not exert a pronounced impact on agricultural productivity. The diverse findings in these studies underscore the complexity of the relationship between land transfer and land efficiency. Further research and nuanced analysis are needed to elucidate the underlying mechanisms and contextual factors contributing to the observed outcome variations. Such endeavours are crucial for informing policies and interventions to optimise land use and agricultural productivity in diverse regional contexts.

The existing literature on non-agricultural employment, land transfer, and land efficiency offers valuable insights but also presents several limitations that this study aims to address. Generally, research has predominantly focused on the economic outcomes of land transfer, such as income changes, often neglecting the broader concept of land efficiency, which encompasses the output value per unit of land area and sustainable land-use practices. Moreover, while previous studies have explored the direct effects of non-agricultural employment on rural economies, more comprehensive models that integrate these employment shifts with land-transfer behaviours and land-efficiency outcomes need to be developed. This gap hinders a holistic understanding of how labour shifts away from agriculture influence land management and efficiency in the long term. Additionally, much of the existing research needs to sufficiently account for regional variations and the nuanced ways in which local policies, such as China's Three Rights Separation Reform, reshape land tenure and labour migration. Our study addresses these shortcomings by incorporating a nuanced econometric analysis that considers various forms of land transfer and their impacts on land efficiency. It provides a more detailed and context-sensitive understanding of these complex relationships.

This study contributes to existing literature in three aspects. Firstly, the paper focuses on the modes of land transfer and its impact on land efficiency after the Three Rights Separation Reform (TRSR) in China. Following the household responsibility system (HRS), the Chinese government introduced a key institutional innovation called the "Three Rights Separation Reform" in 2014. The TRSR, while retaining farmers' land contract rights, allows them to transfer management rights through land leasing, mortgage loans, or equity investment (Liu et al., 2017) [23]. This reform fundamentally reshapes land-tenure security, land-transfer modes, and labour migration. However, research on whether and how the TRSR triggers rural land transfer and utilisation is still limited. Our paper addresses this gap by carefully examining the interactions between non-agricultural employment, land transfer, and land efficiency four years after the implementation of the TRSR, filling the void in existing research.

Secondly, this study focuses on the key variable of land efficiency. Previous literature primarily explores the impact of non-agricultural employment and land transfer on agricultural production and yield, with limited attention to the variable of land efficiency. Land efficiency is crucial for national agricultural capacity and food self-sufficiency, and our study uniquely addresses this gap.

Thirdly, this study thoroughly explores the complex connections and mediating mechanisms between non-agricultural employment, land transfer, and land efficiency. Based on survey data collected in China, we incorporate non-agricultural employment, land transfer, and land efficiency into one econometric model and further explore land transfer by distinguishing between inflow and outflow modes. In addition to the baseline model, we investigate the mediating mechanisms through which land transfer affects land efficiency. Furthermore, we examine the heterogeneous effects among different groups based on factors such as age, gender, and technical guidance. As a result, our study provides a comprehensive empirical analysis of the intricate relationships between non-agricultural employment, land transfer, and land efficiency. This research offers policymakers in China and similar development environments valuable insights.

Section 2 above examines essential theoretical frameworks and the upcoming sections are arranged as follows. Section 3 provides background information and data details. Section 4 discusses empirical methodologies. Section 5 demonstrates this research's empirical results, and Section 6 discusses the findings and policy implications; finally, Section 7 provides concluding remarks.

3. Theoretical Analysis

Agricultural productivity is a multidimensional and comprehensive concept, encompassing land efficiency, labour productivity, cost–profit ratio, total factor productivity, and technological efficiency, among others (Fuglie, 2018) [24]. Given the relevance of land efficiency to agricultural production and food self-sufficiency, this paper employs land efficiency as a measure of agricultural productivity and presents the following theoretical framework.

H1. *Non-agricultural employment has a negative impact on land efficiency.*

Drawing on the existing literature, non-agricultural employment influences land efficiency through at least three pathways (Figure 1):

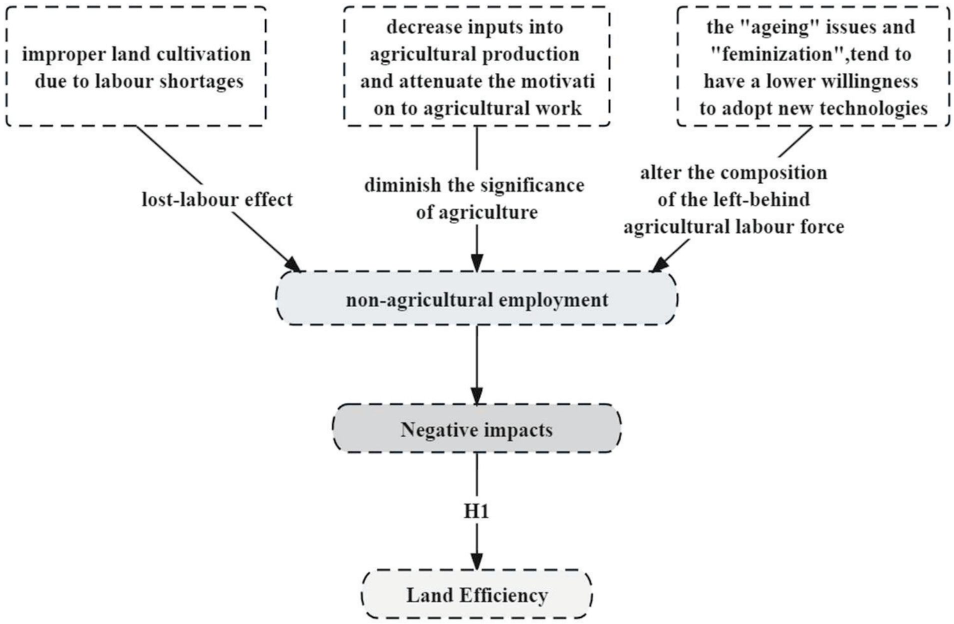

Figure 1. Theoretical mechanism for non-agricultural employment affecting land efficiency.

Firstly, non-agricultural employment can diminish land efficiency through the effect of labour lost. China's agriculture has long been characterised by a state of "overpopulation" and serves as a quintessential example of "involutionary" agriculture (Zongzhi Huang, 2020) [25]. To sustain their livelihoods, rural households often rely on investing more labour to increase output, often disregarding the opportunity costs of labour inputs. With the rapid economic development in China and the increasing availability of non-agricultural employment opportunities, a continually increasing number of surplus rural labourers have migrated to urban areas over the past four decades, leading to a reduction of nearly 300 million agricultural labourers. This excessive loss of agricultural labour can result in improper land cultivation due to labour shortages, leading to decreased land efficiency (Gathala et al., 2021) [26].

Secondly, non-agricultural employment can reduce land efficiency by diminishing the significance of agriculture in rural household economies. As the importance of agriculture diminishes, households may decrease their inputs into agricultural production. Non-agricultural income could gradually shift towards diversification or even part-time engagement in agriculture (Bai et al., 2022) [27]. Additionally, the rise in non-agricultural income could potentially decrease the labour effort of family members left behind by elevating the reservation wage and lowering the opportunity cost of leisure (Naiditch & Vranceanu, 2009) [28].

Thirdly, non-agricultural employment reduces land productivity by altering the composition of the left-behind agricultural labour force. In agricultural production, the land efficiency of the young and middle-aged population is relatively higher. The challenges related to "ageing" and the impacts associated with a more excellent representation of women in the labour force due to workforce outflows influence agricultural productivity outcomes (Roth et al., 2022) [29]. Elderly individuals, due to health conditions and declining physical strength, as well as limitations in their cultural qualifications, tend to reduce human capital and restrain agricultural scale management and technology progress (Zhang et. al., 2023) [30]. The feminisation of agriculture can reduce agricultural productivity due to the lack of resources (Yan et. al., 2022) [31] and opportunities available to women farmers (Kelkar, 2009) [32].

H2. *Land transfer positively affects land productivity.*

Land is a crucial element in agricultural production. Land transfer influences household land efficiency through the following pathways (Figure 2).

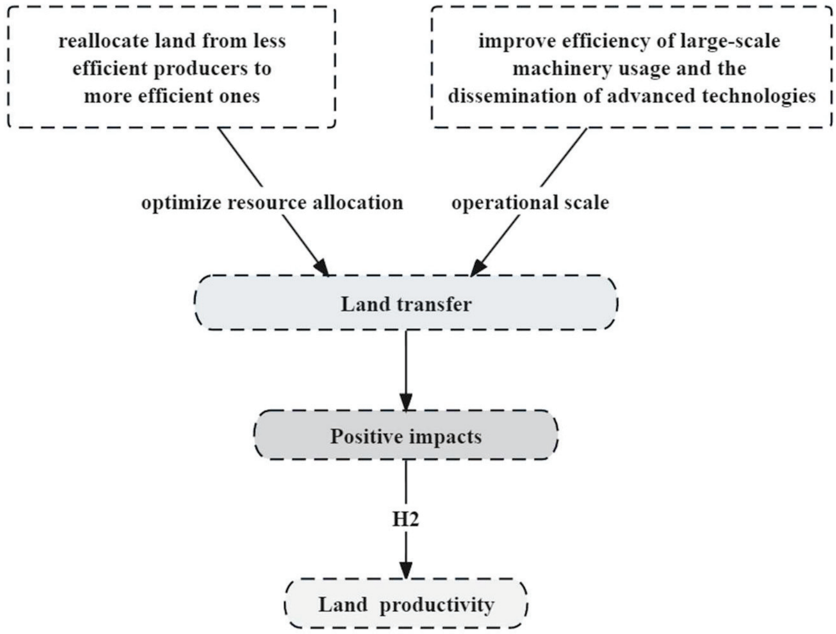

Figure 2. Theoretical mechanism for land transfer affecting land productivity.

Land transfer enhances land efficiency through optimised resource allocation. Some studies suggest that the establishment of land markets and the unrestricted flow of land transfers can lead to a "levelling effect" by reallocating land from less efficient producers to more efficient ones, thereby equalising the marginal output among households (Carter and Yao, 2002) [33] and consequently increasing land efficiency. Scholars also point out that the transfer of rural land contractual management rights can accelerate the process of agricultural land scaling and intensification (Deng et al., 2022) [34], facilitating the redistribution of capital and labour resources and ultimately enhancing productivity (Cao et al., 2007) [35].

Land transfer enhances land efficiency through the operational scale. Multiple research findings indicate that land transfer results in an expansion of the land operating scale. Most studies confirm a 'positive relationship' between land transfer and land productivity, emphasising the enlargement of the land operating scale (Alfaro et al., 2008 [36]; Adamopoulos and Restuccia, 2014 [37]). The primary mechanism is that the development of agricultural scale is a prerequisite for achieving agglomeration effects within agricultural industries, thereby positively impacting transaction efficiency and production efficiency. Additionally, compared to small-scale farmers, large-scale farmers possess a greater resilience against natural disasters, further contributing to an increase in efficiency (Zhou et al., 2020) [38]. The transfer of land might achieve the concentration of agricultural (Neguyen 1996) [39] and enable producers to adjust the production scale to achieve a certain scale effect, thereby improving the economies of scale.

H3. *Land plot size plays a mediating role in the effect of land inflow on land efficiency.*

H3a. *Land inflow has a positive impact on land plot size.*

H3b. *Land plot size has a positive impact on land efficiency.*

Land transfer improves land efficiency by alleviating land fragmentation. Land fragmentation, determined by the number of plots and the amount of land, can be detrimental in agricultural production (Hartvigsen, 2014) [40]. Land transfer, especially land inflow, is expected to increase the average plot size and reduce land fragmentation, thereby enhancing land efficiency. Firstly, larger plot sizes enable farmers to distribute fixed costs (such as purchasing and maintaining machinery) more effectively (MacDonald, Korb and Hoppe, 2013) [41]. This reduces the cost per unit of output, thereby increasing the production efficiency (Roesch-McNally et al., 2017) [42]. Secondly, the increase in plot size allows farmers to utilise advanced agricultural machinery and techniques, which are often uneconomical or impracticable in small-scale production. Mechanisation significantly improves operational efficiency and precision, reduces the demand for labour, and enhances land output (Goyal and Singh, 2020 [43]; Javaid et al., 2022) [44]. Thirdly, larger plot sizes enable farmers to implement crop rotation and planting strategies more effectively; this can therefore improve soil quality, reduces pest and disease incidence, and thus enhances long-term land efficiency (Shah et al., 2021) [45]. Lastly, farmers can organise labour more efficiently on larger parcels, reducing the time and cost associated with transferring labour between parcels, thereby increasing productivity (Roesch-McNally et al., 2017) [42].

4. Data Description

China is experiencing the most significant rural–urban labour migration in its history, with an annual growth rate of 1% over the past four decades. This ongoing labour out-migration phenomenon has exerted profound and far-reaching influences on land utilisation patterns and rural communities in China, offering a valuable opportunity to investigate the implications of non-agricultural employment and land transfers on land efficiency.

The survey took place in 2019 in Zhejiang Province, China. Zhejiang Province is located in the south-eastern coastal area of China and is part of the renowned "Yangtze River Delta." The province has a land area of 105,500 square kilometres. As of 2023, the province's population is 66.27 million, with the service industry dominating the economy. The per capita GDP is 125,000 CNY/person, ranking fourth in China. We select Zhejiang Province as the research area for several reasons. Firstly, the province's level of agricultural modernisation ranks among the top in China. Secondly, rural–urban labour transfer is widespread here. Thirdly, there is a diversity of land-transfer behaviours and active innovation in land-management methods. Specifically, in terms of agricultural machinery and equipment, the comprehensive mechanisation level of crop cultivation and harvesting reached 74.9% in the province in 2021, ranking at the forefront nationwide. Regarding labour force transfer, Zhejiang Province has a high level of urbanisation, with an urbanisation rate reaching 73.4% in 2022, far exceeding the national average of 65.22%. The labour force transfer is active, and employment forms are diverse. In terms of land transfer, Zhejiang Province has a developed land-transfer market, with a large area of land under transfer and diverse transfer entities and forms. As of June 2020, the area of land transferred through leasing, shareholding cooperation, and other means in the province reached 11.2 million mu, with a land-transfer rate of 61.4%. In terms of innovation in land-management methods, Zhejiang is a pilot area for professional cooperatives. The number of new agricultural entities such as various agricultural enterprises, shareholding cooperatives, and family farms has rapidly increased.

The subjects of the survey were agricultural practitioners and migrant workers residing in rural areas. Agricultural practitioners include not only small-scale farmers but also individuals from larger farms, cooperative members, and employees of agricultural enterprises. We employed a stratified random sampling method for the selection of both the study area and interview participants. Initially, we categorised the regions into northern, central, and southern areas, considering the distribution of the agricultural population. Subsequently, we selected five counties—Yuyao, Yinzhou, Xiangshan, Ninghai, and Cixi—to represent these different geographical regions within the three areas, each of which possesses unique characteristics in agricultural development. Within these selected counties, we employed random sampling to choose 2 villages from each, resulting in 10 villages. Finally, we randomly selected 30 rural households from each village for our questionnaire-based interviews.

The questionnaire survey was carried out through face-to-face interviews and encompassed various aspects. It collected information of four parts: First, personal and family basic information, including family composition, age, education level, family income structure, expenditure, and employment details. Second, the land management and transfer of the subjects' households, including crop varieties, area, output value, production costs such as machinery, labour, land, fertilisers, pesticides, and hired labour, as well as land-transfer behaviour, area, method, amount, parties involved, and conflicts of interest. Third, social aspects of the subjects' lives, including housing, healthcare, network, employment, training, etc. Fourth, the terrain, location, and economic development of the surveyed villages. The questionnaire includes fill-in-the-blank, single-choice, multiple-choice, and scale questions. The Likert scale method is used for subjective judgment questions. A total of 300 questionnaires were collected. After carefully reviewing and eliminating questionnaires with incomplete or missing data, 274 valid questionnaires were retained (Table 1), resulting in a questionnaire validity rate of 91.3%.

Table 1. Distribution of survey areas.

Province/City	City/County	No. of Townships	No. of Valid Questionnaires
Zhejiang Province Ningbo City	Yuyao City	2	54
	Yinzhou District	2	56
	Xiangshan County	2	55
	Ninghai County	2	54
	Cixi City	2	55
Total	5	10	274

5. Empirical Strategy

5.1. Econometric Specification

Following the empirical methods of Li et al. (2010) [46] and Feng et al. (2010) [47], this paper establishes the baseline model as follows:

$$\mathrm{Y} = \mathrm{C_i} + \alpha_1 \mathrm{N} + \alpha_2 \mathrm{Ti} + \alpha_3 \mathrm{To} + \sum \delta_i \mathrm{X_i} + \varepsilon_i \tag{1}$$

Furthermore, we draw upon the approach of Jiang (2022) [48] and construct the following model to test the mediating mechanism by which land transfer affects land efficiency:

$$\mathrm{Mid_i} = \beta_0 + \beta_1 \mathrm{Ti} + \beta_2 \mathrm{X_i} + \mathrm{C_i} + \varepsilon_i \tag{2}$$

$$\mathrm{Y} = \varphi_0 + \varphi_1 \mathrm{Ti} + \varphi_2 \mathrm{Mid_i} + \varphi_3 \mathrm{X_i} + \mathrm{C_i} + \varepsilon_i \tag{3}$$

where Y represents the land efficiency; N represents the non-agricultural employment of the households; Ti and To denote land inflow and land outflow, respectively; $\mathrm{X_i}$ represents a set of control variables (as indicated in Table 2); $\mathrm{Mid_i}$ represents the mediating variable, that is, the average land plot size; and ε_i is the error term.

Following the theoretical model presented in the second section of this paper and drawing on relevant existing literature, the following variables are introduced:

The variable Y represents land efficiency, measured as RMB per mu of agricultural profit in 2018. Land efficiency holds substantial significance in the context of agricultural capacity and, by extension, plays a crucial role in influencing food self-sufficiency within China (Qian and Hong, 2016) [49]. However, exploring its relationship with non-agricultural employment and land transfer has been relatively underexplored in the existing literature. Land efficiency, as quantified here, is calculated as the annual profit per unit of land area (mu). It is calculated by deducting the cultivation costs, encompassing expenses like seed costs, applied fertilisers, and land rent, from the total market value of the produce categorised by crop type.

Non-agricultural employment, represented by the variable N is the proportion of non-agricultural labour to the total household labour force. This definition is drawn from Kung's research conducted in 2002 (Kung, 2002) [50]. Non-agricultural labour refers to individuals who migrate to urban regions and participate in non-agricultural industries for six months. This variable provides a means to quantify the extent to which households allocate their labour resources between agricultural and non-agricultural sectors, a dimension that holds relevance in understanding the dynamics of land efficiency and its association with workforce migration and land transfer.

Table 2. Descriptive statistics (N = 274).

Variable	Definition	Mean	Std. Dev.	Min. Level	Max. Level
Land efficiency	Annual profit per mu of land in 2018 (yuan per mu, log value)	3.34	0.33	2.68	4.40
Non-agricultural employment	The ratio of non-agricultural labour to total household labour (%)	49.85	31.59	0	100
Ti	Land transfer—in, dummy variable (1 = The household transfer-in land)	0.25	0.43	0	1
To	Land transfer—out, dummy variable (1 = The household transfer-out land)	0.20	0.40	0	1
Labour input	The ratio of the number of agricultural laborers to actual cultivated land scale (person per mu, log value).	−0.44	0.55	−2.66	0.78
Plot size	The ratio of the total land scale at the end of the year per household to the total numbers of plots (mu)	11.31	65.44	0.20	926.00
Machinery	Annual expenditure on machinery (CNY, log value)	2.43	1.34	0	5.62
Gender of household head	Gender of the household head (1 = male)	0.86	0.34	0	1
Age of household head	Age of the household head	55.28	10.35	31	61
Education of household head	Schooling years of the household head	7.87	2.30	5	14.5
Agricultural training	Count of family members who received the agricultural training	1.71	0.46	0	3
Family average age	Average age of the family	46.82	11.25	22.25	64.50
Proportion of female adults in the household	Share of female adults in household (%)	0.49	0.14	0	1
Family education	Average years of schooling for family members	8.52	1.98	5.00	18.10
Village economy	Annual income of the village (10,000 CNY)	4.04	0.20	3.66	4.65
Village transportation	The time it takes to drive to the county centre (hour)	0.81	0.30	0.25	1.40

Ti and T_O estimate the variable of land transfer. However, the analysis of land-transfer behaviour cannot focus solely on whether households are engaged in land transfer; it also necessitates examining whether farmers participate in land inflow or outflow. This study employs dummy variables such as 'participation in land outflow' (To) or 'participation in land inflow' (Ti) to provide a more precise measurement of their land-transfer behaviours (Feng et al., 2010) [47].

Plot size is quantified by the ratio of the total land scale at the end of the year per household to the total numbers of plots, which reflects the extent of land fragmentation. Land fragmentation can be attributed to China's resource endowment of high population density and limited land resources, with the per capita arable land area being only about one-third of the world average (Wu et al., 2015) [51]. It affects land efficiency by influencing the allocation of other agricultural inputs. Land fragmentation refers to a household's land resources being divided into multiple spatially separated plots (Mcpherson, 1983) [52].

Xi incorporates a comprehensive set of control variables at the individual, household, and village levels to elucidate the determinants of land efficiency. These variables encompass various agricultural production factors, including labour input and machinery. By accounting for these multifaceted characteristics and factors, the analysis aims to provide a more robust and nuanced understanding of the factors influencing land efficiency within the study context. Following existing literature, machinery input is represented by the cost of renting agricultural machinery or the annual depreciation cost of owned agricultural machinery for households (log value).

Moreover, one anticipates that the gender, age, and educational attainment of the household head, along with the demographic attributes and educational backgrounds of other family members, are likely to influence this context.

Household Head Characteristics. The household head typically plays a pivotal role in agricultural production decisions. This study defines the 'household head' as the 'person responsible for managing agricultural accounts.' The gender, age, and educational years of the household head influence agricultural production. A substantial body of literature demonstrates that education and other forms of human capital yield significant benefits in crop production (Jamison and Lau, 1983 [53]; Taylor and Martin, 2001 [54]). In the model, we incorporate three variables for control: Gender of the household head, age of the household head, and educational level of the household head.

Family Characteristics. Household decisions in agriculture often involve joint decisions at the family level (Stark, 1991) [55]. Therefore, the human capital characteristics of the household significantly impact decision-making processes. When assessing the influence of non-agricultural employment on labour loss in agricultural production, it becomes imperative to gauge the productivity of the remaining population. The 'ageing' effect resulting from labour outflow and the 'feminisation' effect may contribute to shaping agricultural productivity (Szabo et al., 2021 [56]; Shweta, 2023 [57]).

Consequently, we consider four variables as indicators of household human capital characteristics: Family education (average education level of family members), family average age, proportion of female adults within the household, and number of individuals receiving agricultural skills training (agricultural training). In alignment with the methodology utilised by the National Bureau of Statistics, family education is calculated using the following formula: Family education = $(P1 \times 6 + P2 \times 9 + P3 \times 12 + P4 \times 16)/P$. Here, Pi represents the number of family members with educational attainment at the primary, middle, high school, or university and above levels. At the same time, P denotes the total count of family members aged six years and older.

Village Characteristics. Previous studies in relevant contexts have seldom considered the influence of village-level factors. However, village characteristics are likely to impact household land efficiency. Therefore, this study incorporates the village's economy and transportation conditions as control variables. The village's economy is assessed using the operational income (in 10k Chinese yuan renminbi/CNY) of the village in 2018. Village transportation is measured by the time (in hours) required to drive to the nearest county centre from the village.

County. Substantial variations in land efficiency exist across diverse regions. The study incorporates county dummy variables (county) to account for this factor. Explanations and descriptive statistics are presented in Table 2.

5.2. Endogeneity

Endogeneity issues may exist among non-agricultural employment, land transfer, and land efficiency. Firstly, non-agricultural employment could influence land transfer. The higher the proportion of non-agricultural employment among household labour, the more likely farmers are to engage in land transfer. Numerous studies confirm that non-agricultural employment effectively stimulates the development of the land-transfer market (Kung, 2002) [50]. Secondly, land transfer can also affect household labour allocation decisions. Farm households involved in land transfer are more likely to have more agricultural labour, potentially leading to a relatively smaller proportion of non-agricultural employment. Simultaneously, if the local land-transfer market is conducive to farmers transferring out the land, the willingness for non-agricultural employment in that region might be higher. Thirdly, potential sample selection bias and reverse causality issues should be considered. To elaborate, households with non-agricultural workers may exhibit a greater land efficiency than those without such workers, as individuals with the highest agricultural efficiency may transition to non-agricultural sectors to access higher income opportunities. Conversely, there may be a counteracting bias suggesting that households with non-agricultural workers are inherently less productive. Therefore, we can only better analyse the impact of non-agricultural employment and land transfer on household land efficiency by effectively addressing endogeneity issues.

6. Research Results

The regression results are presented in Table 3. The effect of non-agricultural employment on land efficiency is positive, although not statistically significant. This implies that the mechanism and direction of the effect of non-agricultural employment on land efficiency are intricate. Amidst the interplay of negative and positive impacts, distinct circumstances can result in diverse effects on land efficiency.

Table 3. Regression results for land efficiency (N = 274).

	Land Efficiency			
	(1)	**(2)**	**(3)**	**(4)**
Non-agricultural employment	0.000122	7.70×10^{-5}	0.000104	0.000106
	(0.000369)	(0.000394)	(0.000411)	(0.000401)
Ti	0.155 ***	0.148 ***	0.151 ***	0.100 **
	(0.0451)	(0.0475)	(0.0489)	(0.0427)
To	−0.00392	−0.00453	−0.00304	−0.00851
	(0.0341)	(0.0349)	(0.0350)	(0.0331)
Labour input	0.184 ***	0.185 ***	0.184 ***	0.204 ***
	(0.0374)	(0.0376)	(0.0393)	(0.0351)
Machinery		−0.000535	−0.00121	−0.00149
		(0.00143)	(0.00143)	(0.00140)
Gender of household head		0.00336	−0.000591	−0.000411
		(0.00513)	(0.00573)	(0.00521)
Age of household head		−0.0118	−0.0104	−0.00725
		(0.0270)	(0.0276)	(0.0268)
Education of household head			0.00177	0.00185
			(0.00134)	(0.00136)
Agricultural training			0.0109	0.0466
			(0.0906)	(0.0886)
Family average age			0.00828	0.00634
			(0.00784)	(0.00718)
Proportion of female adults in the household				0.381 ***
				(0.0791)
Family education				0.134
				(0.0886)
Village economy	3.291 ***	3.312 ***	3.213 ***	1.626 ***
	(0.0355)	(0.118)	(0.158)	(0.362)
Village transportation	0.000122	7.70×10^{-5}	0.000104	0.000106
	(0.000369)	(0.000394)	(0.000411)	(0.000401)
County	0.155 ***	0.148 ***	0.151 ***	0.100 **
Constant	(0.0451)	(0.0475)	(0.0489)	(0.0427)
	−0.00392	−0.00453	−0.00304	−0.00851

Note: *** and ** show significance levels at 1% and 5%.

The negative impact of non-agricultural employment on agricultural production is discernibly manifested in what can be termed the "labour loss effect." This effect reflects the outcome of non-agricultural employment, contributing to negligence in agricultural production and a reduction in family labour input, thereby adversely influencing land productivity (Maharjan et al., 2013) [58]. Non-agricultural employment often results in migrating educated and technically skilled young adults from rural agricultural labour to non-agricultural sectors (Uprety, 2019) [59]. Consequently, this migration reduces the profitability of agricultural land production, ultimately resulting in a decline in land productivity.

Simultaneously, as an indirect investment, non-agricultural employment serves as a source of income for rural households while mitigating agricultural production risks (Stark, 1982) [60]. Firstly, non-agricultural employment generates a positive compensatory effect. The increase in non-agricultural income for rural households alleviates financial and credit constraints that might impede their engagement in agricultural production activities (Kirimi and Kirimi, 2006) [61]. It also stimulates rural households to invest in agricultural productive assets, technology, and agricultural social services (Li et al., 2013 [62]; Jiang, 2022 [11]), thereby enhancing land productivity. Secondly, non-agricultural employment enhances land productivity through risk-reduction mechanisms. By diversifying income sources, non-agricultural income acts as an informal insurance system, enabling rural households to self-finance their agricultural production endeavours and providing a safety net against potential income risks (Lucas, 1987 [63]; Stark, 1982 [60]). In a more specific context, non-agricultural income functions as a mechanism for rural households to manage fluctuations in agricultural product prices and production. This, in turn, enables the transition to agricultural production patterns that support heightened land productivity (Damon, 2010) [64]. Furthermore, non-agricultural employment enhances rural households' capacity to access information. It improves their risk preferences, encouraging risk-averse rural households to participate in high-yield but uncertain investments (Wouterse, 2010) [65].

In summary, the impact of non-agricultural employment on land productivity is multifaceted, with both negative and positive dimensions. While the "labour loss effect" is a notable negative consequence, the positive effects include the compensatory and risk-reducing mechanisms associated with non-agricultural income, which can lead to increased land productivity. The intricate interplay between these factors underscores the complexity of the relationship between non-agricultural employment and land efficiency, necessitating further research and analysis to discern the contextual nuances and policy implications.

Land inflow significantly and positively affects land efficiency, whereas the influence of land outflow on land efficiency does not demonstrate statistical significance. The inflow of land significantly contributes to the enhancement of land efficiency, which aligns with the findings of Hongzhong Fan and Qiliang Zhou (2014) [66]. It is possibly attributed to the allocation of land to the households with a comparative advantage in agricultural production. Upon acquiring land, these households can make more investments on a more concentrated scale; this, in turn, leads to a heightened production technology and management proficiency, optimisation of land-utilisation methods, and the realisation of economies of scale, thus resulting in an elevation in land efficiency (Wang et al., 2011 [67]; Qian et al., 2014 [49]).

Conversely, the impact of land outflow did not yield statistically significant results, implying that land outflow has a limited influence on land efficiency; this could be attributed to the fact that transferring out their land, farmers do not necessarily employ more advanced agricultural machinery and equipment, while the land and labour quality remain the same. Consequently, the configuration and quality of production factors remain akin to the pre-transfer state, thereby causing the lack of a notable influence on land efficiency following land outflow (Chen et al., 2011 [19]). Concerning the control variables, notable factors include three variables: labour input, machinery, and the village economy.

More specifically, the labour input exhibits a positive influence on the land efficiency, in line with the prevailing consensus in the literature (Cheng et al., 2019) [68] that a heightened agricultural labour input can bolster land efficiency. This also indicates that Chinese households are typical small-scale producers who rationally increase labour input per unit of land to boost land efficiency, even though this is achieved at the cost of sacrificing labour productivity (Huang, 2020) [25].

Machinery demonstrates a significant effect on land efficiency. The literature consistently demonstrates a positive impact of machinery on land efficiency, underscoring the pivotal role of mechanisation in augmenting land productivity (Bekchanov et al., 2021) [69]. Agricultural mechanisation brings several noteworthy advantages, including reducing labour-intensive tasks, alleviating labour shortages, and improving productivity and timeliness in various agricultural operations. As mechanisation continues to advance, it leads to the intensified substitution of capital and new technology for labour (Olasehinde-Williams et al., 2020 [70]; Mdoda et al., 2022 [71]). This transition underscores the growing importance of machinery in agricultural processes, particularly in mitigating the dependence on labour-intensive practices. Moreover, adopting advanced machinery further contributes to the augmentation of land productivity (Damba et al., 2020 [72]). This outcome underscores the transformative impact that modern agricultural machinery can have on agricultural practices, ultimately resulting in increased efficiency and productivity in land use (Ignatov et al., 2020) [73].

The village's economy significantly and positively influences the land efficiency, underscoring that the economic prowess of villages and collective economy entities positively impacts land efficiency. In locales characterised by heightened village economic development and a robust economic basis, collective economic organisations possess an increased capacity to construct rural public infrastructure and provide public services. Such areas typically boast well-established, advanced infrastructure, including robust road networks and water facilities. When coupled, irrigation systems and rural roads demonstrate complementary effects on labour while offering substitutive effects on fixed capital. This infrastructure can effectively curtail agricultural production costs, significantly enhancing land productivity (Shamdasani, 2021) [74].

This study further tests the land plot size's mediating role in the effect of land inflow on land efficiency. Column (1) of Table 4 shows that the coefficient for Ti is significantly positive, indicating that land transfer can significantly increase the average land plot size for farmers, allowing for improved rational planting decisions. Column (2) shows that the Ti and plot size coefficients are significantly positive, suggesting that land transfer enhances land efficiency by increasing the average plot size. Thus, it demonstrates the mediating effect of the average land plot size, supporting Hypothesis H3.

Table 4. Test results of the mediating effect.

Variables	**Plot Size (1)**	**Land Efficiency (2)**
Ti	5.295 *	0.0916 **
	(3.098)	(0.0427)
Land scale		0.00161 *
		(0.000975)
Controls	ALL	ALL
County fixed	YES	YES
Constant	−49.23	1.705 ***
	(55.81)	(0.329)

Note: ***, **, and * show the significance level at 1%, 5%, and 10%.

6.1. Heterogeneity Analysis

After testifying to the positive impact of land transfer on land efficiency, this study proceeds to conduct a heterogeneity analysis to identify the groups of farmers who benefit the most and the least from land transfer. This section will examine the heterogeneous impacts of land transfer on land efficiency across farmer groups, categorised by age, gender, and technical guidance. It aims to provide a reliable basis for implementing policies to enhance land efficiency and farmers' welfare.

6.2. Heterogeneity across Age Groups

There are significant differences in the education and intentions embraced by farmers of different ages, leading to variations in decisions related to cultivation and technology adoption and ultimately affecting land efficiency. Therefore, this study further examines the differences in land efficiency among farmers in different age groups after transferring in land. Based on the three age categories of the sampled farmers, they are classified as the new-generation farmers (below 51 years old), middle-generation farmers (51–60 years old), and the older-generation farmers (60 years and above). The study analyses the similarities and differences in the regression coefficients of each group.

Table 5 presents the heterogeneous impact on land efficiency after transferring in land for different age groups, as indicated by Columns (1), (2), and (3). The regression results indicate a significantly positive effect of transferring in land on land efficiency for both the new-generation and middle-generation farmers, with a larger impact on the land efficiency of the middle-generation farmers. However, there is no significant impact on the land efficiency of the older-generation farmers. The new-generation and middle-generation farmers tend to have higher levels of education, making them more willing and able to adopt and apply new agricultural technologies, cultivation methods, or market information. This contributes to an improvement in land efficiency and crop quality. On the other hand, the older-generation farmers are often accustomed to traditional agricultural production methods and technologies, exhibiting lower levels of acceptance and application of new technologies and methods, thereby limiting the improvement of land efficiency.

Table 5. Heterogeneity analysis.

Variables	Age Group			Gender Group		Technical Guidance Group	
	New Generation (1)	Middle Generation (2)	Older Generation (3)	Male (4)	Female (5)	Provided (6)	Not Provided (7)
Ti	0.102 *	0.202 *	0.0402	0.0736 *	0.310	0.158 *	0.0659
	(0.0577)	(0.108)	(0.0670)	(0.0444)	(0.240)	(0.0797)	(0.0487)
Controls	ALL	ALL	ALL	ALL	ALL	ALL	ALL
County fixed	YES	YES	YES	YES	YES	YES	YES
Constant	1.573 **	1.572 *	1.760 ***	1.604 ***	2.190 **	3.489 ***	1.063 ***
	(0.596)	(0.832)	(0.507)	(0.393)	(1.005)	(0.726)	(0.396)
Observations	96	74	104	236	38	76	198
R^2	0.629	0.856	0.828	0.791	0.872	0.579	0.815

Note: ***, **, and * show the significance level at 1%, 5%, and 10%.

6.3. Heterogeneity across Gender Groups

Different gendered farmers bear distinct social and family role expectations, facing varied avenues of resource acquisition, development capabilities, and decision-making environments, thereby influencing land efficiency. Consequently, this study further examines the differences in land efficiency among farmers of different genders after transferring in land. Based on the gender characteristics of the household head, farmers are categorised as male or female, and the similarities and differences in the regression coefficients of different gender characteristics are analysed.

In Table 5, Columns (4) and (5) report the heterogeneous impact on land efficiency after transferring in land for different gendered farmers. The regression results indicate that transferring in land has a significantly positive impact on land efficiency for male farmers, while it does not have a significant impact for female farmers. In traditional Chinese rural society, male farmers are typically regarded as the primary economic backbone of the family, more easily accessing new agricultural technologies, cultivation methods, and agricultural training. This contributes to the improvement of their production skills and land-management capabilities, ultimately enhancing land efficiency. Female farmers, due to certain levels of gender discrimination or traditional customs, may simultaneously bear the dual responsibilities of agricultural production and household care. This limits their time and energy investment in agricultural production, with fewer opportunities for agricultural training, ultimately restricting the improvement of land efficiency.

6.4. Heterogeneity across Technical Guidance Groups

After farmers transfer in land, whether they receive technical guidance plays a crucial role in enhancing land efficiency. Therefore, this study further examines the differences in land efficiency based on whether farmers receive technical guidance after transitioning to agriculture. This is defined based on the questionnaire question "Have you received technical guidance or field guidance during production?". Specifically, receiving technical guidance or field guidance is assigned a value of 1, while not receiving it is assigned a value of 0. The study further analyses the similarities and differences in the regression coefficients of different technical guidance characteristics.

In Table 5, Columns (6) and (7) report the heterogeneous impact on land efficiency after farmers transfer in land based on whether technical guidance is provided. The regression results indicate that providing technical guidance or field guidance to farmers after transitioning to agriculture has a significantly positive impact on land efficiency, while not providing technical guidance does not have a significant impact. The government and agricultural-related departments mainly provide technical guidance to farmers who transfer in land. On the one hand, this can offer knowledge and skills in areas such as the latest agricultural practices, crop management, soil conservation, and water resource management, using more advanced scientific methods to improve land output. On the other hand, it can provide farmers with advice on aspects like market analysis and crop selection, helping them to plant crops that are marketable and in demand, thereby increasing land efficiency.

6.5. Robustness Test

The consideration of endogeneity in this study encompasses the potential issues of omitted variable bias and collinearity. Firstly, in terms of omitted variable bias, the model presented here incorporates variables such as labour input, machinery, household head characteristics, family characteristics, village characteristics, and county-level factors through a stepwise approach. As these variables are progressively included, the coefficients and significance of the crucial variables in the model remain relatively stable. This observation underscores the robustness of the regression results derived in this study and validates the rationality of the empirical specification. For future research, incorporating instrumental variables could further enrich the scope of the investigation.

To address collinearity concerns, this study computes the variance inflation factor (VIF) post-regression, as illustrated in Table 6. The highest VIF recorded is 3.33, notably below the threshold of 10. This finding signifies the absence of multicollinearity concerns among land transfer, non-farm employment, and the other primary variables.

Table 6. Variance inflation factor (VIF) values in the model.

Variable	VIF	1/VIF
Non-agricultural employment	1.37	0.73
Ti	2.41	0.42
To	1.43	0.70
Labour input	3.15	0.32
Land scale	3.33	0.30
Plot size	2.58	0.39
Machinery	1.53	0.66
Gender of household head	1.15	0.87
Age of household head	1.76	0.57
Education of household head	1.90	0.53
Agricultural training	1.25	0.80
Family average age	1.97	0.51
Proportion of female adults in the household	1.09	0.92
Family education	1.99	0.50
Village economy	1.48	0.67
Village transportation	2.50	0.40
Mean VIF	2.00	

7. Discussion

7.1. Main Findings

Firstly, the impact of non-farm employment on land efficiency in rural households is not statistically significant. This result is inconsistent with the findings of Nguyen et al. (2021) [75]. This inconsistency may be due to the complex mechanisms through which non-agricultural employment affects land efficiency, involving both negative and positive impacts. The negative impact primarily arises from the labour-loss effect generated by rural–urban labour transfer, leading toa neglect of agricultural production, reduction in household labour, and decline in labour quality, ultimately resulting in a decrease in land efficiency. The positive impact mainly comes from the compensatory effect of non-agricultural income and risk-reduction effect (Uprety, 2019) [59]. Specifically, non-agricultural income in rural households can alleviate the credit constraints faced by agricultural production. Additionally, by diversifying their sources of income, it enhances the resilience of rural households against risks, facilitating them to make scientific and reasonable planting decisions, thereby improving land productivity (Damon, 2010 [64]). The intricate interplay between these negative and positive factors underscores the complexity of the relationship between non-agricultural employment and land efficiency, necessitating further research and analysis to discern the contextual nuances and policy implications.

Secondly, unlike previous studies, this paper subdivides land-transfer behaviour into land outflow and inflow. The empirical results indicate that land inflow can significantly increase land efficiency, while land outflow does not have a significant impact. Land inflow shows a significant positive effect on land efficiency, consistent with the findings of Chavas et al. (2022) [76]. This may be attributed to reallocating land to households with relative advantages in agricultural production. These households, after acquiring land, can operate at a moderate scale, which helps to improve production techniques and management skills, achieve economies of scale, and ultimately enhance land efficiency (Daymard, 2022) [77]. Conversely, land outflow does not significantly affect land productivity, possibly because farmers, after transferring land out, do not use more advanced agricultural machinery and equipment. Additionally, the land and labour quality remain unchanged, meaning that the configuration and quality of production factors remain similar to before the transfer, thus not significantly increasing land efficiency.

Thirdly, this paper employs a mediation model to empirically examine the mechanism through which land inflow affects land efficiency. The study finds that land inflow enhances land efficiency by reducing the degree of land fragmentation and increasing the average size of land plots. The plausible rationale behind this phenomenon is rooted in the fact that agricultural production necessitates labour input and the significant utilisation of machinery, chemical applications, biotechnological inputs, and the like. Farmers with smaller plots often experience the loss of agricultural inputs. Specifically, small plots reduce fixed asset efficiency and constrain the construction of farmland infrastructure, which is indivisible in agriculture. Due to increased boundaries and ridges between small and dispersed plots, irrigation efficiency falls. Agricultural operation time is wasted, leading to poor field management (Lu et al., 2018) [78]. Furthermore, the presence of small and dispersed land plots has a notable impact on the adoption of machinery and modern agricultural technologies, necessitating farmers to allocate additional resources in terms of labour, time, and psychological efforts (Wei, 2015) [79]. Conversely, following the inflow of land, the fragmentation level of land diminishes, increasing the plot size. This enlargement, in turn, stimulates the utilisation of production factors such as labour, technology, and machinery (Foster and Rosenzweig, 2022 [80]), reduces overall production costs, and improves technical efficiency (Orea et al., 2019 [81]).

7.2. Policy Implications

Firstly, the impact of non-farm employment on land efficiency in rural households remains uncertain. Given the substantial disparities in factors such as land endowment, industrialisation, and urbanisation across various rural areas in China, it becomes imperative to continue promoting agricultural labour migration while concurrently enhancing supporting measures. This approach will allow capable and motivated professional farmers to leverage their positive influence fully. Additionally, careful consideration must be given to the potential adverse effects of excessive labour migration on land utilisation. Employing flexible strategies like demonstration and guidance can encourage resident farmers to adopt new agricultural machinery and production techniques, thereby enhancing land efficiency.

Secondly, as land transfer becomes more prevalent, the land efficiency of households who transfer out land remains mainly unaffected, while land inflow positively impacts increasing land output. Therefore, to enhance land efficiency, efforts should be focused on facilitating smooth land transfers, promoting the development and prosperity of rural land markets, and guiding land transfer towards new forms of agricultural operators, such as skilled farmers, family farms, and agricultural cooperatives. Measures must be taken to encourage land transfer and enhance allocative efficiency by equitably distributing land and labour resources among farmers with varying land–labour endowments.

Thirdly, land inflow contributes to the enhancement of land efficiency through the mediating mechanism of increased land plot sizes and reduced fragmentation. Therefore, while guiding the expansion of land scales, a greater emphasis should be placed on consolidating and reorganising fragmented land, creating substantial and well-managed parcels of arable land. This entails achieving concentrated and contiguous transferable land blocks, ensuring level plots and providing adequate supporting facilities. Simultaneously, proactive efforts should be undertaken to advance the construction of high-standard farmland, creating a favourable environmental foundation for intensive agricultural management and promoting the transformation and development of agriculture.

8. Conclusions

Rural–urban migration and land transfer play a crucial role in land utilisation and agricultural production in China. This study, based on data from 274 on-site surveys in Zhejiang Province, examines the impact mechanisms of non-agricultural employment and land transfer on land efficiency and provides a profound explanation of the underlying mechanisms. In contrast to previous research, our approach integrates non-agricultural employment and land transfer into one econometric model to comprehensively investigate their combined effects on land efficiency. Additionally, we carefully examine the diverse impacts under different land-transfer modes. The results indicate that the impact of non-agricultural employment on land efficiency is not significant, contrary to existing research findings. This complex outcome arises from the dual nature of its impact mechanisms, namely the negative effect of labour loss and the positive effect of remittances. The inflow of land significantly enhances land efficiency, while the outflow of land has an insignificant impact. Furthermore, this study demonstrates the mediating effect of land plot size in the impact of land inflow on land efficiency, providing additional insights into the mechanism. Moreover, we investigates the heterogeneous effects among different groups such as age, gender, and technical guidance in this process. Based on the conclusions, the following policy measures are explored.

Although our study offers insights into the effects and mediating mechanism of rural–urban labour transfer and land transfer on land efficiency, it has limitations that need to be addressed. Firstly, when rural–urban migrant workers find employment in other places, they no longer consume food at home. This may serve as another significant impetus for rural–urban labour transfer among impoverished rural households (Van der Geest, 2010) [82], directly impacting the agricultural productivity of the household (Shi et al., 2011) [83], but it is not included in the theoretical framework. Due to the lack of data on individual food consumption, we are unable to study this factor separately. Secondly, the empirical outcomes of this research indicate that non-agricultural employment has not demonstrated a statistically significant influence on land efficiency. This divergence from the findings of Taylor et al. (2003) [84] and Shi (2018) [85] highlights a potential inconsistency. It is plausible that this incongruity could stem from the study's omission of a differentiated and individualised examination of the diverse modes within the realm of non-agricultural employment. This paper provides a preliminary explanation of this issue but does not delve into detailed empirical analysis.

To address the above issues, future research should focus on detailed classification of non-agricultural employment, distinguishing between seasonal and long-term transitions. Through this approach, it is feasible to meticulously investigate the distinct pathways and orientations through which various migration modes impact land efficiency. To navigate this intricate landscape, prospective research endeavours may find merit in deconstructing the facet of non-agricultural employment into discrete categories of seasonal and long-term transitions. This nuanced approach could facilitate a meticulous examination of their divergent trajectories and the diverse impacts they impart on the intricate tapestry of land efficiency.

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References

1. Central Statistical Authority. Ethiopian agricultural sample enumeration: Results at country level, part I and part II. *Addis Ababa: Cent. Stat. Auth.* **2003**. Available online: https://books.google.co.uk/books/about/Ethiopian_Agricultural_Sample_Enumeratio.html?id=8tdsn504vLYC&redir_esc=y (accessed on 12 May 2024).
2. Zewdu, G.A.; Malek, M. *Implications of Land Policies for Rural-Urban Linkages and Rural Transformation in Ethiopia*; Ethiopian Development Research Institute: Addis Ababa, Ethiopia, 2010; Volume 15, pp. 1–14.
3. Xu, L.; Chen, S.; Tian, S. The Mechanism of Land Registration Program on Land Transfer in Rural China: Considering the Effects of Livelihood Security and Agricultural Management Incentives. *Land* **2022**, *11*, 1347. [CrossRef]
4. Penninx, R. A critical-review of theory and practice-the case of turkey. *Int. Migr. Rev.* **1982**, *16*, 781–818. [CrossRef] [PubMed]
5. Wang, J.; Xin, L.; Wang, Y. How farmers' non-agricultural employment affects rural land circulation in China? *J. Geogr. Sci.* **2020**, *30*, 378–400. [CrossRef]
6. Kharel, A.; Sugden, F.; Dessalegn, M. Labor Shortage and Changes in Land Use Patterns: Experiences from Migrant Communities in Ethiopia and Nepal. 2023. Available online: https://cgspace.cgiar.org/server/api/core/bitstreams/18555c0a-5bed-4ead-9b2b-29c040def4d4/content (accessed on 15 May 2024).
7. Cattaneo, C. Migrants' international transfers and educational expenditure: Empirical evidence from Albania. *Econ. Transit.* **2012**, *20*, 163–193. [CrossRef]
8. Chen, G.; Hamori, S. Solution to the Dilemma of the Migrant Labor Shortage and the Rural Labor Surplus in China. *China World Econ.* **2009**, *17*, 53–71. [CrossRef]
9. Carson, D.A.; Carson, D.B.; Argent, N. Cities, hinterlands and disconnected urban-rural development: Perspectives from sparsely populated areas. *J. Rural Stud.* **2022**, *93*, 104–111. [CrossRef]
10. Li, L.; Tsunekawa, A.; MacLachlan, I.; Li, G.; Koike, A.; Guo, Y. Conservation payments, off-farm employment and household welfare for farmers participating in the "Grain for Green" program in China Empirical evidence from the Loess Plateau. *China Agric. Econ. Rev.* **2020**, *12*, 71–89. [CrossRef]
11. Jiang, X.; Zhong, S.; Huang, C.; Guo, X.; Zhao, J. Blessing or curse? The impact of non-agricultural part-time work of the large farmer households on agricultural labour productivity. *Technol. Econ. Dev. Econ.* **2022**, *28*, 26–48. [CrossRef]
12. Seogo, W.; Zahonogo, P. Do land property rights matter for stimulating agricultural productivity? Empirical evidence from Burkina Faso. *Land Use Policy* **2023**, *125*, 106475. [CrossRef]
13. Nguyen, D.L.; Grote, U.; Trung Thanh, N. Migration, crop production and non-farm labour diversification in rural Vietnam. *Econ. Anal. Policy* **2019**, *63*, 175–187. [CrossRef]
14. Sun, X. Promoting or inhibiting-research on the impact of non agricultural employment on agricultural land efficiency. *Econ. Manag. Res.* **2021**, *42*, 133–144. (In Chinese)

15. Ricker-Gilbert, J.; Chamberlin, J. Transaction Costs, Land Rental Markets, and Their Impact on Youth Access to Agriculture in Tanzania. *Land Econ.* **2018**, *94*, 541–555. [CrossRef]
16. Gottlieb, C.; Grobovsek, J. Communal land and agricultural productivity. *J. Dev. Econ.* **2019**, *138*, 135–152. [CrossRef]
17. Kijima, Y.; Tabetando, R. Efficiency and equity of rural land markets and the impact on income: Evidence in Kenya and Uganda from 2003 to 2015. *Land Use Policy* **2020**, *91*, 104416. [CrossRef]
18. Pender, J.; Fafchamps, M. Land lease markets and agricultural efficiency in Ethiopia. *J. Afr. Econ.* **2006**, *15*, 251–284. [CrossRef]
19. Chen, X.; Wu, K.; He, Y. The impact of agricultural land transfer on farmers' productivity: An empirical analysis based on DEA method. *Agric. Technol. Econ.* **2011**, *8*, 65–71. (In Chinese)
20. Gollin, D.; Udry, C. Heterogeneity, Measurement Error, and Misallocation: Evidence from African Agriculture. *J. Political Econ.* **2021**, *129*, 1–80. [CrossRef]
21. Gai, Q.; Cheng, M.; Zhu, X. Can land transfer affect the efficiency of agricultural land resource allocation-Evidence from fixed observation points in rural areas. *China Econ. Q.* **2020**, *20*, 321–340. (In Chinese)
22. Zhang, J.; Zhu, P.X. Analysis of the impact of different agricultural land transfer models on agricultural production efficiency: A case study of four counties in Jiangsu province. *Resour. Sci.* **2017**, *39*, 629–640. (In Chinese)
23. Liu, S.; Gao, S.; Wang, R. Reconstruction of the Land Rights System under the Separation of Rural Land Rights. *J. Peking Univ. (Philos. Soc. Sci. Ed.)* **2017**, *54*, 134–145. (In Chinese)
24. Fuglie, K.O. Is agricultural productivity slowing? *Glob. Food Secur. Agric. Policy Econ. Environ.* **2018**, *17*, 73–83. [CrossRef]
25. Huang, Z. The Theory of small farmer economy and its implications for "Entrapment" and "De Entrapment". *Open Era* **2020**, *4*, 126–239. (In Chinese)
26. Gathala, M.K.; Laing, A.M.; Tiwari, T.P.; Timsina, J.; Rola-Rubzen, F.; Islam, S.; Maharjan, S.; Brown, P.R.; Das, K.K.; Pradhan, K.; et al. Improving smallholder farmers' gross margins and labour-use efficiency across a range of cropping systems in the Eastern Gangetic Plains. *World Dev.* **2021**, *138*, 105266. [CrossRef]
27. Bai, Y.; Wang, W.; Zhang, L. Off-farm employment experience triggers heterogeneity of exiting part-time farming in rural China. *China Agric. Econ. Rev.* **2022**, *14*, 567–582. [CrossRef]
28. Naiditch, C.; Vranceanu, R. Migrant wages, remittances and recipient labour supply in a moral hazard model. *Econ. Syst.* **2009**, *33*, 60–82. [CrossRef]
29. Roth, A.; Trachsel, S.; Castelberg, S.d.; Schneider, M. How is the issue of overageing of cocoa farming households influenced by their endowment with livelihood capitals. In Proceedings of the Tropentag 2020: Food and Nutrition Security and Its Resilience to Global Crises, Online, 9–11 September 2020.
30. Zhang, H.; Li, J.; Quan, T. Strengthening or Weakening: The Impact of an Aging Rural Workforce on Agricultural Economic Resilience in China. *Agriculture* **2023**, *13*, 1436. [CrossRef]
31. Yan, Z.; Wei, F.; Deng, X.; Li, C.; He, Q.; Qi, Y. Feminization of Agriculture: Do Female Farmers Have Higher Expectations for the Value of Their Farmland?—Empirical Evidence from China. *Agriculture* **2022**, *12*, 60. [CrossRef]
32. Kelkar, G. *The Feminization of Agriculture in Asia: Implications for Women's Agency and Productivity*; Food and Fertilizer Technology Center for the Asian and Pacific Region: Taipei, Taiwan, 2009.
33. Carter, M.R.; Yao, Y. Local versus global separability in agricultural household models: The factor price equalization effect of land transfer rights. *Am. J. Agric. Econ.* **2002**, *84*, 702–715. [CrossRef]
34. Deng, X.; Zhang, M.; Wan, C. The impact of rural land right on farmers' income in underdeveloped areas: Evidence from micro-survey data in Yunnan province, China. *Land* **2022**, *11*, 1780. [CrossRef]
35. Cao, J.; Wang, H.; Huang, X. Evaluation of supply and demand willingness and transfer efficiency in rural land transfer. *China Land Sci.* **2007**, *21*, 54–60. (In Chinese)
36. Alfaro, L.; Charlton, A.; Kanczuk, F. Plant-size distribution and cross-country income differences. *NBER Int. Semin. Macroecon.* **2008**, *4*, 243–272.
37. Adamopoulos, T.; Restuccia, D. The size distribution of farms and international productivity differences. *Am. Econ. Rev.* **2014**, *104*, 1667–1697. [CrossRef]
38. Zhou, X.; Ma, W. Agricultural mechanization and land productivity in China. *Int. J. Sustain. Dev. World Ecol.* **2022**, *29*, 530–542. [CrossRef]
39. Nguyen, T.; Cheng, E.J.; Findlay, C. Land fragmentation and farm productivity in China in the 1990s. *China Econ. Rev.* **1996**, *7*, 169–180. [CrossRef]
40. Hartvigsen, M. Land reform and land fragmentation in Central and Eastern Europe. *Land Use Policy* **2014**, *36*, 330–341. [CrossRef]
41. Macdonald, J.M.; Korb, P.; Hoppe, R.A.; Farm Size and the Organization of U.S. Crop Farming. 2013. Available online: https://ageconsearch.umn.edu/record/262221/?v=pdf (accessed on 15 May 2024).
42. Roesch-McNally, G.E.; Basche, A.D.; Arbuckle, J.G.; Tyndall, J.C.; Miguez, F.E.; Bowman, T.; Clay, R. The trouble with cover crops: Farmers' experiences with overcoming barriers to adoption. *Renew. Agric. Food Syst.* **2018**, *33*, 322–333. [CrossRef]
43. Goyal, R.; Singh, S.; Farm Power and Machinery Management. Cost of Operation of Farm Equipment. 2020, pp. 67–69. Available online: https://agrimoon.com/wp-content/uploads/Farm-Power-and-Machinery-Management.pdf (accessed on 15 May 2024).
44. Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R. Enhancing smart farming through the applications of agriculture 4.0 technologies. *Int. J. Intell. Netw.* **2022**, *3*, 150–164. [CrossRef]

45. Shah, K.K.; Modi, B.; Pandey, H.P.; Subedi, A.; Aryal, G.; Pandey, M.; Shrestha, J. Diversified Crop Rotation: An Approach for Sustainable Agriculture Production. *Adv. Agric.* **2021**, *2021*, 8924087. [CrossRef]
46. Li, G.; Feng, Z.; Fan, L. Are small farmers really more efficient? Empirical evidence from Hubei province. *China Econ. Q.* **2010**, *9*, 95–124. (In Chinese)
47. Feng, S.; Heerink, N.; Ruben, R.; Qu, F. Land rental market, off-farm employment and agricultural production in Southeast China: A plot-level case study. *China Econ. Rev.* **2010**, *21*, 598–606. [CrossRef]
48. Jiang, T. The mediating and moderating effects in causal inference empirical research. *China Ind. Econ.* **2022**, *5*, 100–120. (In Chinese)
49. Qian, L.; Hong, M. Non agricultural employment, land transfer, and changes in agricultural production efficiency: An empirical analysis based on CFPS. *China Rural Econ.* **2016**, *12*, 2–16. (In Chinese)
50. Kung, J.K.S. Off-farm labour markets and the emergence of land rental markets in rural China. *J. Comp. Econ.* **2002**, *30*, 395–414. [CrossRef]
51. Wu, L.; Li, G.; Zhou, X. Changes in factor endowments and the choice of China's agricultural growth path. *China Popul. Resour. Environ.* **2015**, *25*, 144–152. (In Chinese)
52. McPherson, M.F. *Land Fragmentation in Agriculture: Adverse? Beneficial? And for Whom?* Development Discussion Paper No. 145; Harvard Institute for International Development, Harvard University: Cambridge, MA, USA, 1983.
53. Jamison, D.T.; Law, J.L. *Farmer Education and Farm Efficiency*; Johns Hopkins University Press: Baltimore, MD, USA, 1983; Volume 2.
54. Taylor, J.E.; Martin, P.L. Chapter 9, Human capital: Migration and rural population change. In *Handbook of Agricultural Economics*; Elsevier: Amsterdam, The Netherlands, 2001; Volume 1, pp. 457–511.
55. Stark, O.J.F. Migration in less development countries: Risk, Remittances and family. *Financ. Dev.* **1991**, *28*, 39–41.
56. Szabo, S.; Apipoonanon, C.; Pramanik, M.; Leeson, K.; Singh, D.R. Perceptions of an ageing agricultural workforce and farmers' productivity strategies: Evidence from Prachinburi Province, Thailand. *Outlook Agric.* **2021**, *50*, 294–304. [CrossRef]
57. Verma, S. Recognizing Women's Critical Role in Agricultural Productivity for Rural Development: Unveiling the Hidden Strength: A Case Study of the Ranchi District. *Int. J. Multidiscip. Res.* **2023**, *5*, 1–17.
58. Maharjan, A.; Bauer, S.; Knerr, B. International migration, remittances and subsistence farming: Evidence from Nepal. *Int. Migr.* **2013**, *51*, 249–263. [CrossRef]
59. Uprety, D. Does skilled migration cause income inequality in the source country? *Int. Migr.* **2020**, *58*, 85–100. [CrossRef]
60. Stark, O. Research on rural-to-urban migration in LDCs: The confusion frontier and why we should pause to rethink afresh. *World Dev.* **1982**, *10*, 63–70. [CrossRef]
61. Kirimi, S.; Kirimi, L. A test of the new economics of labour migration hypothesis: Evidence from rural Kenya. In Proceedings of the American Agricultural Economics Association Annual Meeting, Long Beach, CA, USA, 23–26 July 2006.
62. Li, L.; Wang, C.; Segarra, E.; Nan, Z. Migration, remittances, and agricultural productivity in small farming systems in Northwest China. *China Agric. Econ. Rev.* **2013**, *5*, 5–23. [CrossRef]
63. Lucas, R.E.B. Emigration to South Africa's mines. *Am. Econ. Rev.* **1987**, *77*, 313–330.
64. Damon, A.L. Agricultural Land Use and Asset Accumulation in Migrant Households: The Case of El Salvador. *J. Dev. Stud.* **2010**, *46*, 162–189. [CrossRef]
65. Wouterse, F. Migration and technical efficiency in cereal production: Evidence from Burkina Faso. *Agr. Econ.* **2010**, *41*, 385–395. [CrossRef]
66. Fan, H.; Zhou, Q. The relationship between farmers' land planting area and land productivity: Based on survey data of farmers in seven counties (cities) in central and western China. *China Popul. Resour. Environ.* **2014**, *24*, 38–45. (In Chinese)
67. Wang, X.; Yu, X. Scale Effects, Technical Efficiency and Land Lease in China. In Proceedings of the 2011 International Congress, Zurich, Switzerland, 30 August–2 September 2011.
68. Cheng, S.; Zheng, Z.; Henneberry, S. Farm size and use of inputs: Explanations for the inverse productivity relationship. *China Agric. Econ. Rev.* **2019**, *11*, 336–354. [CrossRef]
69. Kirui, O.K.; Kornher, L.; Beckchanov, M. Productivity growth and the role of mechanisation in African agriculture. *Agrekon* **2023**, *62*, 80–97. [CrossRef]
70. Olasehinde-Williams, G.; Adedoyin, F.F.; Bekun, F.V. Pathway to achieving sustainable food security inSub-SaharanAfrica: The role of agricultural mechanization. *J. Labour Soc.* **2020**, *23*, 349–366. [CrossRef]
71. Mdoda, L.; Mdletshe, S.T.C.; Dyiki, M.C.; Gidi, L. The impact of agricultural mechanization on smallholder agricultural productivity: Evidence from Mnquma Local Municipality in the Eastern Cape Province. *South Afr. J. Agric. Ext.* **2022**, *50*, 76–101. [CrossRef]
72. Damba, O.T.; Ansah, I.G.K.; Donkoh, S.A.; Alhassan, A.; Mullins, G.R.; Yussif, K.; Taylor, M.S.; Tetteh, B.K.D.; Appiah-Twumasi, M. Effects of technology dissemination approaches on agricultural technology uptake and utilization in Northern Ghana. *Technol. Soc.* **2020**, *62*, 101294. [CrossRef]
73. Ignatov, V.I.; Gerasimov, V.S.; Andreeva, D.V. Major Factors, Influencing on the Engineering Service of the Russian Agro-Industrial Complex. 2020. Available online: https://panor.ru/articles/osnovnye-faktory-vliyayushchie-na-razvitie-inzhenernotekhnicheskoy-sistemy-apk-rossii/43899.html# (accessed on 15 May 2024).
74. Shamdasani, Y. Rural road infrastructure & agricultural production: Evidence from India. *J. Dev. Econ.* **2021**, *152*, 102686.

75. Nguyen, H.-T.-M.; Do, H.; Kompas, T. Economic efficiency versus social equity: The productivity challenge for rice production in a 'greying' rural Vietnam. *World Dev.* **2021**, *148*, 105658. [CrossRef]
76. Chavas, J.P.; Shi, G.; Meng, X. Land rental market and rural household efficiency in China. *Environ. Dev. Econ.* **2022**, *27*, 103–119. [CrossRef]
77. Daymard, A. Land rental market reforms: Can they increase outmigration from agriculture? Evidence from a quantitative model. *World Dev.* **2022**, *154*, 105865. [CrossRef]
78. Lu, H.; Xie, H.; He, Y.; Wu, Z.; Zhang, X. Assessing the impacts of land fragmentation and plot size on yields and costs: A translog production model and cost function approach. *Agric. Syst.* **2018**, *161*, 81–88. [CrossRef]
79. Wei, C. Land Fragmentation Management and Rural Land System Reform: Based on Rural Research in F County, North Guangxi. *Beijing Soc. Sci.* **2015**, *5*, 90–97. (In Chinese)
80. Foster, A.D.; Rosenzweig, M.R. Are there too many farms in the world? Labor market transaction costs, Machine Capacities, and Optimal farm size. *J. Political Econ.* **2022**, *130*, 636–680. [CrossRef]
81. Orea, L.; Perez, J.A.; Roibas, D. Evaluating the double effect of land fragmentation on technology choice and dairy farm productivity: A latent class model approach. *Land Use Policy* **2015**, *45*, 189–198. [CrossRef]
82. Van der Geest, K. Local perceptions of migration from north-west Ghana. *Africa* **2010**, *80*, 595–619. [CrossRef]
83. Shi, X.; Heerink, N.; Qu, F. Does off-farm employment contribute to agriculture-based environmental pollution? New insights from a village-level analysis in Jiangxi Province, China. *China Econ. Rev.* **2011**, *22*, 524–533. [CrossRef]
84. Taylor, J.E.; Rozelle, S.; de Brauw, A. Migration and incomes in source communities: A new economics of migration perspective from China. *Econ. Devel. Cult. Chang.* **2003**, *52*, 75–101. [CrossRef]
85. Shi, X. Heterogeneous effects of rural-urban migration on agricultural productivity: Evidence from China. *China Agric. Econ. Rev.* **2018**, *10*, 482–497. [CrossRef]

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Article

A Multi-Attribute Approach for Low-Carbon and Intensive Land Use of Jinan, China

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Abstract: This paper establishes an evaluation system based on the low-carbon intensive land use in Jinan city from 2010 to 2017 and uses a multi-attribute approach named grey fuzzy integral to build the evaluation model. In this model, based on the Mobius transformation coefficient of subjective and objective weights of index factors and the interaction degree between index factors, 2-additive fuzzy measures can be obtained; therefore, evaluation of low-carbon and intensive land use in Jinan city is processed by combining the grey correlation degree and Choquet fuzzy integral. The results show that in the study period, land input intensity, land use degree, land output benefit and land sustainability in Jinan city all show a good upward trend, but the low-carbon land use level of has been in a declining state. Although there is a good development trend of low-carbon and intensive land use in Jinan, the state is not stable. A Low-carbon and intensive land use pattern will not be achieved completely overnight, and it is bound to be a dynamic game process.

Keywords: the grey fuzzy integral; low-carbon; intensity; land use

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1. Introduction

Science has allowed us to find new sources of energy, new raw materials, better machinery and new methods of production. Nanotechnology, genetic engineering and artificial intelligence can redefine "production" and resource shortages may be overcome, but the real enemy of the modern economy is ecological collapse. Ecological collapse would lead to economic collapse, political instability and a decline in living standards that could threaten the very existence of human civilization [1]. One of the causes for ecological collapse is greenhouse gas emission, especially carbon emission, which causes global warming. Most scholars and a growing number of politicians have begun to realize the reality and extent of the danger of global warming. There is extensive discussion about global warming, but when it comes to reality, humans are unwilling to make real economic, social or political sacrifices to stop the scourge. Instead of reducing greenhouse gas emissions from 2000 to 2010, it grew at an annual rate of 2.2%, whereas, during 1970–2000, its annual growth rate was only 1.3% [2]. The Kyoto Protocol, a 1997 agreement to reduce greenhouse gases, aims only to slow rather than stop global warming, but the US, the world's largest polluter, refuses to sign up and makes no attempt to significantly reduce greenhouse gas emissions for fear of hindering its economic growth [3,4]. The Paris Agreement on global climate governance, which entered into force on 4 November 2016 and had been signed by 195 countries and ratified by 190 countries on January 2021, is no less than a binding and universal agreement. This agreement is designed to limit greenhouse gas emissions to levels that would prevent global temperatures from increasing more than 2 °C (3.6 °F) above the temperature benchmark, which is set before the beginning of the Industrial Revolution, but the measures necessary to achieve this goal have been put off until 2030, or even the second half of the 21st century [5]. So far, neither comments nor related seminars, summits nor agreements on global warming have been able to curb global emissions of greenhouse gases. The Emission Database for Global Atmospheric Research (EDGAR) [6] shows that emissions fell only during periods of economic crisis and stagnation. The small and obvious decline in greenhouse gas emissions between 2008 and 2009 was caused by the global financial crisis and not the Copenhagen Accord, which was proclaimed in December, 2019. A viewpoint is that the only sure way to stop global warming is to stop economic growth; however, no government would want to do that at the expense of people's material well-being [1]. Therefore, finding ways to sustain economic growth and at the same time mitigating greenhouse gas emissions is particularly important and rewarding.

Since human behaviors on land and the maintenance and transformation of land use are the main sources of terrestrial carbon emissions [7], and regional land use change has a great impact on the carbon emissions from land use [8,9], analyzing the change of carbon emissions caused by land use from the perspectives of "low carbon" and "intensity" is conducive to optimizing the allocation of land resources and controlling regional carbon emissions to a certain extent. Additionally, there has been a growing consensus in the literature that climate change mitigation efforts should be location-based, especially in the midst of urbanization since there are no universal strategies that are guaranteed to be effective in all settings as local geography, demography, resources, cultural values, etc. [10,11]. At the same time, feedbacks among the aspects of sustainability, for example, the Sustainable Development Goals (SDGs), adopted by the United Nations as part of its 2030 Agenda, have to be considered in policymaking and implementation [12–14].

As for the researches on mitigating carbon emission, there are several aspects, such as investments and stocks, carbon strategy, carbon trade, low-carbon transition, low-carbon land usage and other aspects.

From the aspect of investments and stocks, Choi D, Gao Z and Jiang W [15] proposed that in financial markets, stocks of carbon-intensive firms underperform firms with low carbon emissions in abnormally warm weather. Monasterolo I and De Angelis L [16] indicated that stock market investors have started to consider low-carbon assets as an appealing investment opportunity after the Paris Agreement but have not yet penalized carbon-intensive assets. Schoenmaker D [17] found that a low carbon allocation can be done without undue interference to the transmission mechanism of a monetary policy. Liu P and Qiao H [18] studied carbon asset stranding risks under climate policy. Benz L, Paulus S, Scherer J, et al. [19] examined the exposure to and management of carbon risks of different investor types. Cheng S and Qi S [20] assessed the potential of carbon-intensive sectors and non-carbon-intensive sectors in attracting China's Foreign Direct Investment to identify the major determinants of investment, as well as to inform China's investment policy, and render positive contributions to the Green Belt and Road Initiative based on location and sector information. Sun X, Fang W, Gao X, et al. [21] indicated that the carbon market is an important mechanism to promote carbon reduction, and the document announcing the formal launch of China's carbon trading system prompted the dominant market of their causality shifting from carbon market to stock markets.

Some researchers discuss low-carbon from the perspective of companies' behaviors on carbon strategy and voluntary carbon disclosure (VCD). Moussa T, Allam A, Elbanna S, et al. [22] provided evidence of the mediating effect of carbon strategy on the relationship between board environmental orientation (BEO) and carbon performance. Abd Rahman NR, Rasid SZA, and Basiruddin R [23] investigated the quality of VCD in the annual report of publicly listed Malaysian companies operating in carbon-intensive industries and suggested that VCD practices of these public listed companies are more symbolic rather than, and to have carbon disclosure regulated and independently assured is necessary. Lu W, Zhu N and Zhang J [24] investigated the impact of carbon disclosure on financial performance and put forward policy recommendations for the construction of China's carbon disclosure system.

Some research has been conducted on the aspect of carbon trade. Hotak S, Islam M, Kakinaka M, et al. [25] addressed how carbon trade balances relate to carbon emissions under a globalized world with fragmented production. Sun C, Chen L, and Zhang F [26] explored the embodied CO_2 emission effect by measuring the marginal net trading embodied CO_2 emissions and decomposing the exporting embodied CO_2 emissions from the international division perspective. Ji C-J, Hu Y-J, Tang B-J, et al. [27] discussed the price drivers in Chinese carbon emissions trading scheme pilots and provided policy implications for the development of pilots and the national carbon market. Ma N, Yin G, Li H et al. [28] investigated the economic and environmental effects of four possible industrial carbon tax rate models under carbon intensity constraints from 2021 to 2030 by a dynamic input–output optimization model to calculate the optimal industrial carbon tax for China, which is subject to certain constraints.

Progress in and methods of low-carbon energy transition and energy technology innovation are still discussed popularly. Wang J, Hu M, Tukker A, et al. [29] aimed to investigate the potential contribution of regional convergence in energy-intensive industries to CO_2 emissions reduction and to meeting China's emissions goals. Du W and Li M [30] analyzed the influences of environmental regulation on the low-carbon transformation of China' foreign trade from the perspective of export enterprises' dual margin and pointed out that government departments in China should improve and develop environmental policies and further strengthen environmental monitoring capabilities to achieve the structural adjustment and low-carbon transformation of China's foreign trade. Rosenloom D and Rinscheid A [31] structured the fragmented strands of research engaging with the purposive decline of carbon-intensive systems and their components (e.g., technologies and practices), interrogating the role it may play in decarburization. Considering that energy-intensive industries are the primary sectors of energy and resources consumption and carbon emissions, and exploring the temporospatial pattern and influencing factors of carbon emission efficiency (CEE) of energy-intensive industries helps discover the contribution of energy-intensive industries to regional carbon emissions and formulate different regional low-carbon industry development strategies, Zhu R, Zhao R, Sun J et al. [32] estimated the CEE of the energy-intensive industries of China from the provincial level using a three-stage data envelopment analysis (DEA) model and analyzed the temporospatial distribution and influencing factors of CEE by spatial autocorrelation analysis and Tobit model. Dong K, Ren X, and Zhao J [33] found that low-carbon energy transition shows significant bidirectional causality with energy poverty alleviation and provided an important reference for the government to formulate relevant policies that promote the alleviation of energy poverty. In the context of achieving carbon neutrality, Zhao D and Zhou H [34] quantitatively explored the relationships among livelihoods, technological property constraints, and the selection of low-carbon technologies by farmers to promote agricultural modernization and carbon neutrality in the agricultural sector of China. Wang X, Liang S, Wang H et al. [35] analyzed the impact of fossil fuel price distortions on low-carbon transitions. The level of price distortions in coal, gasoline and diesel was evaluated based on which of the CO_2 mitigation potentials in China's Energy intensive industries (EIIs) were estimated and revealed that there is still much room for improvement in China's fossil fuel market reform. Through constructing the embodied carbon emission networks through industrial linkages and identifying the key nodes and paths of carbon risk transmission under low-carbon transition, Han M, Liu W, and Yang M [36] provided practical quantified supports and policy implications for the sustainable low-carbon transition and potential risk prediction related to China's energy-intensive industries. Xin L, Sun H, Xia X, et al. [37] examined the mechanism, spatial spillover effects, regional boundaries, and industry heterogeneity of renewable energy technology innovation (RETI) on manufacturing carbon intensity (MCI) using the spatial Durbin model and the findings provide empirical evidence for formulating targeted and differentiated policy in manufacturing low-carbon development.

Some researchers focus on the low-carbon land usage. Since the development of low-carbon agriculture is promising for mitigating climate change, Wang Z-b, Zhang J-z, Zhang L-f [38] used adjustments to the planting structure in Zhangbei County, China, as an example to evaluate whether the carbon footprint per unit of economic benefit is a suitable indicator of low-carbon agriculture and to determine if low-carbon agriculture is not necessarily low-input non-intensive agriculture. Wang J, Xue D, Ma B and Song Y [39] investigated and analyzed the intensive and agricultural carbon emission levels and their coupling coordinated development types of five provinces in Northwestern China by setting up the index system of intensive use of arable land and the agricultural carbon emission, and using the coupling coordination model and ArcGIS spatial analysis method.

Carbon neutrality is such popular an issue that a wide range of relevant aspects are discussed. For instance, since the decarbonization of energy-intensive systems (e.g., heat and power generation, iron, and steel production, petrochemical processes, cement production, etc.) is an important task for the development of a low-carbon economy, Cormos A-M, Dragan S, Petrescu L et al. [40] calculated, compared, and discussed the most significant technoeconomic and environmental performance indicators of various fossil-based industrial applications that have been decarbonized by two reactive gas–liquid (chemical scrubbing) and gas–solid CO_2 capture systems. Nurdiawati A and Urban F [41] analyzed various technological trajectories and key policies for decarbonizing energy-intensive industries and concluded that it may be technically feasible to strongly decarbonize energy-intensive industries by 2045, given financial and political support. At the same time, carbon storage by plants is explored, for example, Roman M, de los Santos CB, Roman S et al. [42] researched sea grass carbon stocks and influence factors.

In conclusion, research on mitigating carbon emission is prosperous, and the research on land use is otherwise relatively absent internationally. Therefore, the research on evaluating land use pattern and providing some recommendations for low-carbon land usage could contribute to the endeavors of mitigating carbon emission and, at the same time, enriching the relevant research area.

Since China, as a populous country, has been undergoing a rapid and extensive urbanization process, which is in parallel with economic growth and rising material living standards, how to use the valuable land resources in a way that could mitigate carbon emissions is now an urgent issue. Since the intensive land use could attribute to carbon emission mitigation, this research picks out the intensity of land use as a parallel dimension together with the dimension of low-carbon. This paper uses Jinan city in Shandong Province as a case study to provide empirical evidence of land use on the two dimensions of low-carbon and intensity to forecast the healthy land use prospects and possibilities of mitigating carbon emission.

In the multi-attribute comprehensive evaluation area, the grey comprehensive evaluation method is one of the conventional approaches, which integrates grey correlation numbers by using linear weighted average operator. Its advantages are that the analytical logic is clear, the loss caused by data asymmetry can be reduced to a large extent, and the requirements for sample data and distributions are low, therefore, this approach can greatly reduce the workload, whereas it assumes that the attributes of the object to be evaluated are independent from each other, which is difficult to exist in real life.

However, in the fuzzy integral based on fuzzy measures, the Choquet integral of the nonlinear integration operator can fully consider the interaction between attributes; therefore, the grey comprehensive evaluation method, fuzzy measure and fuzzy integral are organically combined in this research to establish a complete, scientific and reasonable evaluation system, named the grey fuzzy integral evaluation model, to apply to multi-attribute decision-making.

This multi-attribute approach is adopted to build the low-carbon and intensive land use evaluation model. This approach of combining advantages of grey relational degree and fuzzy integral, provides a new method of evaluation with a tolerance for the inconsistency of indicators. The results show that although there is a good development trend of low-carbon and intensive land use in Jinan, the state is still dynamic. The transformation of land use pattern from the extensive "high consumption and high emissions" one to the intensive "low consumption, low emission, high benefit" one would not be accomplished completely overnight, and it is bound to be a dynamic game process.

On the basis of the results of the study, this article puts forward the corresponding policy recommendations for low-carbon and intensive land utilization of Jinan. Since global society gradually adopts a new perspective of quality of life and sufficiency standards of service under a number of complex social, climate, disaster and unpredictable risks [43], this theoretical approach can be used by other cities, regions or nations for reference.

2. Materials and Methods

2.1. Study Area

Jinan is located in the mid-west of Shandong Province, bordering Mount Tai in the south and the Yellow River in the north. Since the Ming Dynasty in China's history, Jinan has always been the capital of Shandong Province, which is a big economic province in the east coast of China. After the founding of the People's Republic of China, besides being the capital of Shandong Province, Jinan has also become one of the 15 subprovincial cities of China; the central city in the south of Bohai Rim region; the political, economic, cultural, educational, transportation and science and technology center of the province; and the core city of the Shandong Peninsula city group and Jinan metropolitan circle. Besides being a provincial capital city with political status and so on, Jinan is also a historical and cultural city with a splendid civilization. It is one of the famous historical and cultural cities in China, with its beautiful natural scenery and numerous scenic spots. According to historians, there have been traces of human activity since as early as 45 centuries BC, and the city is also the birthplace of prehistoric Longshan culture. Even more distinct about Jinan is its unique geological structure, which makes it a spring enrichment zone with the most famous Spouting Spring group; therefore, Jinan is also known as the Spring City. Since the ancient city of Jinan is built on the spring group, spring water is not only used for living, but also for city defense and other functions. The moat surrounding the old city of Jinan is the only river formed by the confluence of spring water in China. In addition to the unique rich spring group, there are three major water systems: Yellow River and Xiao Qing River together with the famous Da Ming Lake. Besides water resources, Jinan is also rich in mineral, forest, planting and breeding resources, which has laid a solid material foundation for Jinan's economic development and urban and rural construction [44].

At the same time, Jinan is also one of the important cities for the emergence and development of modern industries in China. It occupies a pivotal position in the whole country and has a very rich industrial heritage. It is also required by the planning and layout of traditional industry to be classified as an industrial zone [45].

As a city with the mixed statuses of politics, economies, historical culture, natural landscape, transportation, etc., the land use of Jinan confronts the complex conflicts of different expectations; therefore, it is a typical example for the research in the urbanization process of China.

Figure 1 illustrates the geographical location of Jinan in Shandong Province together with the rough land use categories. Unlike the previous statistical caliber, since 2010, the relative standards of classification for statistics of land use in Jinan have been divided into eight categories, including cultivated land, garden, forest, grass, urban village and industrial and mining land, transportation land, land for water and facilities as well as other land, which is roughly consistent with the first-level standard of Land Use Classification [46] edited by Ministry of Land and Resources and jointly issued by General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China and Standardization Administration in 2007; therefore, to ensure the uniformity of data, the starting year of this study was set as 2010.

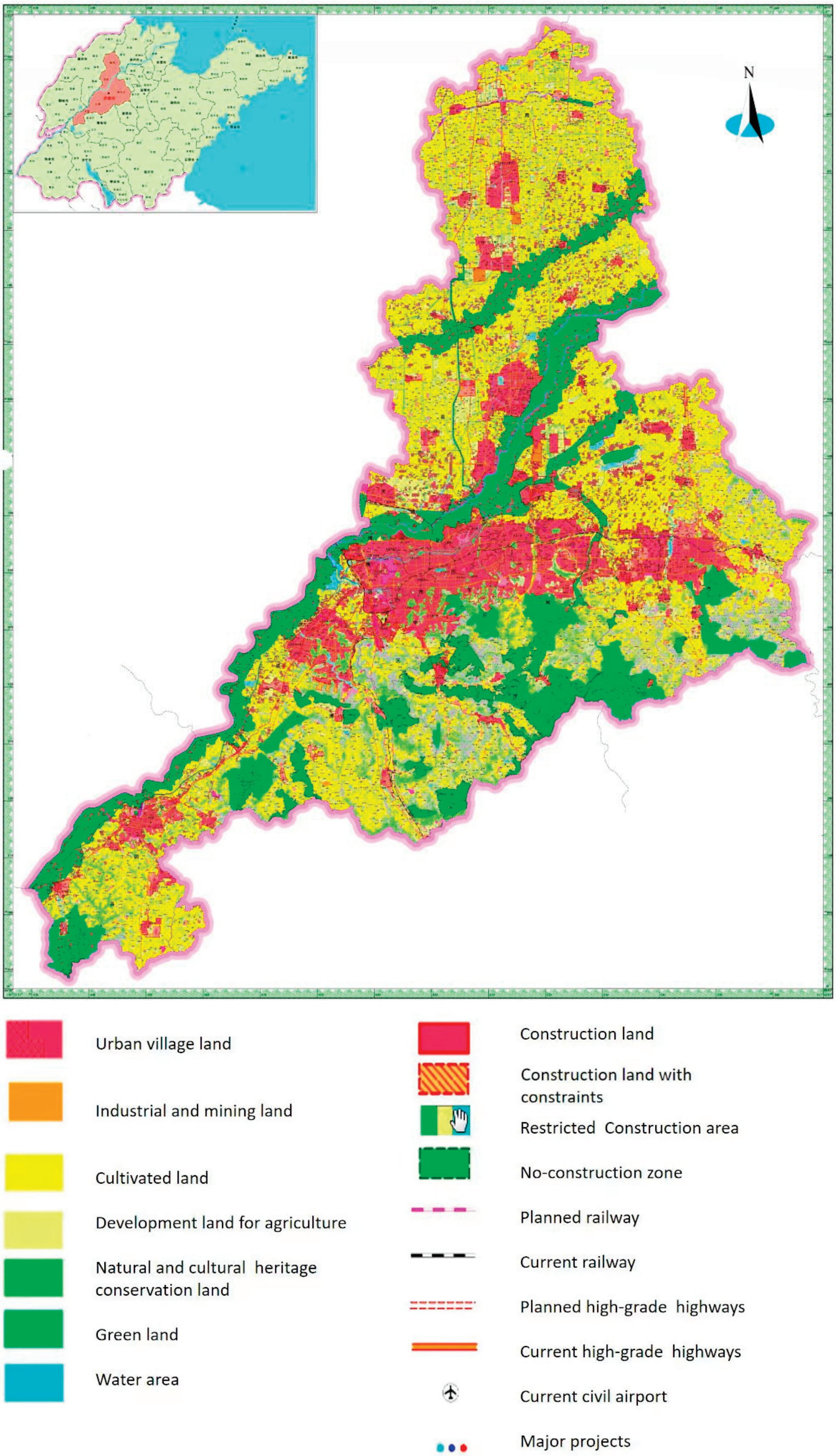

Figure 1. Land use plan of Jinan (2006–2020) by Jinan Urban Design Institute.

In 2017, the Shandong provincial government issued the Development Plan for Shandong Peninsula Urban Agglomeration (2016–2030), which clearly aims to make the Jinan metropolitan circle and Qingdao metropolitan circle better and stronger, supports Jinan and Qingdao in building national central cities, and includes Laiwu city into the Jinan metropolitan circle [47]. After that, on 26 December 2018, the state council approved the adjustment of Laiwu's administrative division in Shandong Province, abolishing Laiwu city and putting the area under the jurisdiction of Jinan city [48]; therefore, the relevant introduction of the study area in this paper is limited to the area before the zoning adjustment of Jinan city, and the termination year is set as 2017; the data is up to the statistical results in the 2018 edition of relevant yearbooks.

2.2. Data Sources and Processing

2.2.1. Changing Trend of Land Use Categories in Jinan

The socio-economic data of this study are mainly from the China Statistical Yearbook (2011–2018), Shandong Statistical Yearbook (2011–2018) and Jinan Statistical Yearbook (2011–2018). The relevant data are calculated according to the definition of index factors. Additionally, the weights and measures used in the yearbook are all international standard units of measurement, and the statistical caliber includes Jinan urban area, Pingyin County, Jiyang County and Shanghe County.

The data of land use type area change from 2010 to 2017 were collected from the Jinan Statistical Yearbook from 2011 to 2018. After analyzing the data obtained (Table 1), it can be seen that from 2010 to 2017, the value of cultivated land area in Jinan City showed a downward trend on the whole and only picked up a little in 2013; however, it returned to a continuous decline in 2014, with the largest decline in 2014–2015. From 2015 to 2016, the total area of cultivated land continued to decline, but slightly slowed down. During 2016–2017, the decline increased again. In addition, the area of garden land, forest land and grassland also showed a sharp downward trend year by year, especially during 2012–2013. After the growth period of 2010–2011, the land area of water and water conservancy facilities also entered a state of decline year by year. At the same time, the overall area of urban and village land, industrial and mining land, and transportation land showed an increasing trend year by year. The area of urban, village, industrial and mining land was the inflection point in 2014, and there was a trend of slowing growth before 2014. After 2014, there was a significant increase, especially during 2014–2015 and 2016–2017. Transportation land also only changed during 2012–2013 and recovered with a large increase after a relatively small reduction. After a sharp decrease year by year, the area of other land gradually rose in 2013 as the inflection point and the sharpest rising happened during 2013–2014, then the rise slowed down. After that, there was an inflection point in 2016, and a decreased trend happened significantly again during 2016–2017.

Table 1. Area change of land use categories in Jinan 2010–2017 (Unit: Hectare).

Year \ Category	Cultivation	Garden	Forest	Grass	UIM	Transportation	Water and Its Facilities	Others
2010	362,303	26,790	86,663	58,894	135,194	28,190	51,195	50,612
2011	361,251	26,632	86,070	58,404	137,306	28,459	51,324	50,395
2012	360,279	26,485	85,682	58,193	139,087	28,742	51,246	50,127
2013	361,012	26,233	85,100	57,520	140,218	28,740	51,155	49,863
2014	360,241	26,180	84,963	57,430	140,772	29,068	51,039	50,150
2015	358,568	26,054	84,676	57,250	142,969	29,135	50,962	50,227
2016	357,601	25,957	84,484	57,151	144,219	29,319	50,875	50,236
2017	355,659	25,801	84,175	57,018	146,819	29,617	50,696	50,055

Note: UIM—Urban village, Industrial and Mining land as one category. Transportation land refers to land used for the purpose of transportation, including roads and railways.

There are many reasons for these changes, mainly due to the acceleration of urbanization and industrialization in Jinan under the general trend of national urbanization. Although the cultivated land increased a little in 2013 through ways of land reclamation and other measures, the general trend is that a large number of cultivated land, garden land, forest land and grassland are transformed into urban and village land, industrial and mining land or transportation land to meet the needs of economic construction.

2.2.2. Energy Consumption Situation in Jinan

The energy consumption data used in this paper are from the Jinan Statistical Yearbook (2011–2018). Since energy consumption mainly comes from the industrial sector, the data of energy consumption of industries above a designated size in Jinan City was selected as the energy consumption index. According to the availability of data and the actual situation of energy consumption in Jinan City, six energy sources, including coal, gasoline, kerosene, diesel, fuel oil and electricity, were selected for carbon emission calculation. Data of land use change from 2010 to 2017 were also taken from the Jinan Statistical Yearbook from 2011 to 2018.

Carbon dioxide emissions from fossil fuel consumption are calculated using the following formula, based on the baseline methodology provided by the Department of Energy Section of the IPCC Guidelines for National Greenhouse Gas Inventories 2006 [7]:

$$\text{Carbon dioxide emissions} = \text{fossil fuel consumption} \times \text{carbon dioxide emission coefficient}$$

$$\begin{aligned}\text{Carbon dioxide emission coefficient} = {} & \text{low calorific value} \times \text{carbon emission factor} \times \text{carbon oxidation rate} \\ & \times \text{carbon conversion coefficient}\end{aligned}$$

As the above coefficients refer to the empirical values of foreign countries, they are not necessarily consistent with the actual conditions of China; therefore, the Department of Resource Conservation and Environmental Protection of the National Development and Reform Commission and the first Industrial Standard of the Standardization Administration have put forward the new General Principles for Calculation of Total Production Energy Consumption (GB/T2589-2008) [49]. This standard specifies the definition and calculation method of comprehensive energy consumption, which is applicable to the calculation and management of the indicators of energy consumption per unit of energy use. It provides the average low calorific value of fossil fuels and the conversion coefficient of standard coal [49].

To further strengthen the capacity of provincial greenhouse gas inventories, the Department of Climate Change of the National Development and Reform Commission organized experts from the Institute of Energy Research of the National Development and Reform Commission, Tsinghua University, Institute of Atmospheric Sciences of the Chinese Academy of Sciences, Institute of Environmental Protection and Development of the Chinese Academy of Agricultural Sciences, Institute of Environmental Protection and Environmental Protection of the Chinese Academy of Forestry, Climate Center of the Chinese Academy of Environmental Protection and other units to compile the Guide for the Compilation of Provincial Greenhouse Gas Inventories (Trial) with the support of national key basic research and development programs.

The guidelines specify CO_2 emission coefficients for major fossil fuels: raw coal, 1.9003 kg-CO_2/kg; fuel oil, 3.1705 kg-CO_2/kg; gasoline, 2.9251 kg-CO_2/kg; kerosene, 3.0179 kg-CO_2/kg; diesel oil, 3.0959 kg-CO_2/kg; etc. This also includes the average carbon dioxide emission coefficient of power supply per unit of Chinese regional power grid [50].

To sum up, the calculation formula of carbon emissions of energy consumption is as follows:

$$C = \sum C_i = \sum M_i E_i \tag{1}$$

where C is the total carbon emission, C_i is the total carbon emission of the i-th energy consumption, M_i is the i-th energy consumption, and E_i is the carbon emission coefficient of the i-th energy.

Although carbon emissions related to living consumption of Chinese residents show an increasing trend year by year [51], the proportion is still relatively small, and energy consumption mainly comes from the industrial sector, so the energy consumption data of Jinan industrial subsectors are selected as the energy consumption index. According to the availability of data and the actual situation of energy consumption in Jinan City, six kinds of energy sources, including coal, gasoline, kerosene, diesel, fuel oil and electricity were selected for carbon emission calculation. Although heat consumption was included in the original data, it was not included in the calculation because carbon emissions of heat mainly came from fossil energy, such as raw coal. According to Formula (1) and relevant data, the total carbon emission, carbon emission intensity and carbon emission per capita of Jinan City can be obtained, where carbon emission intensity is the carbon emission per unit of GDP, as shown in Table 2.

Table 2. Total carbon emission, carbon emission intensity and per capita carbon emission in Jinan 2010–2017.

EC / Year	Total Carbon Emission	Carbon Intensity	Carbon Emissions per Capita
2010	39,246,241,462.00	10,036,041.52	64,968,615.85
2011	41,981,465,515.00	9,527,621.99	69,203,259.78
2012	37,081,527,865.00	7,719,416.17	60,868,219.28
2013	35,144,037,816.00	6,719,457.19	57,307,848.05
2014	37,308,803,330.00	6,465,324.81	60,019,631.81
2015	36,184,060,122.00	5,931,589.48	57,826,954.31
2016	37,004,399,194.00	5,661,523.84	58,474,470.54
2017	33,924,190,968.00	4,710,410.91	52,708,416.41

Notes: EC—energy consumption; carbon emissions per capita—kg/10 thousand people. Unit of total carbon emission—kg; unit of carbon intensity—kg/100 million yuan.

2.3. Methodology

At present, there are many methods for analyzing and synthesizing various linear and nonlinear systems, but the methods for systems that are too complex to be analyzed accurately are still quite lacking. Such complex systems, pervasive in philosophy, economics, psychology, and the social sciences, preclude the possibility of classical mathematical analysis. The main reason why classical mathematical methods are difficult to deal with complex system problems is that they cannot describe fuzzy things effectively. By fuzzy, we mean uncertainty arising not from randomness but from lack of clarity from one member to another. The concept of fuzzy sets was proposed by Zadeh L.A. in 1965 [52]. Fuzzy set theory and research has formed a complete system since its concept was proposed, and fuzzy technology has been deeply applied in pattern recognition, image processing, decision support, automatic control and other fields. As a branch of fuzzy set theory, fuzzy measure and fuzzy integral were first formed in the 1970s, focusing on the non-additive case, which is the extension of classical measure and integral. This branch of research enriches nonlinear mathematical theory because measure additivity is only an ideal state and practical problems are usually non-additivity. Thus, it is widely used to describe non-additive and nonlinear systems, such as decision analysis and subjective evaluation, in the mathematical model [53–58]. Japanese scholar M. Sugeno proposed the concept of fuzzy measure for the first time in 1974, and defined the integral of measurable function with respect to fuzzy measure accordingly [59]. Its most classical characteristic is non-additivity, so fuzzy measure is usually called non-additivity measure [60]. In the multi-attribute evaluation, the candidate set represents the evaluation item, and the fuzzy measure is not only the weight value of the evaluation item but also the degree to which the object to be tested belongs to the candidate set [56].

In multi-attribute evaluation, different attributes not only have different importance but also have interactions with other attributes. For an evaluation index system, the relationship between the two groups of attributes can be divided into three situations: repeated or negative cooperation; complementary or active cooperation; or independence. In general, the three situations in an attribute set often exist simultaneously, and the 2-additive fuzzy measure can describe them at the same time [61].

The grey comprehensive evaluation method is a comprehensive evaluation method based on expert evaluation and guided by grey relational analysis theory. It uses the known information to generate and develop the unknown information of the system. Yet, the traditional comprehensive evaluation method is based on the assumption that index factors are independent of each other, but in practical application, there is usually a certain degree of interaction between index factors. In order to solve this problem, combining the respective advantages of grey relational degree and fuzzy integral, this paper designs a grey fuzzy integral multi-attribute evaluation model for data analysis. In the designed model, the Mobius transformation coefficient is determined based on the subjective and objective weights of index factors and the degree of interaction between index factors, and the 2-additive fuzzy measure was obtained by calculation. Then, the grey correlation degree and Choquet fuzzy integral are combined to evaluate the low-carbon intensive use of land. The specific steps of grey fuzzy integral multi-attribute evaluation method are as follows.

2.3.1. Establishment of Index System

Assuming that there are m evaluated objects, a systematic, scientific and practical evaluation index system is established by taking the characteristics of the evaluated objects and the purpose preference of decision-makers as the reference basis. The evaluation system is divided into b levels, and the evaluation of each level can be subdivided under some secondary indexes, with each independently belonging to the same index level, and at the same time, there is only one kind of relationship between every two secondary indexes under the same level, which could be repeatable, complementary, or independent. In addition, the degrees of interaction between indexes are obtained by expert scoring.

2.3.2. Indicator System Description

The evaluation system of intensive land use based on low-carbon goal needs to integrate the three characteristics of intensive, low carbon and ecological, as well as the natural, economic, social, energy and environmental aspects in an orderly manner. In order to guarantee the relative objectivity and rationality of the evaluation process and results, this study follows the principles of systematicity, scientificity, consistency, flexibility and practicability with reference to the Procedures for Evaluating the Potential of Intensive Use of Urban Land (Trial) [62] and the literature on low-carbon intensive land use and low-carbon economy research during the process of index system construction. Based on the status quo of land resources, the regional environment and the social and economic development of Jinan and fully considered the availability of data and expert advice, index factors are selected from five aspects: Land input intensity, Land use degree, Land output efficiency, Land low-carbon level and Land sustainability. On this basis, an evaluation index system of low-carbon intensive land use is established as shown in Table 3, including target layer, criterion layer and index factor layer, and the index layer contains 21 factors. The margin of index definition or calculation formula indicates that the data are directly from the statistical data.

Table 3. Evaluation index system of low-carbon intensive land use.

Target	Critierion	Index Factor	Index Definition or Calculation Formula	Unit of Measurement
Evaluation index system of low-carbon intensive land use	B_1 Land input density	C_{11} Fixed asset investment per hectare	Fixed assets investment/Total land area	10,000 yuan/ha
		C_{12} Average employment	Total number of employees/Total land area	10,000 people/km_2
		C_{13} Energy consumption per unit GDP	Energy consumption/GDP	Ton of standard coal/100 million yuan
		C_{14} Transportation land area per 10,000 people	Transportation land area/Total population	ha/10,000 people
	B_2 Land use degree	C_{21} Urban population density		People/km^2
		C_{22} Construction land area per 10,000 people	Construction land area/Total population	km^2/10,000 people
		C23 Percentage of urban, village, industrial and mining land area	Urban, village, industrial and mining land area/Total population	%
	B_3 Land output efficiency	C_{31} GDP per hectare	GDP/Total population	100 million yuan/ha
		C_{32} Retail sales of social consumer goods per capita	Retail sales of social consumer goods/Total population	100 million yuan/ha
		C_{33} Fiscal revenue per hectare	Financial revenue/Total population	10 thousand yuan/ha
		C_{34} Wastewater discharge amount per hectare	Wastewater discharge amount/ Total population	10 thousand ton/ha
	B_4 Land low-carbon level	C_{41} Carbon emissions per hectare	Total carbon emissions/Total population	ton/ha
		C_{42} Energy consumption elasticity coefficient		
		C_{43} Percentage of greenbelt coverage	Greenbelt area/Total population	%
		C_{44} Fertilizer and pesticide usage per unit cultivated area		kg/ha
		C_{45} Operating vehicles per 10,000 people	Total operating vehicles/ Total population	vehicles/10,000 people
		C_{46} PM10 annual mean concentration		kg/ha
	B_5 Land sustainability	C_{51} Percentage of water and its conservancy facilities area	Water and its conservancy facilities area/Total population	%
		C_{52} Cultivated land area per capita		mu
		C_{53} Green coverage rate of built district		%
		C_{54} Centralized sewage treatment rate	Sewage treatment quantity/Sewage quantity to be treated	%

(1) Land input density. The ideal state of land intensive use is that the marginal cost of land use input is equal to the marginal revenue, and the land use benefit reaches the maximum ideal value, while the land input density reflects the input level of land-use-related factors. In the index factors of land input density, Fixed asset investment per hectare, Average Employment, Energy consumption per unit GDP and Transportation land area per 10,000 people correspond to the capital input, the human labor input, the energy input and the infrastructure input, respectively. In the existing studies, the factor of land average energy consumption is mostly adopted to correspond to the environmental input index since the factor of land average energy consumption reflects the energy input in the land use process and mainly reflects the development degree of the city, while the amount of land average energy consumption in developed areas is higher than that in areas with a low degree of development. The calculation method of the factor is the ratio of the total energy consumption of various industries in a region to the total regional area, which can reflect the degree of carbon emission in the process of land input, The energy consumption per unit GDP can reflect not only the energy input in the land use process but also help to reflect the connotation of low-carbon intensive land utilization as a result of its nature itself that is associated with the gross national product, which strengthens the constraint of the factor in low carbon [63]. The calculation method of the factor is the ratio of energy consumption in the region to the GDP.

(2) Land use degree. The degree of land use can reflect the current situation of land use. Generally, the greater the population density is within the land area, the higher the intensity of land use becomes. Construction land area per 10,000 people reflects the reasonable degree on a regional scale. In the existing land use structure, urban, village, industrial and mining land and other carbon-source land are the inevitable results of economic and social development, which can reflect the degree of effective land use to a certain extent and have an important impact on the intensity of urban land use.

(3) Land output efficiency. The total benefit of land use is reflected by the land output efficiency, which mainly involves the economic efficiency, the social efficiency and the ecological efficiency in the process of land use. GDP per hectare, Retail sales of social consumer goods per capita and Fiscal revenue per hectare correspond to the economic and social efficiency in the process of land use, among which Fiscal revenue per hectare of local finance is an important indicator to measure the disposable financial resources of a local government; the fiscal revenue adopts the amount of general public budget income. The ecological benefit index chooses to consider the discharge of the industrial "three wastes", which are the main pollution sources: the discharge of local waste gas, local waste water and local solid waste; however, the statistical data show that the solid waste is treated completely after the processes of comprehensive utilization, storage or disposal, and finally achieves zero emission; therefore, it is not included in the index system. Due to the variation of statistical caliber and statistical types during the study period, the indicator of waste gas emission on the average ground level was abandoned since the data is hard to be unified. In view of the continuity and availability of data, this study adopted Wastewater discharge amount per hectare as an ecological efficiency indicator.

(4) Land low-carbon level. The low-carbon level of land is mainly evaluated from the perspective of low carbon by means of two indexes, i.e., Carbon emissions per hectare and Percentage of greenbelt coverage which is the proportion of forest, grassland and garden plots, as well as Energy consumption elasticity coefficient, Fertilizer and pesticide usage per unit cultivated area, Operating vehicles per 10,000 people and PM10 annual mean concentration in terms of carbon sources. The calculation formula of Energy consumption elasticity coefficient is: Energy consumption elasticity coefficient = Δ Total energy consumption/ΔGDP. The operating vehicles include buses, trolleybuses and taxis. The use of chemical fertilizers and pesticides is not only easy to cause environmental pollution but also deteriorates the physical properties of the soil, disperses the soil colloids, destroys the soil structure and causes land consolidation, which not only affects the yield and quality of crops, but also destroys the carbon storage capacity of the soil and releases the carbon in

the soil into the atmosphere. In addition, a significant amount of nitrogen fertilizer either evaporates directly from the soil surface or is converted by microorganisms into nitrogen and nitrogen oxides and enters the atmosphere. In consideration of the above causes, the fertilizer and pesticide usage per unit of cultivated land area is included in the criterion layer of land low-carbon level.

(5) Land sustainability. The impact of urban land use structure layout on natural resources and ecological environment is mainly reflected by land sustainability. Because the cultivated land, water area and land for water conservancy facilities play a certain role in alleviating the traffic congestion, ground hardening and crowds gathering in order to mitigate the pollution of the environment, the two index factors, Percentage of water and its conservancy facilities area and Cultivated land area per capita, together with Green coverage rate of built district are incorporated into the system to reflect the sustainability of land use from the aspect of carbon mitigation. Centralized sewage treatment rate reflects the sewage treatment capacity and efficiency of the study area, and also reflects the environmental protection effort and environmental sustainability of the study area to a certain extent. The above four index factors reflect the requirements of utilization of natural resources and ecological environment protection in the land use process.

2.3.3. The calculation Process

(1) Acquisition of Initial Evaluation Data

In this paper, the index data of the criterion layer are all quantitative indexes, and the scoring of quantitative indexes can be obtained by statistical means. The socio-economic data in this paper are mainly from the China Statistical Yearbook (2011–2018), Shandong Statistical Yearbook (2011–2018) and Jinan Statistical Yearbook (2011–2018).

The sample data come from 10 experts in related research fields in Jinan, Qingdao, Wuhan, Chongqing and other places. By means of questionnaire survey, experts were invited to score the index factors screened out in the indicator system and determine the values of the interaction degree of index factors. In this part, consistency of scoring is not necessary due to the characteristics of this approach, because some fuzzy measures between evaluation indexes are super additive, and some are sub-additive, or even zero additive. By using the weight score set by experts as fuzzy measures, we can better use the fuzzy measures to deal with the correlation among indexes, and enhance the correctness and acceptability of the comprehensive evaluation result of fuzzy integrals.

(2) Determine the single weight of index factors

Calculate the subjective weight of each indicator. The subjective weight value of each indicator can be obtained by expert scoring method. At first, the relevant experts give the weight value of each indicator after comprehensively considering the actual situation and the goal preference of decision-makers, among other factors, and then take the average value of the weight values given by each expert. After that, add the weight values of each indicator to get the sum of the weights, and finally, the ratio of the weight values of each indicator to the sum of the weights is the final weight value of the indicator. The scoring criteria for subjective weight of index factors are shown in Table 4.

Table 4. Scoring criteria of index factors' subjective weight.

Degree of Importance	Very Unimportant	Less Important	Unimportant	Important	More Important	Very Important
Scoring standard	0	0.20	0.40	0.60	0.80	1

Calculate the objective weight of each indicator. The decision matrix A1 is obtained by reordering the index factors according to their importance of attributes from large to small. Calculate the mean value and standard deviation of each column of sample matrix

A1 and obtain the normalized matrix S. Matrix V is obtained by Schmidt orthogonal to the normalized matrix S. Then, normalize matrix V to obtain the Mahalanobis distance matrix D. The SNR (signal noise ratio) is calculated according to the Mahalanobis distance matrix D, and the objective weight of an indicator, which belongs to a single attribute index, is obtained.

The comprehensive weight of a single attribute index is obtained by integrating the subjective and objective weights.

(3) Determine the interaction degree between index factors

The existing multi-attribute decision making methods assume that there is no interaction between various influencing factors or index factors, and grey comprehensive evaluation method is no exception; however, this assumption does not exist in real life, so the interaction relationship and interaction degree between attributes should be taken into account. According to the experience of experts, problems about whether there is an interactive relationship between two index factors in the evaluation level and the degree of interaction between them can be determined. If two index factors have no interaction relationship and are completely independent of each other, then the interaction degree of the two index factors is 0. If there is a certain degree of complementarity between the two index factors and a more accurate evaluation can be obtained by the combination of the two index factors, then the interaction degree of the two index factors is greater than 0, and the larger the value of the interaction degree, the stronger the complementarity between the two index factors. If repeatability exists between two index factors, the interaction degree is less than 0, and the smaller the value of the interaction degree, the stronger the repeatability between the two index factors. The scoring criteria for the interaction degree between two index factors are shown in Table 5 [64].

(4) Calculate Mobius transformation coefficients of index factors

To calculate the grey fuzzy integral relational degree, the fuzzy measure should be determined firstly, and the 2-additive fuzzy measures can be calculated by defining the Mobius transformation coefficients m_n and m_{nj}. Suppose $b_1 = \{b_{11}, b_{12}, \ldots, b_{1i}\}$ is the attribute set under the evaluation level of b_1; the weight sets of b_1 can be expressed as $W_1 = \{w_{11}, w_{12}, \ldots, w_{1i}\}$, then the Mobius transformation coefficients of the single attributes $b_{1n}(n \leq i)$ and two-attributes $\{b_{1n}, b_{ij}\}(n, j \leq i, n \neq j)$ are shown as follows, respectively:

$$m_n = \frac{w_{1n}}{P} \tag{2}$$

$$m_{nj} = \frac{\xi_{nj} w_{1n} w_{1j}}{P} \tag{3}$$

The interaction degree between b_{1n} and b_{1j} is ξ_{nj}, the value range is [–1, 1]; P is the sum of importance of all the single attributes $b_{1n}(n \leq i)$ and the two-attributes $\{b_{1n}, b_{ij}\}(n, j \leq i, n \neq j)$, and it is expressed as $P = \sum\limits_{n \in b_1} w_{1n} + \sum\limits_{n,j \subset b_1} \xi_{nj} w_{1n} w_{1j}$.

(5) Calculation 2-additive fuzzy measures

The 2-additive fuzzy measure can solve the contradiction between precision and complexity because their parameter values can measure the interaction factors and importance factors in the interaction. The 2-additive fuzzy measure is further defined by the *k*-additive fuzzy measure based on the pseudo Boolean function and the Mobius transformation, so by using the Mobius transform coefficients of the single attributes m_n and the two-attributes m_{nj} and according to Formula (3), the 2-additive fuzzy measure of the attribute can be calculated:

$$g(K) = \sum_{n \in K} m_n + \sum_{\{n,j\} \in K} m_{nj}, \forall K \subseteq X \tag{4}$$

Table 5. Scoring criteria for the interaction degree between two index factors.

Interaction Degree	Extremely Repetitive	Very Repetitive	Repetitive	Slightly Repetitive	Independent	Slightly Complementary	Complementary	Very Complementary	Extremely Complementary
Scoring standard	−0.90	−0.70	−0.50	−0.30	0	0.30	0.50	0.70	0.90

In the formula, m_n is the Mobius transform coefficient of the single attribute x_n, and m_{nj} is the interaction degree between attributes x_n and x_j as well as the Mobius transform coefficient of the two-attribute $\{x_n, x_j\}$.

(6) Calculate grey correlation coefficients

The optimal index and grey correlation coefficient matrix are calculated as follows:

$$\xi_i(m) = \begin{bmatrix} \xi_1(1) & \xi_1(2) & \dots & \xi_1(m) \\ \xi_2(1) & \xi_2(2) & \dots & \xi_2(m) \\ \dots & \dots & \dots & \dots \\ \xi_i(1) & \xi_i(2) & \dots & \xi_i(m) \end{bmatrix} \quad (5)$$

$\xi_i(m)$ is the grey correlation coefficient of indicator i in scheme m.

(7) Grey fuzzy integral correlation degree of each decision scheme

Based on the theory of fuzzy measure, Choquet fuzzy integral represents a nonlinear function. To define the grey fuzzy integral correlation degree on the basis of Choquet fuzzy integral could make the grey relational degree be used for decision making, and at the same time, the interaction between attributes can be fully considered.

Suppose that a row of vector expression of evaluation matrix C is $C_i = \{C_i(m)\}$, which is called the comparison sequence of system referring to the evaluation vector of indicator i, which is on the evaluation level b_1 of object m, and $C_0 = \{C_0(m)\}$ is the reference sequence, then the grey fuzzy integral correlation degree of C_n and C_0 could be given by the formula:

$$\int \gamma(C_n, C_0) dg = \sum_{n=i}^{i} [\gamma_{0n}(x_{(m)}) - \gamma_{0n}(x_{(m-1)})] g(X_{(m)}) \quad (6)$$

In the formula, (m) is the subscript after sorting according to $\gamma_{0n}(x_{(1)}) \leq \gamma_{0n}(x_{(2)}) \leq \ldots \leq \gamma_{0n}(x_{(i)})$, $X_{(m)} = \left\{x_{(m)}, x_{(m+1)}, \ldots, x_{(i)}\right\}$, $\gamma_{0n}(x_{(0)}) = 0$. The final decision result can be determined by sorting the grey fuzzy integral correlation degree [65].

3. Empirical Results and Analyses

Due to the limitation of space, this paper gives merely the empirical results as shown in Tables 6 and 7, and the analyses.

Table 6. The 2-additive fuzzy integral comprehensive evaluation values (B_1–B_5) of 2010–2017.

Evaluation Value \ Year	2010	2011	2012	2013	2014	2015	2016	2017
Grey fuzzy Choquet integral evaluation value (B_1)	0.6078	0.5965	0.5758	0.4725	0.4729	0.4658	0.5069	0.6304
Grey fuzzy Choquet integral evaluation value (B_2)	0.3330	0.3554	0.3792	0.4350	0.4760	0.5316	0.7361	1.0000
Grey fuzzy Choquet integral evaluation value (B_3)	0.3333	0.3668	0.4247	0.5716	0.6485	0.7471	0.7166	0.9015
Grey fuzzy Choquet integral evaluation value (B_4)	0.6510	0.6977	0.5537	0.5625	0.5308	0.4963	0.4715	0.4601
Grey fuzzy Choquet integral evaluation value (B_5)	0.3333	0.3654	0.4273	0.5856	0.6601	0.7542	0.6849	0.8518

Table 7. Comprehensive evaluation values of Jinan low-carbon intensive land use of 2010–2017.

Evaluation Value \ Year	2010	2011	2012	2013	2014	2015	2016	2017
Grey fuzzy Choquet Integral evaluation value	0.5235	0.5877	0.4295	0.4105	0.4213	0.4461	0.4765	0.7991

Line B1 represents the change in the trend of land input intensity in the criterion layer; it experienced a slow decline and then a rising process during 2010–2017 was observed, which can be divided into two stages: The first is the decline stage from 2010 to 2015, in which the decline degree from 2012 to 2013 is the most obvious. The evaluation value from 2013 to 2015 is generally low, and the lowest value occurred in 2015. The second is the period of rapid improvement from 2015 to 2017. For the study period as a whole, the assessment value in 2017 was only 0.0226 higher than that in 2010, with an overall growth rate of about 3.72%; however, during the upgrading period from 2015 to 2017, the land input intensity increased by 35.34%, with an average annual growth rate of 17.67%, showing an obvious trend of rapid improvement. All in all, the results show that during the study period, the land input intensity in Jinan city gradually shows a relatively positive increase trend after the idle period of decline and slow increase.

Line B2 represents the change trend of the degree of land use in the criterion layer; it is in an overall rising stage from 2010 to 2017, and is divided into two stages with 2015 as the turning point: one is a slow rising stage from 2010 to 2015; the second is the period of rapid improvement from 2015 to 2017. In terms of the study period as a whole, the annual average growth rate of evaluation value in 2017 compared with 2010 is about 28.57%. The degree of land use can only reflect the degree of intensive urban land use during the upgrading period from 2015 to 2017, and the average annual growth rate of its assessed value is 44.06%, showing an obvious trend of rapid improvement, indicating that the degree of intensive land use in Jinan is getting higher and higher during the study period.

Line B3 represents the change trend of the land output efficiency in the criterion layer, and it is in an overall rising stage during 2010–2017, only slightly declining during 2015–2016, and rapidly rising after 2016 with a growth rate of 25.80%. For the study period as a whole, the average annual growth rate in 2017 compared to 2010 is about 24.35%. The results show that the overall situation of land output efficiency in Jinan is good during the study period.

Line B4 represents the low-carbon land level in the criterion layer, and it is in an overall decline stage during 2010–2017: after the increase in 2010–2011, it enters an obvious decline stage during 2011–2012. After the non-significant increase during 2012–2013, it enters the stage of gradual annual decline during 2013–2017. For the study period as a whole, the average annual decline in 2017 compared to 2010 is about 4.19%. Although the annual decline rate of low-carbon land assessment value is small, the overall trend of decline is very obvious. This shows that the situation of low-carbon land use in Jinan is still relatively grim.

Line B5 represents the land sustainability in the criterion layer; it is in an overall rising stage from 2010 to 2017 and only in a declining stage from 2015 to 2016. For the study period as a whole, the average annual growth rate in 2017 compared to 2010 is about 22.22%. Although the overall upward trend of land sustainability evaluation value is obvious, the fluctuation of the values between 2015 and 2017 is also obvious. Considering that the land low-carbon level of in criterion layer B_4 in Figure 2 has been declining significantly in recent studies and that the indexes of criterion layer B_4 and B_5 are repeatable, this indicates that the situation of land use sustainability in Jinan is not stable and still needs close attention.

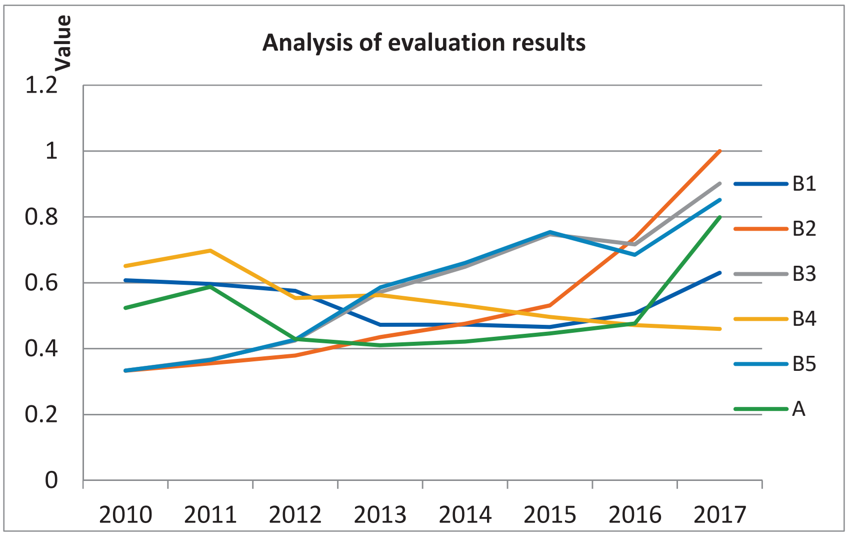

Figure 2. Change trend diagrams of criteria level and purpose level.

In conclusion, during the study period, the low-carbon land use level in Jinan has been declining, and the situation is severe. Although the change trends of land input intensity fluctuated slightly, the land input intensity, the land use degree, the land output efficiency and the land sustainability show a good upward trend on the whole.

Line A represents the change trend of comprehensive evaluation of low-carbon intensive land use. It can be seen from Figure 2 that the comprehensive evaluation results of low-carbon and intensive land use in Jinan fluctuate on the whole from 2010 to 2017. After the rise in 2010–2011, the evaluation value decreases sharply in 2011–2012, even lower than that in the beginning of the study. After the insignificant downward trend during 2012–2013, it enters the slow upward stage during 2013–2016 with 2013 as the turning point. At the end of the study period from 2016 to 2017, it shows a rapid upward trend. For the study period as a whole, the average annual growth rate in 2017 compared to 2010 is about 7.52%; however, the numerical fluctuation during the study period is very obvious, indicating that although the low-carbon intensive land use in Jinan has a good development trend, the state is not stable.

All in all, after a period of extensive development focused solely on economic benefits, China's 12th Five Year Plan and 13th Five Year Plan have promised to limit carbon emissions, emphasized the in-depth implementation of the scientific outlook on development, and accelerated the construction of a "resource-conserving and environmentally friendly" society. In the process of rapid urbanization, Jinan has actively responded to the call of the central government and formulated the corresponding low-carbon industrial upgrading, low-carbon energy transformation and other supporting carbon-reduction systems and measures. The transformation from the "high consumption and high emission" extensive land use pattern to the of "low consumption, low emission and high benefit" low-carbon intensive land use pattern will not be accomplished overnight, and it must be a dynamic game process. This is also reflected in the evaluation results of each criterion level, and the whole index system of land low-carbon and intensive use. The low-carbon and intensive land use in Jinan still needs to be paid enough attention. This paper will put forward suggestions on the path and guarantee mechanism of low-carbon and intensive land use in Jinan in order to promote the sustainable and healthy development of land use.

4. Policy Recommendations

Based on the dynamic mechanism and the main factors affecting the evolution of urban space environment of modern urban development, this paper proposes the guaranteed mechanism of low-carbon and intensive land use in Jinan from five perspectives:

(1) Perspective of policy system. The land use control mode in China is a comprehensive land use control mode which is oriented by planning, and the direct guidance and basis function are land use planning and urban planning. On the basis of the evaluation results of low-carbon and intensive land use, Jinan city needs to formulate land use planning that integrates urban and rural regions to ensure the coordination and unity of urban planning and land use planning. Since land use planning and urban planning are important statutory plannings for local governments to implement land space management, the integration of the two regulations is conducive to unified management by the government.

(2) Perspective of science and technology. On the one hand, scientific and technological revolution and innovation can produce new technological industries and accelerate the upgrading of traditional industries, thus optimizing the industrial structure of the whole society and promote social development. On the other hand, speeding up the construction of carbon emission trading system will also rely on market-oriented means to promote enterprises to actively improve industrial technology level and accelerate scientific and technological innovation so as to make the enterprises achieve the goals of energy conservation and mitigation of carbon emission.

(3) Perspective of society and culture. Establishing the concept of "green and low-carbon development", changing the environmental protection mode of "pollution first, treatment later", correctly guiding people's consumption concept, advocating moderate consumption, eliminating luxury and waste phenomena, controlling the discharge of pollutants and reducing the use of pesticides and fertilizers, and promoting the use of green energy as well as forming a social and cultural atmosphere for sustainable development could guarantee and promote the low-carbon and intensive land use in Jinan to should be emphasized to a certain extent.

(4) Perspective of resources and environment. Under the guidance of sustainable development concept, the coexistence of natural resources development and protection, the pursuit of natural environment protection and other sustainable development modes are given priority from various aspects of concept, consciousness and measures, which will certainly help to provide a powerful guarantee for the low-carbon and intensive land use in Jinan.

(5) Perspective of regional integration. When Jinan meets the challenge of regional development, it should also find the following opportunities: firstly, it could take advantage of the status of the core city to strengthen the connection with the surrounding areas in economy, transportation, ecology and other aspects, and complement each other while realizing resource sharing. secondly, carrying out actively intensive, coordinated and group-developed urbanization within each region, together with scientific and technological innovation, optimizing the layout of land use structure, transforming enterprises with serious pollution and backward technology, and developing high-tech industries according to local conditions of the characteristics of cities at all levels in Shandong province should be focused. It not only closely links with the surrounding areas for the coordinated development, but also strengthens Jinan's driving ability both in Shandong and in relevant economic regions, such as Bohai Rim, and actively guides and implements the low-carbon and intensive land use in a wider geographical range.

5. Conclusions

This paper establishes an evaluation system based on the low-carbon intensive land use in Jinan city from 2010 to 2017, and uses the grey fuzzy integral multi-attribute evaluation model, which is the integration of respective advantages of grey relational degree, and fuzzy integral for data analysis in view of the large amount of interaction between index factors. In this model, based on the Mobius transformation coefficient of subjective and objective weights of index factors and the interaction degree between index factors, 2-additive fuzzy measures can be obtained; therefore, evaluation of low-carbon intensive land use in Jinan city is processed by combining the grey correlation degree and Choquet fuzzy integral. The results show that in the study period, land input intensity, land use degree, land output benefit and land sustainability in Jinan city all show a good upward trend, but the low-carbon land use level of has been in a declining state. Although there is a good development trend of low-carbon intensive land use of Jinan, the state is not stable, and the transformation of land use from the "high consumption and high emissions" extensive land use pattern to the "low consumption, low emission, high benefit" low-carbon and intensive land use pattern will not be accomplished overnight, and it is bound to be a dynamic game process; therefore, this paper puts forward the corresponding recommendations for low-carbon intensive land use in Jinan city.

With the adjustment of the zoning scope at the end of 2018 and the beginning of 2019, the relevant statistical data of Jinan city will inevitably change accordingly. The current research data and results are applicable before the adjustment of administrative division, which can provide a reference for future refinement and in-depth research; however, for data processing after the adjustment, the influence brought by it, needs to be considered. Although the research scopes or research objects, for instance, target city or target region, could be different, the research method is still worth being used for reference.

Although there could be a common goal of humankind or international treaties to mitigate the carbon emission to make the global environment suitable for the survival of humankind, there are always conflicts of interest between countries in political and economic aspects, and once the balance of various forces is broken, it is easy to cause friction; therefore, when conflicts or wars break out, all carbon mitigation targets and measures together with international collaborations would be abandoned. In conflicts, energy could also become a bargaining chip between countries. When the international environment for energy cooperation is damaged, the priority of the countries concerned is the survival and livelihood of their citizens, rather than the mitigation of carbon emissions. This would undoubtedly shift the global climatic environment, which has been greatly affected by the increase in carbon emissions, from bad to worse. It is more fundamental and significant to seek an international environment of peace, friendship, and common development and prosperity for humankind so as to adopt appropriate policies, measures and technological means to mitigate carbon emissions.

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References

1. Harari, Y.N. *Homo Deus: A Brief History of Tomorrow*; Citic Publishing House: Beijing, China, 2017.
2. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2014: Mitigation of Climate Change—Summary for Policymakers*; Edenhofer, O.R., Pichs-Madruga, Y., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., et al., Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2014.
3. United Nations Environment Programme (UNFP). *The Emissions Gap Report 2012*; UNEP: Nairobi, Kenya, 2012.
4. International Energy Agency (IEA). *Energy Policies of IEA Countries: The United States*; IEA: Paris, France, 2008.
5. United Nations (UN). *Paris Agreement under the United Nations Framework Convention on Climate Change*; UN: Paris, France, 2015. Available online: https://www.britannica.com/topic/Paris-Agreement-2015 (accessed on 12 September 2021).
6. The European Economic Area. The Relative Change in Main Global Economic and Environmental Indicators from 1970 to 2018. *European Environment Agency.* 2021. Available online: https://www.eea.europa.eu/data-and-maps/figures/relative-change-in-main-global (accessed on 12 September 2021).
7. IPCC. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*; Prepared by the National Greenhouse Gas Inventories Programme; IGES: Tokyo, Japan, 2006.
8. Houghton, R.A.; Hackler, J.L.; Lawrence, K.T. The U.S. carbon budget: Contributions from land-use change. *Science* **1999**, *285*, 574–578. [PubMed]

9. Houghton, R.A.; Hackler, J.L. Emissions of carbon from forestry and land-use change in tropical Asia. *Glob. Chang. Biol.* **1999**, *5*, 481–492.
10. Hester, R.T., Jr. *Design for Ecological Democracy*; MIT Press: Cambridge, MA, USA, 2006.
11. Romero-Lankao, P.; Gurney, K.R.; Chester, M.; Duren, R.M.; Hughes, S.; Stokes, F. A critical knowledge pathway to low-carbon, sustainable futures: Integrated understanding of urbanization, urban areas, and carbon. *Earth's Future* **2014**, *2*, 515–532. [CrossRef]
12. United Nations (UN). *Transforming Our World: The 2030 Agenda for Sustainable Development*; UN: Paris, France, 2015. Available online: https://sustainabledevelopment.un.org/post2015/transformingourworld (accessed on 12 September 2021).
13. The World in 2050 (TWI2050). *Transformations to Achieve the Sustainable Development Goals*; Report Prepared by The World in 2050 Initiative; International Institute for Applied Systems Analysis (IIASA): Laxenburg, Austria, 2018. Available online: https://www.twl2050.org (accessed on 12 September 2021).
14. Sachs, J.D.; Schmidt-Traub, G.; Mazzucato, M.; Massner, D.; Nakicenovic, N.; Rockstroam, J. Six Transformations to Achieve the Sustainable Development Goals. *Nat. Sustain.* **2019**, *2*, 805–814.
15. Choi, D.; Gao, Z.; Jiang, W. Attention to Global Warming. *Rev. Financ. Stud.* **2020**, *33*, 1112–1145.
16. Monasterolo, I.; de Angelis, L. Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. *Ecol. Econ.* **2020**, *170*, 106571.
17. Schoenmaker, D. Greening monetary policy. *Clim. Policy* **2021**, *21*, 581–592. [CrossRef]
18. Liu, P.; Qiao, H. How does China's decarbonization policy influence the value of carbon-intensive firms? *Financ. Res. Lett.* **2021**, *43*, 102141. [CrossRef]
19. Benz, L.; Paulus, S.; Scherer, J.; Syryca, J.; Truck, S. Investors' carbon risk exposure and their potential for shareholder engagement. *Bus. Strategy Environ.* **2021**, *30*, 282–301. [CrossRef]
20. Cheng, S.; Qi, S. The potential for China's outward foreign direct investment and its determinants: A comparative study of carbon-intensive and non-carbon-intensive sectors along the Belt and Road. *J. Environ. Manag.* **2021**, *282*, 111960.
21. Sun, X.; Fang, W.; Gao, X.; An, H.; Liu, S.; Wu, T. Complex causalities between the carbon market and the stock markets for energy intensive industries in China. *Int. Rev. Econ. Financ.* **2022**, *78*, 404–417.
22. Moussa, T.; Allam, A.; Elbanna, S.; Bani-Mustafa, A. Can board environmental orientation improve US firms' carbon performance? The mediating role of carbon strategy. *Bus. Strategy Environ.* **2020**, *29*, 72–86. [CrossRef]
23. Abd Rahman, N.R.; Rasid, S.Z.A.; Basiruddin, R. Hard and soft carbon disclosures: Malaysia's carbon intensive industries. In Proceedings of the 9th International Economics and Business Management Conference (IEBMC), Melaka, Malaysia, 2–3 November 2019.
24. Lu, W.; Zhu, N.; Zhang, J. The Impact of Carbon Disclosure on Financial Performance under Low Carbon Constraints. *Energies* **2021**, *14*, 4126. [CrossRef]
25. Hotak, S.; Islam, M.; Kakinaka, M.; Kotani, K. Carbon emissions and carbon trade balances: International evidence from panel ARDL analysis. *Environ. Sci. Pollut. Res.* **2020**, *27*, 24115–24128.
26. Sun, C.; Chen, L.; Zhang, F. Exploring the trading embodied CO_2 effect and low-carbon globalization from the international division perspective. *Environ. Impact Assess. Rev.* **2020**, *83*, 106414.
27. Ji, C.-J.; Hu, Y.-J.; Tang, B.-J.; Qu, S. Price drivers in the carbon emissions trading scheme: Evidence from Chinese emissions trading scheme pilots. *J. Clean. Prod.* **2021**, *278*, 123469.
28. Ma, N.; Yin, G.; Li, H.; Sun, W.; Wang, Z.; Liu, G.; Xie, D. The optimal industrial carbon tax for China under carbon intensity constraints: A dynamic input-output optimization model. *Environ. Sci. Pollut. Res.* **2022**, *29*, 53191–53211. [CrossRef]
29. Wang, J.; Hu, M.; Tukker, A.; Rodrigues, J.F.D. The impact of regional convergence in energy-intensive industries on China's CO_2 emissions and emission goals. *Energy Econ.* **2019**, *80*, 512–523.
30. Du, W.; Li, M. Influence of environmental regulation on promoting the low-carbon transformation of China's foreign trade: Based on the dual margin of export enterprise. *J. Clean. Prod.* **2020**, *244*, 118687. [CrossRef]
31. Rosenbloom, D.; Rinscheid, A. Deliberate decline: An emerging frontier for the study and practice of decarbonization. *WIREs Clim. Chang.* **2020**, *11*, e669. [CrossRef]
32. Zhu, R.; Zhao, R.; Sun, J.; Xiao, L.; Jiao, S.; Chuai, X.; Zhang, L.; Yang, Q. Temporospatial pattern of carbon emission efficiency of China's energy-intensive industries and its policy implications. *J. Clean. Prod.* **2021**, *286*, 125507. [CrossRef]
33. Dong, K.; Ren, X.; Zhao, J. How does low-carbon energy transition alleviate energy poverty in China? A nonparametric panel causality analysis. *Energy Econ.* **2021**, *103*, 105620. [CrossRef]
34. Zhao, D.; Zhou, H. Livelihoods, Technological Constraints, and Low-Carbon Agricultural Technology Preferences of Farmers: Analytical Frameworks of Technology Adoption and Farmer Livelihoods. *Int. J. Environ. Res. Public Health* **2021**, *18*, 13364. [CrossRef] [PubMed]
35. Wang, X.; Liang, S.; Wang, H.; Huang, S.; Liao, B. Do Fossil-Fuel Price Distortions Impact the Low-Carbon Transition in China's Energy Intensive Industries? *Front. Energy Res.* **2022**, *9*, 805224. [CrossRef]
36. Han, M.; Liu, W.; Yang, M. Carbon risk transmission of China's energy-intensive industries under low-carbon transition: From the embodied carbon network perspective. *Geogr. Res.* **2022**, *41*, 79–91.
37. Xin, L.; Sun, H.; Xia, X.; Wang, H.; Xiao, H.; Yan, X. How does renewable energy technology innovation affect manufacturing carbon intensity in China? *Environ. Sci. Pollut. Res.* **2022**, *29*, 59784–59801. [CrossRef]

38. Wang, Z.-B.; Zhang, J.-Z.; Zhang, L.-F. Reducing the carbon footprint per unit of economic benefit is a new method to accomplish low-carbon agriculture. A case study: Adjustment of the planting structure in Zhangbei County, China. *J. Sci. Food Agric.* **2019**, *99*, 4889–4897. [CrossRef]
39. Sun, Y.; Cheng, Y.; Zhang, H. Impact of urban industrial land intensive use on carbon emission efficiency—Take China's 15 sub-provincial cities as an example. *Resour. Environ. Yangtze Basin* **2020**, *29*, 1703–1712.
40. Cormos, A.-M.; Dragan, S.; Petrescu, L.; Sandu, V.; Cormos, C.-C. Techno-Economic and Environmental Evaluations of Decarbonized Fossil-Intensive Industrial Processes by Reactive Absorption & Adsorption CO_2 Capture Systems. *Energies* **2020**, *13*, 1268.
41. Nurdiawati, A.; Urban, F. Towards Deep Decarbonisation of Energy-Intensive Industries: A Review of Current Status, Technologies and Policies. *Energies* **2021**, *14*, 2408. [CrossRef]
42. Roman, M.; de los Santos, C.B.; Roman, S.; Santos, R.; Troncoso, J.S.; Vazquez, E.; Olabarria, C. Loss of surficial sedimentary carbon stocks in seagrass meadows subjected to intensive clam harvesting. *Mar. Environ. Res.* **2022**, *175*, 105570. [CrossRef] [PubMed]
43. The World in 2050 (TWI2050). *Innovations for Sustainability. Pathways to an Efficient and Post-Pandemic Future*; Report prepared by The World in 2050 Initiative; International Institute for Applied Systems Analysis (IIASA): Laxenburg, Austria, 2020.
44. Jinan Municipal Bureau of Statistics. *Jinan Statistical Yearbook 2017*; NBS Survey Office in Jinan, Ed.; China Statistics Press: Beijing, China, 2017.
45. Xun, Q. *History and Culture of Tianqiao District (Industry Volume)*; Jinan Publishing House: Jinan, China, 2012.
46. *GB/T21010-2007*; Land Use Classification. General Administration of Quality Supervision, Inspection and Quarantine of PRC, Standardization Administration: Beijing, China, 2007.
47. People's Government of Shandong Province. Development Plan for Shandong Peninsula Urban Agglomeration (2016–2030). Jinan. 2017. Available online: http://zwfw.sd.gov.cn/art/2017/2/3/art_1684_734.html (accessed on 12 September 2021).
48. Jinan Municipal Bureau of Statistics. *Jinan Statistical Yearbook 2021*; NBS Survey Office in Jinan, Ed.; China Statistics Press: Beijing, China, 2021.
49. *GB/T2589-2008*; General Principles for Calculation of Total Production Energy Consumption. Department of Resource Conservation and Environmental Protection of the National Development and Reform Commission, the first Industrial Standard of Standardization Administration: Beijing, China, 2008.
50. National Development and Reform Commission (NDRC). *Guide for the Compilation of Provincial Greenhouse Gas Inventories (Trial)*; NDRC: Beijing, China, 2011.
51. Wang, H.; Zhang, R.; Bi, J. Carbon emission accounting of Chinese cities: A case study of Wuxi City. *China Environ. Sci.* **2011**, *31*, 1029–1038.
52. Zadeh, L.A. Fuzzy sets. *Inf. Control.* **1965**, *8*, 338–353. [CrossRef]
53. Dubios, D.; Prade, H.; Sabbadin, R. Qualitative Decision Theory with Sugeno Integrals. In *Fuzzy Measures and Integrals: Theory and Application*; Grabisch, M., Murofushi, T., Sugeno, M., Eds.; Physica Verlag: New York, NY, USA, 2000; pp. 314–332.
54. Murofushi, T.; Sugeno, M. The Choquet Integral in Multiattribute Decision Making. In *Fuzzy Measures and Integrals: Theory and Application*; Grabisch, M., Murofushi, T., Sugeno, M., Eds.; Physica Verlag: New York, NY, USA, 2000; pp. 333–347.
55. Grabisch, M.; Roubens, M. Application of the Choquet Integral in Multicriteria Decision Making. In *Fuzzy Measures and Integrals: Theory and Application*; Grabisch, M., Murofushi, T., Sugeno, M., Eds.; Physica Verlag: New York, NY, USA, 2000; pp. 348–374.
56. Ishii, K.; Sugeno, M. A Model of Human Evaluation Process Using Fuzzy Measure. *Int. J. Man-Mach. Stud.* **1985**, *22*, 19–38. [CrossRef]
57. Tanaka, K.; Sugeno, M. A Study on Subjective Evaluation of Printed Color Images. *Int. J. Approx. Reason.* **1991**, *5*, 213–222. [CrossRef]
58. Kwon, S.H.; Sugeno, M. A Hierarchical Subjective Evaluation Model Using Non-Monotonic Fuzzy Measures and the Choquet Integral. In *Fuzzy Measures and Integrals: Theory and Application*; Grabisch, M., Murofushi, T., Sugeno, M., Eds.; Physica Verlag: New York, NY, USA, 2000; pp. 375–391.
59. Xie, J.; Li, Q.; Chen, S.; Huang, H. The fuzzy metric space based on fuzzy measure. *Open Math.* **2016**, *14*, 603–612. [CrossRef]
60. Sugeno, M. Theory of Fuzzy Integrals and Its Applications. Ph.D. Thesis, Tokyo Institute of Technology, Tokyo, Japan, 22 January 1974.
61. Grabisch, M. K-order Additive Discrete Fuzzy Measure. In Proceedings of the Sixth International Conference Information Processing and Management of Uncertainty in Knowledge-Based System, Granada, Spain, 1–5 July 1996; pp. 1345–1350.
62. Ministry of Land and Resources of the People's Republic of China. *Evaluating the Potential of Intensive Use of Urban Land (Trial)*; Ministry of Land and Resources of the People's Republic of China: Beijing, China, 2007.
63. Zeng, H.; Dong, L.-M. Evaluation of land intensive use in Wuhan city based on low carbon background. *Hubei Agric. Sci.* **2014**, *53*, 3456–3461.
64. Li, Y.; Gong, X.; Hui, H.; Tian, J. Construction of evaluation index system of government-civilian interaction degree under the condition of government microblog. *J. Chongqing Univ. (Soc. Sci. Ed.)* **2016**, *22*, 172–179.
65. Chang, Z.; Cheng, L. Grey fuzzy integral relational degree decision 5making model. *Chin. Manag. Sci.* **2015**, *23*, 105–111.

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Article

Expanded Residential Lands and Reduced Populations in China, 2000–2020: Patch-Scale Observations of Rural Settlements

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Abstract: The spatiotemporal transformations of rural residential lands and populations reflect changes in rural human–land relations. This study uses high-precision rural residential land patches and population distribution data to detect the area, population density, and spatial heterogeneity of newly added rural residential land (NARRL) in China from 2000 to 2020 through spatial local clustering and geographically weighted regression. The patch results were summarized into county-level units for regional comparison, spatial clustering identification, and policy recommendations. The main conclusions are as follows: (1) The total rural residential area increased by 13.86% between 2000 and 2020. The average population density of NARRL (APDNARRL) at patch scale is 701.64 person/km^2, significantly exceeding the 507.23 person/km^2 of the remaining patches. (2) There are obvious spatial differences in the distribution of APDNARRL as per county-level statistics. There are significant differences in APDNARRL on both sides of the Hu Huanyong Line; the APDNARRL on the left is significantly lower than that on the right. (3) Spatial heterogeneity was found to be among the driving factors of APDNARRL. This study also detected the number and location of hollowing counties; it is significant for monitoring dynamic changes in rural residential lands, revealing their spatial distribution patterns and driving factors, thus improving the optimization of rural land resources.

Keywords: rural residential land; population density; patch scale; geographically weighted regression; spatial local clustering; China

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1. Introduction

Rural residential areas, which constitute an important type of land-use category in rural areas, are also spatial carriers of rural development [1,2]. After reform and opening-up, with rapid regional socioeconomic development, China embarked on an accelerated urbanization process unprecedented in global history, leading to sharp changes in urban–rural land-use patterns, particularly in regard to two aspects. First, because of the consistently increasing urbanization levels, urban construction land has rapidly expanded and spread [3,4]. Second, a large share of the rural labor force has transferred to cities, but the scale of rural residential areas has increased instead of decreasing [5]. This has led to continuing changes in the spatial layout and morphological characteristics of rural residential areas [6–8].

The changes to China's urban–rural land-use patterns are driven by transformations in social structures, as can be clearly seen in the rapid increase in the population's urbanization rate, from 19.72% in 1978 to 65.22% in 2022. This shows that China's traditional agricultural social structure has been giving way to a predominantly urban society [9] over the course of just 40 years. While the social and structural development of cities in China has been much researched globally, the country's rural areas have received far less attention from scholars. For example, in the Web of Science database, there are only 901 articles with the keywords "rural residential land, China" from 1978 to 2023, which is much lower than the 22,719 records retrieved with the keywords "urban land, China". The key topics in the few existing rural studies include the spatial patterns of rural residential land [6,7], its spatial and temporal evolution [1,10,11], analyses of the driving mechanisms of change [8,12], its consolidation and optimization [13–15], and the dynamics of human–land relations [16,17].

This study focuses on the area and population density of rural residential land. Scholars have found that the area of rural residential land in China has been expanding, by using GIS, remote sensing, and other methods. For example, based on the data interpreted from remote sensing images, from 1990 to 2000 the rural residential area increased by 7.88×10^5 ha [18], and from 2009 to 2016 the rural residential area increased at an average annual rate of 0.55%, which are significantly higher than the average annual growth rate of 0.10% between 1996 and 2008 [1] and 0.09% between 2000 and 2005 [5]. Most of the new rural residential land is used for cultivation [19,20], which poses a potential threat to the regional ecological environments [21]. Although the size of residential areas has been expanding, the rural population has continued to decline. China's rural population decreased at an average annual rate of 2.07% from 2009 to 2016. A similar change was noted in the Yellow River Basin, for example, from 2010 to 2016 [17]. The average annual decline in the rural population has been 2.57% [22]. The urbanization rate of China's permanent population reached 65.22% in 2022. However, most of those who live in cities and towns all year round but have a rural registered residence continue to choose to return to their registered residences to build housing. This peculiar phenomenon of a fall in population without a fall in settled land has led to the increased use of rural residential land in many rural areas, although there is a trend of consistently high housing vacancy rates [23]. The consequent problems of population loss and the hollowing out of villages, and scattered and disordered village construction, places enormous pressure on resources and the environment; the destruction of rural landscapes, as well as urban villages, is increasingly prominent [24], resulting in a clear imbalance in rural human–land relations [25].

Relative to the previous extensive analysis of the decoupling relationships between rural residential land and the resident population at the national, regional, and individual city levels, based on statistical yearbook data at the administrative district level [22], there has been limited research on the relationship between rural residential land changes and population changes at the micro-patch scale. Because of the fragmented and scattered distribution of rural residential areas, patch-scale analysis can be used to detect additional spatial details, such as the spatial clustering and differentiation that are characteristic of human–land relationships within a region, relative to an administrative-district-scale analysis. Therefore, this study uses vector polygons (patches) of rural residential land, interpreted from 30×30 m remote sensing images, and a 1×1 km grid LandScan population distribution produced by Oak Ridge National Laboratory, United States, as the basic data to explore human–land changes in China's rural areas from 2000 to 2020. We attempted to answer the following questions: what is the state of the average population density of the newly added rural residential land (APDNARRL) in China? Are there obvious agglomeration and differentiation characteristics across space, and what drives them? To the best of our knowledge, this study is the first to determine APDNARRL on a fine-patch scale across China, and by using the same data over time, it supports the possibility of cross-regional comparisons.

2. Study Area and Data

Mainland China, excluding Taiwan, Hong Kong, and Macau, was selected as the research area, covering a total of 2877 county-level administrative regions (Figure 1). While there are many forms of county-level administrative units in China, the main types are municipal districts, counties under the jurisdiction of cities, and county-level cities. A prominent feature of a municipal district is that the urban built-up area is a core component, with urban residents constituting its main population, and the urbanization of this core is generally at a high level. However, counties that are under the jurisdiction of cities are usually dominated by rural populations that have low urbanization rates. County-level cities are usually county-level units adjusted after their economic development level, population urbanization rate, total population, and other indicators meet certain conditions, which were set at the beginning of China's reform and opening-up. County-level cities have more authority in terms of economic management and urban construction than counties under the jurisdiction of cities.

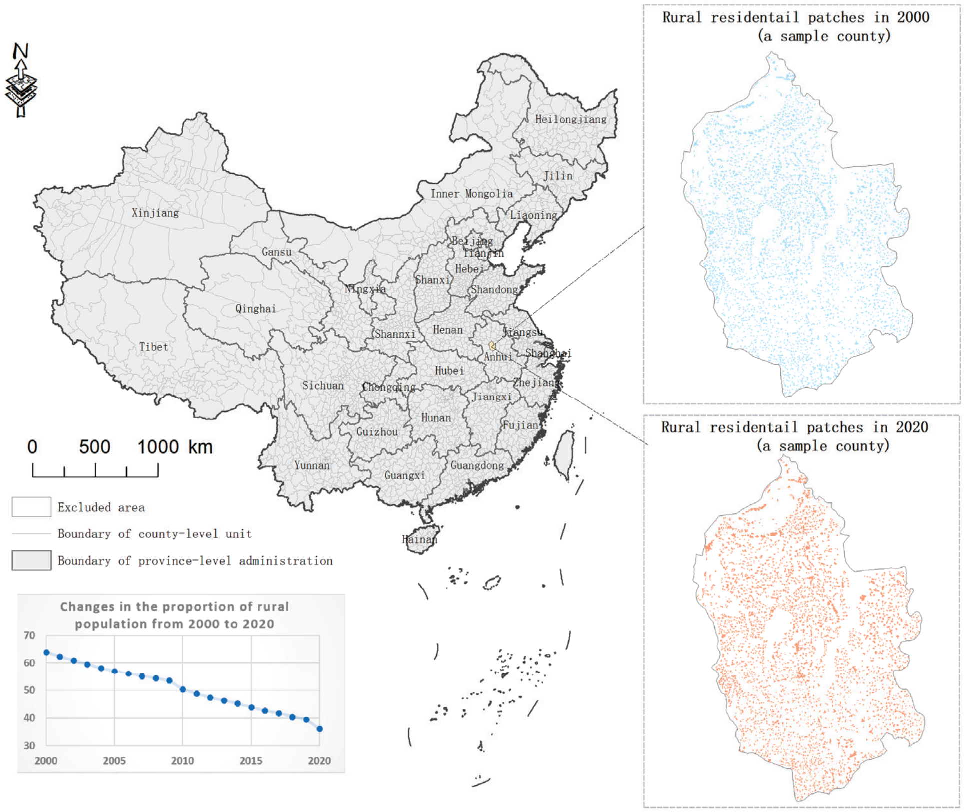

Figure 1. Study area.

China's rapid urbanization has been widely studied globally. As a result of this process, a large number of farmers are leaving rural areas and moving to cities each year. Statistics show that the rural population has decreased year after year from 2000 to 2020, from 63.91% in 2000 to 36.11% in 2020, showing an average annual decline of 1.39 percentage points. However, the area of rural residential land in China has not declined with this massive loss of population; rather, it has shown a trend of increasing year after year, resulting in a huge waste of rural land resources. For example, according to the 2017 China Rural Development Report, published by the Rural Development Institute of the Chinese Academy of Social Sciences, between 2000 and 2010, the annual increase in rural idle housing caused by rural population transfer reached 594 million m^2, equivalent to a market value of about 400 billion yuan. The population leaving rural areas and the large number of empty houses left behind have resulted in significant rural hollowing out.

This study mainly examines three types of data: land-use data, the spatial distribution of the population, and basic auxiliary data (geographic maps and socioeconomic statistical data). The land-use data with 30×30 m spatial resolution are from the National Land Use/Cover Database of China (NLUD-C), released by the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences. They were produced using Landsat TM/ETM and China Brazil Earth Resources Satellite as the main sources of information through image correction, visual interpretation, supervised classification, and field investigation. It was found that the NLUD-C classification accuracy reached over

90% [26], enabling it to be considered accurate and reliable. This database includes multiple periods of land use over the years. This study selected the data between 2000 and 2020, and extracted the land class with code 52 as the analytical source for subsequent rural residential area patches. Figure 2 shows the spatial distribution of the area of rural residential land in each county-level unit in 2000 and 2020.

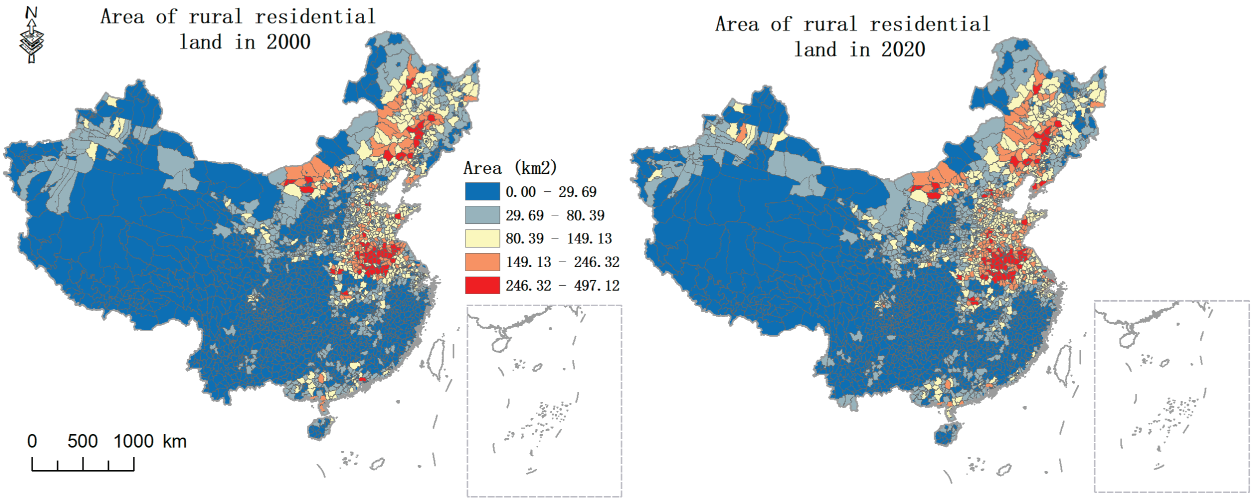

Figure 2. Spatial distribution of the area of rural residential land in each county-level unit in 2000 and 2020.

Because this study's aim was to calculate population density at the patch scale, it was not possible to use the population data based on administrative units for calculation, so we used the spatial distribution population program LandScan (Oak Ridge National Laboratory, Oak Ridge, TN, USA) with a high spatial resolution (about 1 × 1 km). LandScan uses the best available census data, which is recognized as authoritative and as providing accurate spatial population data, and is widely used in population research [27]. A weighted model based on geographic information systems and partition density models has been established to better reflect the spatial distribution of the population (https://landscan.ornl.gov, accessed on 5 July 2022). To improve the accuracy of the data, they were manually corrected and modified.

Other data, including geographic information data (including on roads, rivers, administrative boundaries, and government locations), were taken from the National Earth Systems Science Data Center of the Institute of Geography, Chinese Academy of Sciences (www.geodata.cn). The socioeconomic data (GDP, value added of primary/secondary/tertiary industries) are from statistical yearbooks and the social and economic development bulletins of various districts and counties.

3. Methodology

3.1. Research Framework

We designed the method framework diagram shown in Figure 3 based on the issues we sought to understand. Using the land-use vector-map patch data interpreted from remote sensing images, we detected the spatiotemporal changes of rural residential land in China between 2000 and 2020. During this period, China's economy grew rapidly, and the rural landscape underwent tremendous changes due to rapid urbanization and industrialization. Supported by high-precision data on the spatial distribution of the population, the population density of each newly added or retained patch was detected, and a county-scale summary analysis was conducted. Then, the spatial characteristics of the changes in the quantity, pattern, and density of the population of rural residential land were analyzed at the county scale, and the driving factors and differences in spatial heterogeneity between the changes in population density were detected. Conventional spatial analysis methods, such as spatial overlay, spatial statistics, vector to raster, raster to point, and summary statistics, which can be directly implemented in ArcMap software, have not been described in detail. We focus on the calculation of APDNARRL, spatial autocorrelation *t*-test, and geographically weighted regression (GWR) modeling in the following text.

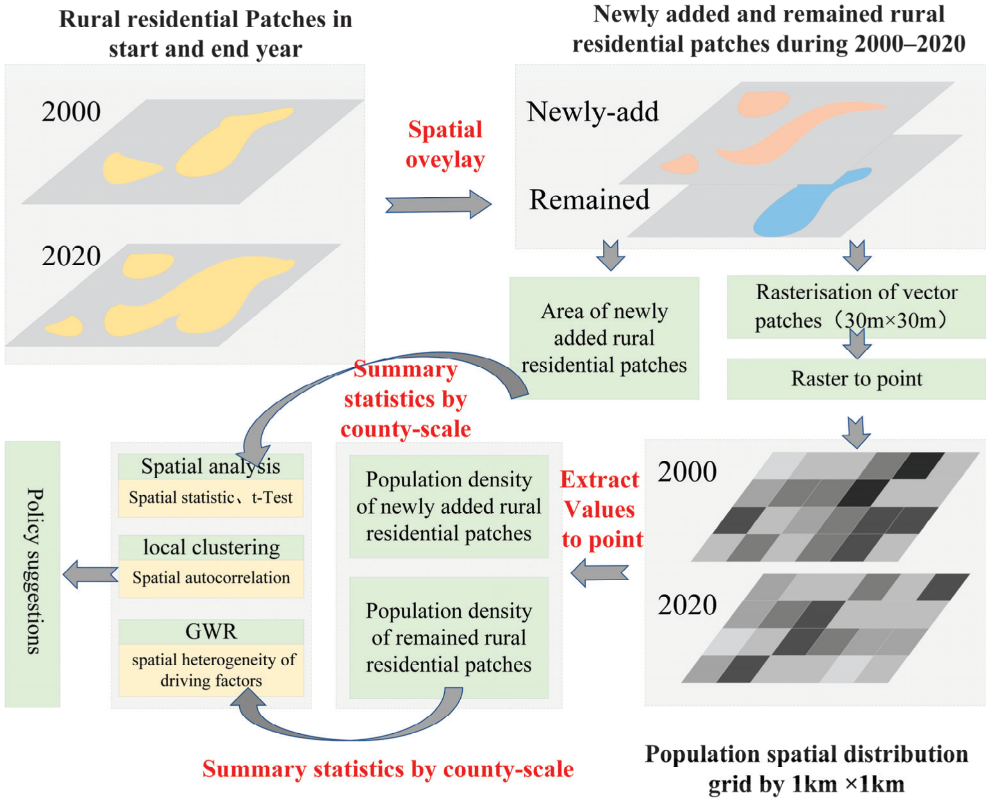

Figure 3. Diagram of overall method framework.

3.2. Calculation of APDNARRL

By employing the "erase" tool in ArcMap, the newly added rural residential patches during 2000–2020 were extracted from the two years of rural residential patches in 2000 and 2020. To determine the population density of each patch, the newly added patches (in vector format) were superimposed on the population distribution data (landscan in raster format). However, due to the irregularities and size differences of the residential patches, direct overlaying did not yield accurate average population density values. Consequently, an additional step was taken to convert the vector form into a grid form, with a resolution of 30 m × 30 m, using the "Raster to Point" tool in ArcMap. Subsequently, the grid was transformed into vector points, and these points were overlaid once again with the gridded population distribution layer. This process ensured that each patch contained multiple points, denoted as 'm'. By employing the "Extract values to points" function in ArcMap, the grid values (i.e., population density) corresponding to each point could be extracted. Ultimately, the population density of each patch was calculated using the following equation:

$$\text{APDNARRL}_{patch\_i} = \frac{\sum_{j=1}^{m} p_j}{m} \quad (1)$$

where APDNARRL_i represents the population density of the *i*-th patch, p_j is the population density of the *j*-th point under the patch, and m represents the number of all points covered under the patch.

Further, we obtained the APDNARRL for each county unit by summing the population density of all the new patches weighted by area.

$$\text{APDNARRL}_{county\_p} = \sum\nolimits_{e=1}^{f} \text{APDNARRL}_{patch\_e} \times \frac{Area_{patch\_e}}{A} \quad (2)$$

where $\text{APDNARRL}_{county\_p}$ represents the population density of the p-th county, $\text{APDNARRL}_{patch\_e}$ and $Area_{patch\_e}$ are the population density and patch area of the e-th patch in the county, respectively, f is the total number of patches, and A is the total area of all patches.

3.3. Spatial Autocorrelation Detection

Spatial autocorrelation refers to the interdependence of variables on a spatial scale, which can be used to judge whether there is aggregation or outliers in the research areas. This study indicates the local similarities between the areas of newly added rural residential land (ANARR) and APDNARRL for the county-level units in China using the LISA cluster diagram [28].

$$I_i = \frac{n(x_i - \overline{x}) \sum_{j=1}^{n} w_{\text{ij}} (x_j - \overline{x})}{\sum_{i=1}^{n} (x_i - \overline{x})^2} \quad (3)$$

In this equation, n refers to the number of county-level units and x_i and x_j are the values for x for the i-th and j-th counties, where $\overline{x}$ is the average value of x_i and w_{ij} is the spatial weight matrix. I_i represents the local Morans' I value of the i-th county, and $I_i > 0$ indicates that there is a small spatial difference in the variable values between adjacent regions, which is either high-high clustering or low-low clustering. $I_i < 0$ indicates significant spatial differences in the variable values between adjacent regions, classified as high-low clustering or low-high clustering. The specific implementation can be achieved through the Cluster and Outlier Analysis (Anselin Local Morans'I) toolkit of the ArcMap 10.6 software.

3.4. t-Test

In this article, we aim to employ the t-test to examine potential significant differences in key indicators between the two distinct groups of samples. The groups under investigation were formed based on a comparison between APDNARRL and the average population density of the remaining rural patches (APDRRP) for all county-level units across the entire country. Specifically, one group comprises units where APDNARRL > APDRRP, while the other group consists of units where APDNARRL < APDRRP. Our objective is to assess whether significant differences exist in some key socio-economic indicators between these two groups of county-level units. The t-test process involves several steps, including assessing whether the distribution of data in each group conforms to the normal distribution, conducting hypothesis tests to determine the equality of average indicator values in the two sample groups (homogeneity test of variance), calculating t-values and significance levels, and performing other necessary operations. To facilitate these analyses, we utilized SPSS 25 software.

3.5. Spatial Heterogeneity of the Driving Forces of APDNARRL

GWR was used to detect the driving factors and spatial heterogeneity of APDNARRL. GWR is an improvement to an ordinary linear regression model. Its principle is to compare and analyze the data for a certain variable to other variables in the adjacent area, and the calculated values of the change in the model relative to changes in geographical location, thereby identifying the differences in various spaces according to heterogeneity [29]. The general expression for the GWR model is as follows:

$$y_i = \beta_0(\mu_i, v_i) + \sum\nolimits_{j=1}^{k} \beta_k(\mu_i, v_i) x_{ij} + \varepsilon_i; i = 1, 2, \ldots, n \quad (4)$$

In the above equation, (μ_i, v_i) is the geographical spatial coordinate of the i-th sample and $\beta_k(\mu_i, v_i)$ is the i-th regression coefficient of the i-th sample. Positive or negative values of $\beta_k(\mu_i, v_i)$ represent the pushing or inhibitory effect of x_{ij} on y_i. ε_i is the random error. The difference between the explanatory variable, y_i, and the observed value, y, in the model is the residual. The smaller the value here, the better the fit between the GWR model and the observed data.

Based on the research case of this study and with reference to previous literature, 11 factors were selected from 4 dimensions: convenience of life/production, urban radiation, construction cost, and socioeconomic development level (Table 1). The factors of the first three dimensions were directly calculated based on the spatial location of the newly added patches, and then they were summarized by county. The socioeconomic factors were calculated from the regional statistical yearbook.

Table 1. Selected driving factors used in geographically weighted regression.

Dimension	Factors	Descriptions	Reasons	References
Convenience of life/production	Dis_TR	Distance to town-level road	Residential houses located alongside roads enhance accessibility to schools, hospitals, shopping centers, and various destinations via the road network. Conversely, buildings situated adjacent to rivers facilitate activities such as water collection and farm irrigation, thus supporting agricultural practices.	[14,30–35]
	Dis_CR	Distance to county-level road		
	Dis_R	Distance to river		
Construction cost	AE	Average elevation	The higher elevation entails potential topographical intricacies that can escalate the expenses associated with foundation filling and reinforcement of buildings.	
Urban radiation	Dis_CC	Distance to county center	Generally, the closer to the county center and city, the more convenient life is and the more services there are for residents.	
	Dis_EU	Distance to existing urban land		
Socioeconomic development level	IGDP	Increasing rate of GDP	The level and pace of social and economic development positively influence farmers' inclination to enhance housing conditions and encourage the establishment of new residential areas. The dynamics of the industrial structure mirror the transformations occurring in agriculture, industry, and the service sector. The primary industry's added value is directly linked to farmers' income levels, whereas the expansion of the secondary industry necessitates the occupation of rural land and the absorption of rural populations. Furthermore, the development of a tertiary industry also contributes to employment opportunities for rural and non-rural populations, exerting direct or indirect effects on rural residential patterns.	[24,31,36–40]
	IAPE	Increasing rate of added value of the primary sector		
	IASE	Increasing rate of added value of the secondary sector		
	IATE	Increasing rate of added value of the tertiary sector		
	CRP	Change rate of resident population		

4. Results and Analysis

Rural residential land exhibited rapid growth between 2000 and 2020, with the total number of patches growing from 782,052 to 812,382—increasing by 3.878%. The total area grew from 1.269×10^5 km^2 to 1.445×10^5 km^2, increasing by 13.86%. After taking the residential population into account, we found that the total rural population was reduced from 8.073×10^8 to 5.098×10^8, decreasing by 36.86%, meaning that the average population of each residential patch decreased from 1032.40 persons to 627.52 persons; the increasing inefficiency in the use of residential land is clear.

4.1. Area Change of Rural Residential Land

The average increase in the rural residential area of the 2877 county-level units covered in this study is 6.234 km^2, with 2307 county-level units increasing in area, accounting for 80.18% of the total county-level units. Then, 580 county-level units decreased in area, accounting for only 19.82% of the total county-level units, indicating that the vast majority of county-level units in China are experiencing increases in rural residential area. The county-level unit with the largest increase in area was Xinmi City, which is close to the urban area of Zhengzhou and the national airport economic comprehensive experimental zone, with an increase of 148.461 km^2. The potential driving force behind this is that farmers obtain huge economic benefits from the demolition of their rural houses to make way for urban construction, which is linked to the area of the houses to be demolished, thus enabling them to build new rural homesteads. Dongguan, known as the world's factory, saw the biggest decline in rural residential area, reaching 345.74 km^2, reflecting the encroachment of industrialized and urbanized land on rural areas.

Local clustering detection (Figure 4) shows that increasing the area presents three typical regions, namely, the northeast (Heilongjiang and Jilin, marked 1) and the vast southwest (marked 3), forming a low-value clustering area. Significant differences can be seen between the terrains of the two regions; while the former constitutes largely plains, the latter is made up of plateaus and hills. In recent years, population loss in Northeast China has received widespread attention, and because of weak economic growth in the region, the proportion of those who have left and then returned is the lowest in this area. There is little motivation to expand rural residential areas, and cities also appear to be shrinking. The latter (marked 3) is the main export destination for migrant workers who support the prosperity of factories and the construction of infrastructure in the developed regions of China, such as Guangzhou and Shenzhen in the Pearl River Delta region, Shanghai, Hangzhou, and Suzhou in the Yangtze River Delta region, and Sichuan Province, Chongqing City, Guizhou Province, and others. The proportion of migrant workers who choose to live in cities has significantly increased, and more elderly people seem to have been left behind to live in rural houses. High-value areas are concentrated in the plains of North China and the Middle and Lower Yangtze Valley Plain (marked 2 in Figure 3). These areas have a high urbanization rate, including the Jing-Jin-Ji and the Yangtze River Delta Urban Agglomeration. The proportion of the rural population is lower, and the urban–rural income gap is likewise low. The enabling of the marketization of rural housing transactions has stimulated the construction of a large number of rural houses, thus forming a high-value cluster area.

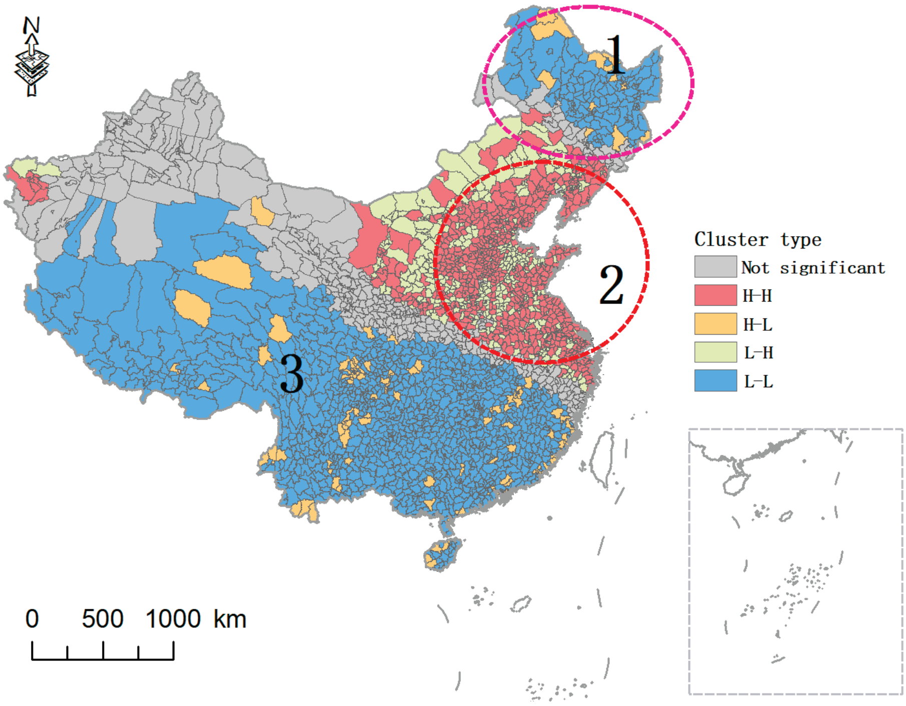

Figure 4. Local clustering distribution of the area of newly added rural residential land in county-level units.

4.2. Population Density of Newly Added Rural Residential Areas

The detection of population density per patch shows that the APDNARRL in 2000–2020 was 701.6446 persons/km^2. The distribution of APDNARRL is characterized by the eastern parts (782 persons/km^2) being greater than the central regions (634.31 persons/km^2), which are greater than the western parts (552.48 persons/km^2) of the country; a similar pattern to the basic overall pattern of population distribution and economic development level in

China. We first counted the APDNARRL for all provinces (Figure 5). Among the 11 eastern provinces, 7 are among the top 10 APDNARRL values. Shanghai, Guangdong, Fujian, Zhejiang, and Beijing have APDNARRL values that exceed 1000 persons/km^2. Shanghai, in particular, has the highest APDNARRL, 2507 persons/km^2, reflecting its role as the leading city in China's economy. High-density populations also directly promote the new residential density of rural residential land to meet the living needs of the employed population in suburban areas. Tibet, located in the west of China, has the lowest APDNARRL, with only 134.87 persons/km^2, far below the national average. This is related to the topographic conditions of Tibet, which is located on the Tibetan Plateau, often referred to as the Roof of the World, having the lowest population density in China because of its poor living environment. Further, we also found that Chongqing and Sichuan Province, in western China, have relatively high APDNARRL values, with 1410 and 883.6 persons/km^2, respectively. In particular, Chongqing ranks third in terms of APDNARRL. This is related to the rapid development of the twin-city economic circle between Chengdu (capital of Sichuan Province) and Chongqing (Chongqing), which exists across the two regions. Located at the intersection of the Belt and Road and the Yangtze River Economic Belt, they are the initiation points of the land and sea passages in the west, and they also rank among the most attractive cities in China all year round. Chengdu, in particular, tops the list of China's new first-tier cities (Shanghai, Beijing, Guangzhou, and Shenzhen are considered the traditional first-tier cities), and population inflows are also driving the increase in APDNARRL.

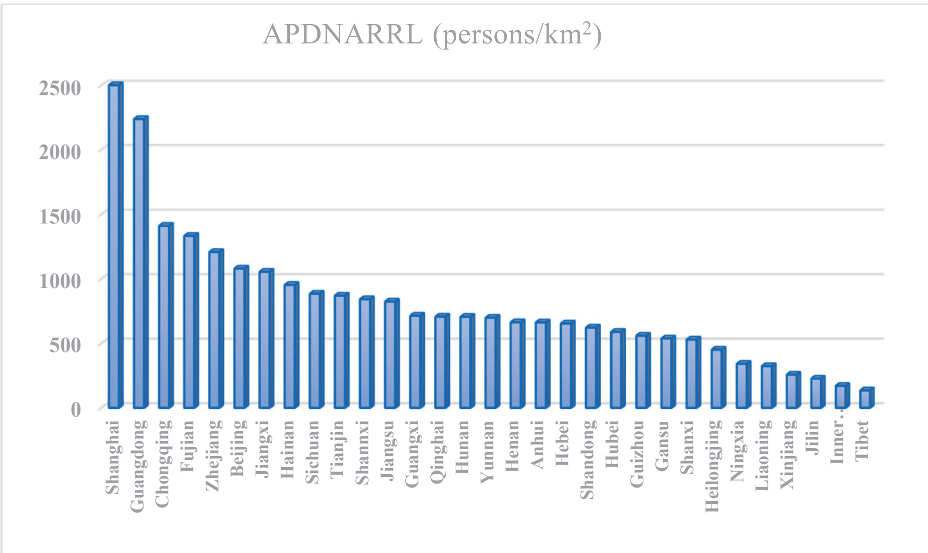

Figure 5. Provincial APDNARRL in descending order.

Figure 6 presents the spatial distribution of APDNARRL and local clusters in relation to county-level statistics. There is an obvious gap between the two sides of the Hu Huanyong Line, the famous dividing line for population density distribution in China; the APDNARRL on the left side is clearly lower than that on the right. In particular, the eastern and southern coastal areas (marked 1) and Chongqing and Sichuan Province (marked 2) form obvious high-concentration areas, confirming the conclusion we reached above using provincial statistics. Correspondingly, low-value accumulation areas can be seen in the three northeastern provinces (marked 3) and almost the entire left side of the Hu Huanyong Line.

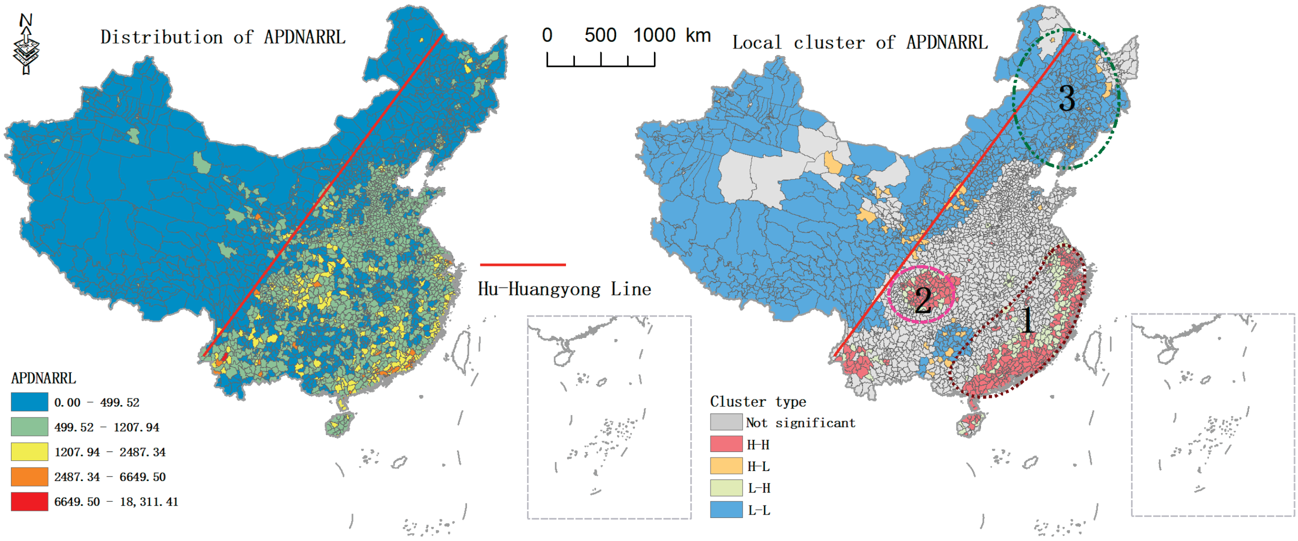

Figure 6. Spatial distribution and the local clusters of APDNARRL by county-level units.

4.3. Spatial Non-Stationarity of the Relationship between APDNARRL and Driving Factors

China is a vast country having tremendous differences in terms of social and economic development levels and natural conditions among its regions. As the geographical location varies, the relationship or structure of variables also changes. Using GWR, we found that the relationship between the selected associated factors and APDNARRL shows significant spatial heterogeneity (see Figure 7). This heterogeneity may have a guiding significance for regions as they develop targeted policy recommendations. We discuss the regions that have passed the significance test and several frequently occurring provinces as the objects of analysis, including Sichuan and Yunnan in the west and Guangdong in the east. Other significant regions are presented in Table 2. Among these, the APDNARRL of Sichuan Province shows a positive correlation with Dis_TR, CRP, and IAPE, whereas it shows a negative correlation with AE, Dis_CC, and IGDP. Thus, the newly added populations in the rural areas of Sichuan Province have mainly accumulated near county towns rather than along rural roads; there is a tendency to establish residential land in areas with low terrain and small surface undulations, leading to lower construction costs. The primary sector's development can be driven by the efficient improvement of labor. The transfer of the rural surplus labor to support urban development may not only improve the scale effect and production efficiency of the primary sector (which can be improved with agricultural machinery and technology) but also improve overall GDP growth. This is usually because the efficiency of the urban production sector is greater than that of the rural sector, but these require the transfer and supplementing of rural labor. Therefore, this will reduce APDNARRL. In Yunnan Province, APDNARRL is positively correlated with Dis_EU and IATE, and it is negatively correlated with Dis_TR, Dis_CR, CRP, and IGDP changes, indicating that the province is dominated by tourism (i.e., the tertiary sector). The distance from cities and along village and county roads can promote APDNARRL because they can minimize the impact of urbanization and maintain natural beauty in and among tourist attractions. However, increases in GDP and POP inhibit APDNARRL, suggesting that the new population is moving to cities, and the increase in urban productivity then further attracts people from the surrounding countryside. Guangdong Province, in the east, has the largest manufacturing sector in China, and it has the highest GDP. It likewise hosts a large number of migrant workers. We found that Dis_EU, CRP, IAPE, and SecondAdd are all negatively correlated with APDNARRL. On the one hand, industry (i.e., the secondary sector) has a huge demand for labor, which greatly promotes the transfer of rural labor and prompts rural populations to leave the countryside to work in cities. Simultaneously, it provides an opportunity for the primary sector to improve production efficiency and promote output value. On the other hand, the accumulation of a large number of workers in the industrial sector in cities has also promoted a boom in the rural housing rental market in suburban areas because rents are cheaper than in urban areas. The closer a rural area is to an urban center, the more attractive it is to workers looking for rental residences.

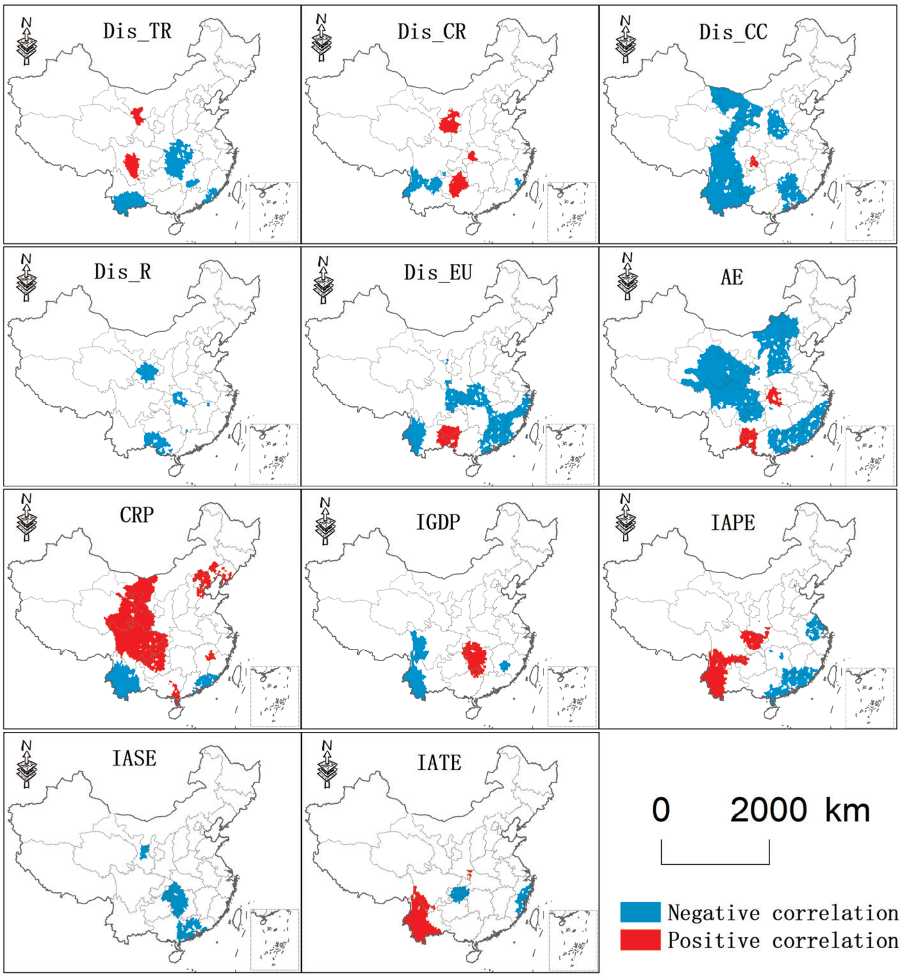

Figure 7. Areas where the relationship between driving factors and APDNARRL is significant.

Table 2. Main regions with a significant relationship between driving factors and APDNARRL.

Factors	Main Distribution Area/Coefficient Range (Positive Correlation)	Main Distribution Area/Coefficient Range (Negative Correlation)
Dis_TR	Sichuan/(0,19.45]	Yunnan, Hubei, and Hunan/[−11.43,0)
Dis_CR	Guizhou, border between Ningxia and Gansu/(0,45.53]	Yunnan/[−23.48,0)
Dis_CC	Chongqing/(0,18.59]	Guizhou, Sichuan, Shanxi, and Guangdong/[−33.79,0)
Dis_R	None	Gansu, Guangxi, and Hubei/[−21.56,−7.94)
Dis_EU	Junction of Guangxi, Yunnan, and Guizhou provinces/(0,45.38]	Zhejiang, Guangdong, Fujian, Chongqing, Hubei, Jiangxi, and western Yunnan/[−99.63,0)
AE	Western Hubei, western Guangxi, and southern Guizhou/(0,0.65]	Southeast coastal provinces, Qinghai, Sichuan, Gansu, and Shanxi/[−2.04,0)
CRP	Gansu, Sichuan, Chongqing, Guizhou, and northern Hebei/(0,5.93]	Yunnan, eastern Guangdong/[−7.63,0)
IGDP	Hunan/(0,0.76]	Western Yunnan and Western Sichuan/[−0.82,0)
IAPE	Western Yunnan and Sichuan/(0,0.79]	Guangdong and Jiangsu/[−1.82,0)
IASE	None	Guangdong and Hunan/[−0.45,−0.05)
IATE	Yunnan/(0,0.21]	Zhejiang, Fujian, and Chongqing/[−0.33,0)

5. Discussion

5.1. Comparison of Population Density between New and Remaining Rural Residential Lands

In comparing the APDNARRL with the average population density of the remaining rural patches (APDRRP), the remaining rural patches means patches of rural settlements that existed in both 2000 and 2020. It was found that, overall, APDNARRL significantly exceeds APDRRP, which is 507.22946 persons/km^2, indicating that the hollowing out of original residential areas is pronounced and should be a focus of future village renovations. However, not all counties have an APDNARRL exceeding the APDRRP. We found that the APDNARRL of 1239 counties in China (accounting for about 42.91% of the total number) is lower than the APDRRP, and the APDNARRL of the other 1628 counties exceeds the APDRRP. The spatial distribution of these counties is shown in Figure 8. It can be observed that the Qinghai Tibet Plateau and the eastern coastal and eastern inland regions, as well as the southern Guangdong and Hainan provinces, form low-value clustering areas, while high-value clustering areas have formed in the regions of Xinjiang and Northeast China.

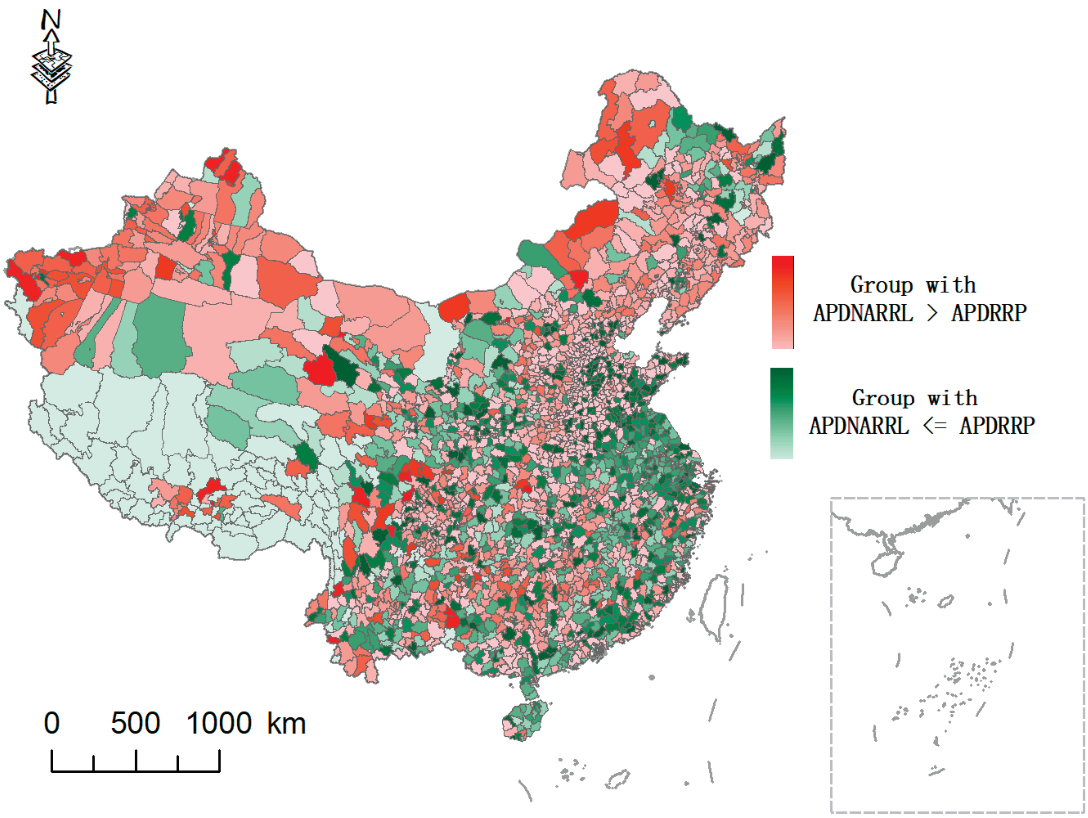

Figure 8. Spatial distribution of the two groups (note: the red group indicates districts with APDNARRL > APDRRP, and the green group indicates APDNARRL < APDRRP; the darker the color, the greater the difference).

Further, to identify whether there are significant differences in the socioeconomic indicators of the two groups of cities shown in Figure 7, we conducted a *t*-test on some of the important socioeconomic indicators for the two groups of county-level units (Table 3). A significant difference in the GDP growth rate and the change rate of added value in the tertiary sector can be observed (sig. (2-tailed) <0.05). The mean of the red group (i.e., APDNARRL > APDRRP) is significantly higher than that of the green group (Sig. (1-tailed) <0.05). We also found no significant differences between the two groups of cities in terms of the rate of change of the total population and the rate of change of the added value of the primary and secondary sectors. This potentially indicates that the GDP growth is faster and the employed population (not the total population) brought by the rapid growth of the service industry could promote population density in new rural residential land. This may be related to the fact that the tertiary industry can further attract employed people. According to the survey, the proportion of the employed population in China's tertiary sector significantly exceeds that of the primary and secondary sectors. For example, in China in 2021, the proportions of employed people in the primary, secondary, and tertiary sectors were 22.9%, 29.1%, and 48.0%, respectively (https://www.gov.cn/xinwen/2022-06/08/content_5694541.htm, accessed on 6 June 2023). The rapid growth of the service sector generated further employment in the sector; however, workers could not afford to purchase commercial housing in cities and chose cheaper suburban and rural newly built small property houses (also a type of rural construction land), thus driving the increase in APDNARRL.

Table 3. *t*-test for socioeconomic indicators among counties where APDNARRL > APDRRP and where APDNARRL < APDRRP.

Indicators	Group	Average Value	Equal Variances Assumed	Sig. (2-Tailed)	Sig. (1-Tailed)
IGDP	Red Group	1111.140	Equal variances assumed	0.048	0.028
	Green Group	1052.363			
CRP	Red Group	−2.265	Equal variances assumed	0.604	0.302
	Green Group	0.476			
IAPE	Red Group	498.216	Equal variances assumed	0.179	0.090
	Green Group	478.313			
IASE	Red Group	1434.415	Equal variances assumed	0.272	0.136
	Green Group	1303.976			
IATE	Red Group	1765.351	Equal variances assumed	0.005	0.003
	Green Group	1616.987			

We also found that among the three main types of county-level administrative regions in China, that is, municipal districts, county-level cities, and counties under the jurisdiction of cities, the APDNARRL is lower than the APDRRP by 62.78%, 59.70%, and 57.53%, respectively. This indicates a trend that the higher an area's urbanization rate, the lower the population density of the newly added rural residential patches relative to the original rural residential patches. This could be because areas that have higher levels of urbanization tend to have a higher level of economic development. The driving force of land expropriation is stronger in urban development, which makes the function of new rural residential areas for direct residence weaker, showing economic strength or seeking greater compensation for demolition and other purposes, resulting in, to a certain extent, a decline in the utilization rate of new residential areas.

5.2. Policy Suggestions

Comparing the population densities of the remaining rural residential land between 2000 and 2020 revealed that the population density of 688 county-level units (24.00% of the total) features a declining trend (as shown in Figure 9 for spatial distribution); that is, there is a trend of hollowing out. In particular, Sichuan, Anhui, and Guizhou provinces have the largest number of such districts and counties, with 77, 61, and 59 counties, respectively, reflecting the phenomenon of the hollowing out of the remaining rural residential land. These three provinces also happen to have the largest number of migrant workers in China, and it is clear that the large number of farmers who are going to cities for work is the direct cause of this phenomenon. Therefore, we believe that in areas facing a hollowing out of their population, policy should focus on narrowing the income gap between urban and rural areas, and encouraging labor to return to their home areas of residence for employment. At present, the reason for farmers leaving the countryside and not intending to return is that the gap between urban and rural economic development is too large. The focus of policy should be on guiding rural areas to actively develop secondary and tertiary industries, increase the added value of their industries, promote the development of township enterprises, develop characteristic aspects of village collective economies, such as "one village, one product," provide a large number of employment opportunities for young and middle-aged people, and reduce the gap between urban and rural per capita disposable income. The government should actively attract college students to return to their hometowns for construction and strongly support this policy by providing funding and land.

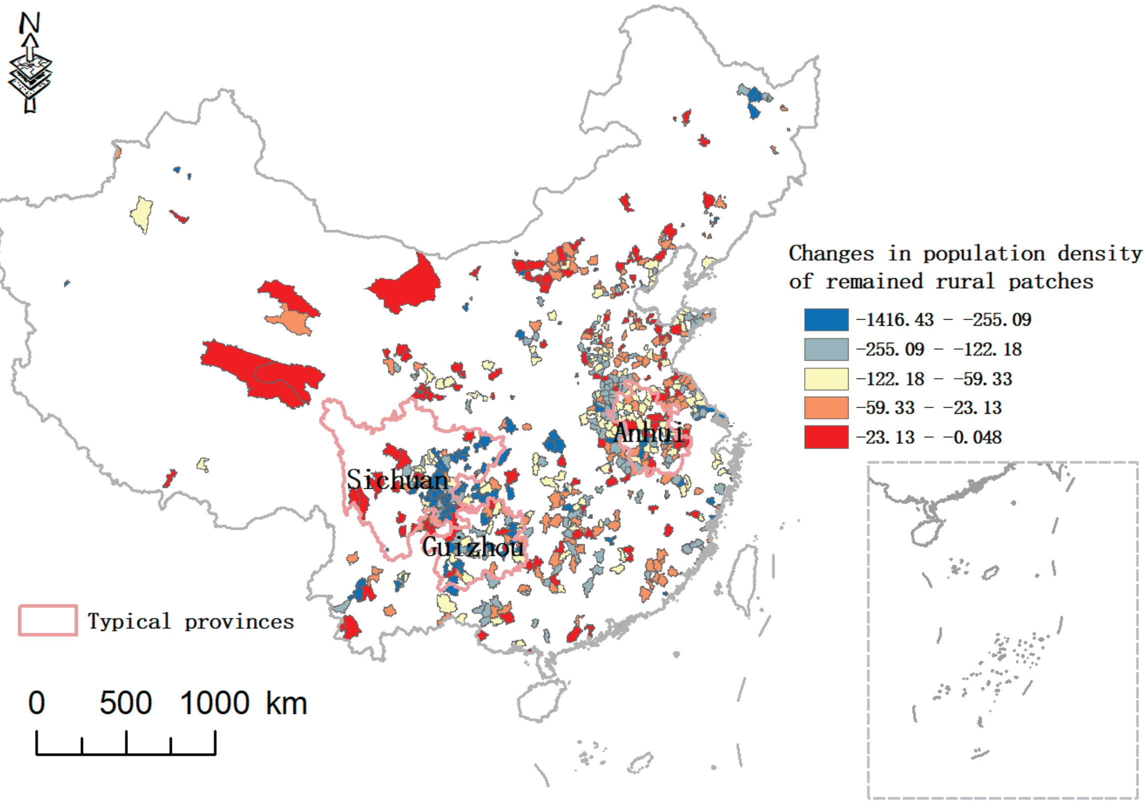

Figure 9. Spatial distribution of county-level units with a declining trend of population density in remaining rural patches.

An extensive and inefficient NARRL is mainly found in Hainan Province, eastern inland areas, and in southern Guangdong Province. In these areas, the unapproved construction of new houses and the development of arable land should be strictly prohibited. The "three rights separation" of ownership, qualification rights, and use rights should be explored for existing residential land, providing guidance and a policy basis for the circulation of rural households' idle rural residential land, to improve the utilization efficiency of rural residential land, and effectively revitalize rural idle assets to demonstrate the resource and asset values of rural residential land.

In view of the large population density of the remaining rural residential land (with densities of more than 2000 persons/km^2), there is indeed a new demand for rural residential land; these areas are mainly concentrated on the eastern coast, where populations are dense and a township industry has developed. In these areas, policies may be considered to encourage centralized construction, prevent scattered construction, and develop large areas of residential land. At the same time, planned reserved villages (usually central villages) with potential can be sorted out and developed, together with carrying out centralized reconstruction in accordance with the standards of rural communities, thus encouraging the construction of multi-story housing, the building of multi-family rows according to local conditions, strictly controlling single family housing and single courtyards, and gradually realizing the coexistence of population aggregation with intensive land use.

6. Conclusions

As China's economy develops and urbanization advances, the rural population is constantly migrating to cities, and the permanent population in rural areas is decreasing. This trend is increasing year after year, leading to idle houses, low land-use efficiency, and a large amount of land resources being wasted in rural areas. In this context, this study breaks the traditional limitations of statistical data based on administrative units. At the patch scale, high-precision rural residential patches and population distribution data are used to detect ANARR areas in China from 2000 to 2020, as well as the spatial heterogeneity of APDNARRL's driving mechanisms. Regional comparisons, local spatial clustering, and policy recommendations are summarized and analyzed for units at the county level. The main conclusions of this study include the following three points:

(1) The total area of rural residential land in China grew rapidly between 2000 and 2020, from 1.269×10^5 km^2 to 1.445×10^5 km^2. In more than 80% of counties, the area of rural residential land has increased. In terms of spatial distribution, low-value clusters, in terms of ANARR, have formed in the northeast and the vast southwest, while high-value clusters have formed in the North China plain area and the Middle and Lower Yangtze Valley plain area.

(2) The APDNARRL of the new patches was 701.64 person/km^2 for 2000–2020, significantly exceeding the average of 507.23 person/km^2 of the remaining patches. The GDP growth rate and the rate of change of added value in the tertiary sector are important indicators for distinguishing the difference in density between the new and remaining patches. Overall, the APDNARRL in the eastern parts (782 person/km^2) is greater than in the middle regions (552.48 person per km^2), which is greater than in the western parts (634.31 person per km^2) of the country. In particular, the population densities on the two sides of the Hu Huanyong Line are significantly different; the APDNARRL on the left is significantly lower than that of the right.

(3) The spatial heterogeneity of the driving factors of APDNARRL was analyzed using Sichuan and Yunnan provinces in the west and Guangdong province in the east as examples. Of these, the APDNARRL of Sichuan Province is positively correlated with toVillage, POPChange, and FirstAdd; the APDNARRL of Guangdong Province is negatively correlated with toUrban, POPChange, FirstAdd, and SecondAdd. The APDNARRL of Yunnan Province is positively correlated with toUrban and Third, and the APDNARRL of Guangdong Province is negatively correlated with changes in toVillage, toCountryR, POP, and GDP. The spatial heterogeneity of the above provinces reflects the migration logic of populations that have been left behind by the improvement of agricultural efficiency (the primary sector), the development of the processing and manufacturing industry (the secondary sector), and the development of a new eco-tourism industry (the tertiary sector).

It should be acknowledged that we analyzed the two main indicators (ANARR and APDNARRL) relatively independently, but we have not investigated any coupling relationship between them or their correlation with other socioeconomic indicators. This is partly because our research scale is patchy, and socioeconomic indicators are difficult to calculate. Second, the calculation indicators of coupling relationships are usually based on multiple time series; however, our study was limited because of the limited acquisition of data, which were only obtained for one time period (2000–2020) and did not form a multi-period sequence. These deficiencies are data-level constraints. In the future, as more research data sharing and open-access technologies are developed, these deficiencies are expected to be resolved.

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References

1. Pan, W.; Wang, J.; Qin, X.; Li, Y. Trends and types of rural residential land use change in China: A process analysis perspective. *Growth Chang.* **2021**, *52*, 2437–2452. [CrossRef]
2. Li, Y.; Liu, Y.; Long, H.; Cui, W. Community-based rural residential land consolidation and allocation can help to revitalize hollowed villages in traditional agricultural areas of China: Evidence from Dancheng County, Henan Province. *Land Use Policy* **2014**, *39*, 188–198. [CrossRef]
3. Zhang, Z.; Wen, Q.; Liu, F.; Zhao, X.; Liu, B.; Xu, J.; Ju, H. Urban expansion in China and its effect on cultivated land before and after initiating "Reform and Open Policy". *Sci. China Earth Sci.* **2016**, *59*, 1930–1945. [CrossRef]
4. Liu, F.; Zhang, Z.; Zhao, X.; Liu, B.; Wang, X.; Yi, L.; Wang, Y. Urban expansion of China from the 1970s to 2020 based on remote sensing technology. *Chin. Geogr. Sci.* **2021**, *31*, 765–781. [CrossRef]
5. Song, W.; Liu, M. Assessment of decoupling between rural settlement area and rural population in China. *Land Use Policy* **2014**, *39*, 331–341. [CrossRef]
6. Zhou, Z. Landscape changes in a rural area in China. *Landsc. Urban Plan.* **2000**, *47*, 33–38.
7. Yang, R.; Xu, Q.; Long, H. Spatial distribution characteristics and optimized reconstruction analysis of China's rural settlements during the process of rapid urbanization. *J. Rural Stud.* **2016**, *47*, 413–424. [CrossRef]
8. Qu, Y.; Jiang, G.; Yang, Y.; Zheng, Q.; Li, Y.; Ma, W. Multi-scale analysis on spatial morphology differentiation and formation mechanism of rural residential land: A case study in Shandong Province, China. *Habitat Int.* **2018**, *71*, 135–146.
9. Chen, R.; Ye, C.; Cai, Y.; Xing, X.; Chen, Q. The impact of rural out-migration on land use transition in China: Past, present and trend. *Land Use Policy* **2014**, *40*, 101–110. [CrossRef]
10. Shan, Z.; Feng, C. The Redundancy of Residential Land in Rural China: The evolution process, current status and policy implications. *Land Use Policy* **2018**, *74*, 179–186. [CrossRef]
11. Tian, G.; Qiao, Z.; Gao, X. Rural settlement land dynamic modes and policy implications in Beijing metropolitan region, China. *Habitat Int.* **2014**, *44*, 237–246. [CrossRef]
12. Chen, Z.; Liu, X.; Lu, Z.; Li, Y. The expansion mechanism of rural residential land and implications for sustainable regional development: Evidence from the Baota District in China's Loess Plateau. *Land* **2021**, *10*, 172. [CrossRef]
13. Li, J.; Lo, K.; Zhang, P.; Guo, M. Reclaiming small to fill large: A novel approach to rural residential land consolidation in China. *Land Use Policy* **2021**, *109*, 105706. [CrossRef]
14. He, Q.; Tan, S.; Yin, C.; Zhou, M. Collaborative optimization of rural residential land consolidation and urban construction land expansion: A case study of Huangpi in Wuhan, China. *Comput. Environ. Urban Syst.* **2019**, *74*, 218–228. [CrossRef]
15. Pan, H.; Wu, Y.; Choguill, C. Optimizing the rural comprehensive land consolidation in China based on the multiple roles of the rural collective organization. *Habitat Int.* **2023**, *132*, 102743. [CrossRef]
16. Liu, S.; Ma, L.; Yao, Y.; Cui, X. Man-land relationship based on the spatial coupling of population and residential land–A case study of Yuzhong County in Longzhong Loess Hilly Region, China. *Land Use Policy* **2022**, *116*, 106059. [CrossRef]
17. Cai, E.; Chen, W.; Wei, H.; Li, J.; Wang, H.; Guo, Y.; Feng, X. The coupling characteristics of population and residential land in rural areas of China and its implications for sustainable land use. *Sustain. Dev.* **2020**, *28*, 646–656. [CrossRef]
18. Tian, G.; Yang, Z.; Zhang, Y. The spatio-temporal dynamic pattern of rural residential land in China in the 1990s using Landsat TM images and GIS. *Environ. Manag.* **2007**, *40*, 803–813. [CrossRef]
19. Zhou, Y.; Zhong, Z.; Cheng, G. Cultivated land loss and construction land expansion in China: Evidence from national land surveys in 1996, 2009 and 2019. *Land Use Policy* **2023**, *125*, 106496. [CrossRef]
20. Long, H.; Li, T. The coupling characteristics and mechanism of farmland and rural housing land transition in China. *J. Geogr. Sci.* **2012**, *22*, 548–562. [CrossRef]
21. Chen, Z.; Li, Y.; Liu, Y.; Liu, X. Does rural residential land expansion pattern lead to different impacts on eco-environment? A case study of loess hilly and gully region, China. *Habitat Int.* **2021**, *117*, 102436. [CrossRef]
22. Shi, L.; Wang, Y. Evolution characteristics and driving factors of negative decoupled rural residential land and resident population in the Yellow River Basin. *Land Use Policy* **2021**, *109*, 105685. [CrossRef]
23. Qu, Y.; Zhan, L.; Jiang, G.; Ma, W.; Dong, X. How to Address "Population Decline and Land Expansion (PDLE)" of rural residential areas in the process of Urbanization: A comparative regional analysis of human-land interaction in Shandong Province. *Habitat Int.* **2021**, *117*, 102441. [CrossRef]
24. Liu, Y.; Liu, Y.; Chen, Y.; Long, H. The process and driving forces of rural hollowing in China under rapid urbanization. *J. Geogr. Sci.* **2010**, *20*, 876–888. [CrossRef]

25. Zhu, S.; Kong, X.; Jiang, P. Identification of the human-land relationship involved in the urbanization of rural settlements in Wuhan city circle, China. *J. Rural Stud.* **2020**, *77*, 75–83. [CrossRef]
26. Lai, L.; Huang, X.; Yang, H.; Chuai, X.; Zhang, M.; Zhong, T.; Thompson, J. Carbon emissions from land-use change and management in China between 1990 and 2010. *Sci. Adv.* **2016**, *2*, e1601063. [CrossRef]
27. Anselin, L. Local indicators of spatial associations—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
28. O'Sullivan, D. Geographically weighted regression: The analysis of spatially varying relationships. *Geogr. Anal.* **2003**, *35*, 272–275. [CrossRef]
29. Li, Y.; Liu, X. How did urban polycentricity and dispersion affect economic productivity? A case study of 306 Chinese cities. *Landsc. Urban Plan.* **2018**, *173*, 51–59. [CrossRef]
30. Feng, Y.; Yang, Q. Evolution characteristics and its driving force of rural residential land at village level during 1980-2012. *Trans. Chin. Soc. Agric. Eng.* **2016**, *32*, 280–288.
31. Zhou, Y.; Li, X.; Liu, Y. Land use change and driving factors in rural China during the period 1995–2015. *Land Use Policy* **2020**, *99*, 105048. [CrossRef]
32. Feng, C.; Zhang, H.; Xiao, L.; Guo, Y. Land use change and its driving factors in the rural–urban fringe of Beijing: A Production–Living–Ecological perspective. *Land* **2022**, *11*, 314. [CrossRef]
33. Chi, G.; Ventura, S.J. Population change and its driving factors in rural, suburban, and urban areas of Wisconsin, USA, 1970–2000. *Population* **2011**, *12*, 13. [CrossRef]
34. Wang, D.; Zhu, Y.; Zhao, M.; Lv, Q. Multi-dimensional hollowing characteristics of traditional villages and its influence mechanism based on the micro-scale: A case study of Dongcun Village in Suzhou, China. *Land Use Policy* **2021**, *101*, 105146. [CrossRef]
35. Wen, Q.; Li, J.; Ding, J.; Wang, J. Evolutionary process and mechanism of population hollowing out in rural villages in the farming-pastoral ecotone of Northern China: A case study of Yanchi County, Ningxia. *Land Use Policy* **2023**, *125*, 106506. [CrossRef]
36. 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]
37. Li, C.; Wu, K. Driving forces of the villages hollowing based on geographically weighted regression model: A case study of Longde County, the Ningxia Hui Autonomous Region, China. *Nat. Hazards* **2017**, *89*, 1059–1079. [CrossRef]
38. Zhang, H.; Zhang, S.; Liu, Z. Evolution and influencing factors of China's rural population distribution patterns since 1990. *PLoS ONE* **2020**, *15*, e0233637. [CrossRef]
39. Liu, Y.; Shu, L.; Peng, L. The Hollowing Process of Rural Communities in China: Considering the Regional Characteristic. *Land* **2021**, *10*, 911. [CrossRef]
40. Ma, W.; Jiang, G.; Wang, D.; Li, W.; Guo, H.; Zheng, Q. Rural settlements transition (RST) in a suburban area of metropolis: Internal structure perspectives. *Sci. Total Environ.* **2018**, *615*, 672–680. [CrossRef]

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