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The Socio-Economic Values in Land Resource Management

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Article

Evolution Mode, Influencing Factors, and Socioeconomic Value of Urban Industrial Land Management in China

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Abstract: (1) Background: Accurate measurement of the matching relationship between urban industrial land change and economic growth is of great value for industrialized and re-industrialized countries to perform land resource management in territorial spatial planning. (2) Methods: Based on the combination of the Boston Consulting Group matrix, Geodetector, and decoupling model, we constructed a new method integrating "model evolution + driving mechanism + performance evaluation + policy design" in this paper, and conducted an empirical study on the economic value of urban industrial land management in the Yangtze River Delta. (3) Results: The evolution modes of urban industrial land in the Yangtze River Delta are divided into four types: stars, cows, dogs, and question, distributed in structures ranging from an "olive" shape to a "pyramid" shape, with high spatial heterogeneity and agglomeration and low autocorrelation. The government demand led by driving economic growth and making large cities bigger is the key factor driving the change in urban industrial land and the influence of transportation infrastructure and the business environment has remained stable for a long time. The mechanisms of industrialization, globalization, and innovation are becoming increasingly complicated. Industrial land change and value-added growth in most cities have long been in a state of strong and weak decoupling, with progressive decoupling occurring alongside the unchanged stage and regressive decoupling. The government outperforms the market in terms of urban industrial land management, and the degradation of the synergy between urban industrial land and corporate assets emerges as a new threat to sustainable and high-quality development of the region. (4) Conclusions: This paper establishes a technical framework for zoning management and classification governance of urban industrial land to divide the Yangtze River Delta into reduction-oriented transformation policy zoning, incremental high-quality development zoning, incremental synchronous growth zoning, and reduction and upgrading development zoning. It also proposes an adaptive land supply governance strategy for quantitative and qualitative control, providing a basis for territorial spatial planning and land resource management.

Keywords: urban industrial land; decoupling model; land resource management; China

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1. Introduction

1.1. Background

Urban industrial land is the most important spatial carrier for cities to promote the development of the manufacturing industry and real economy, and research on its spatial distribution and evolution patterns has attracted many scholars' attention [1]. Industrial land change is a major feature of the spatial evolution of the real economy of cities, and management and control of the quantity, structure, and layout of industrial land are important elements of territorial spatial planning, industrial economics, and land use planning [2,3].Therefore, it is of great value to analyze the spatio-temporal evolution of urban industrial land, control the scale of urban industrial land in a rational manner, and realize the dynamic balance between land and economy to promote high-quality industrial development and sustainable urban development [4].

The Outline of the 14th Five-Year Plan for National Economic and Social Development and Vision 2035 of the People's Republic of China puts forward the strategy of strengthening manufacturing. Against the background of tight constraints on land resources, it is necessary to further strengthen the management of industrial land supply and change and explore the planning technology and management methods of high-quality utilization of urban industrial land in order to promote high-quality development of the manufacturing industry. Since the reform and opening up, China has enjoyed rapid industrialization, relying on its unique land system and industrial land allocation mode, making it the "world factory" [5,6]. Land has played a vital role in China's industrialization, and the academic circles have widely accepted the role of urban industrial land growth in promoting urban economic development [7]. However, with the process of industrialization and urbanization, economic, social, and environmental problems brought about by extensive use, low output, standing idle, and low productivity are constantly emerging, including declined efficiency of land resource allocation [8], increased land rent-seeking and plundering [9], constant land conflicts [10] and mismatches [11], and deteriorated ecological and environmental quality [12,13].

In territorial spatial planning, it is necessary for us to control the scale of urban industrial land and formulate its spatial allocation plan to realize the mutual matching between land change and industrial economic growth. It is worth noting that no other studies have analyzed the dynamics and economic effects of industrial land use and its implications for territorial spatial planning. It is worth noting that some papers have analyzed the relationship between industrial land and manufacturing economic change (characteristics of industrial land supply and its contribution to economic growth) [14,15], but the analysis results have not been applied to territorial spatial planning and a technical approach to integrate "land dynamics-economic value-management policy" is lacking. Therefore, it is of great importance to analyze the characteristics, process, pattern, and performance of industrial land changes in Chinese cities; reveal the land demand and change patterns; and apply the research findings to the process of urban planning, spatial planning, industrial planning, and land management policy design to promote industrial transformation and upgrade and improve urban functions [16].

1.2. Questions and Framework

This paper conducts an empirical study of the Yangtze River Delta based on GIS tools and multiple models, mainly trying to answer the following questions. (1) What are the characteristics of the urban industrial land evolution mode in the Yangtze River Delta? (2) What factors affect the change in urban industrial land using Geodetector software? (3) What is the relationship between urban industrial land change and real economic growth in the Yangtze River Delta according to the decoupling model, from the government's and enterprises' views? (4) How can the analysis results be applied to the practical process of policy design?

This paper consists of six parts. The first part is the introduction, which explains the background of this study. The second part is the literature review, which analyzes the characteristics and shortcomings of the existing studies, and defines the starting point for research and the core issues concerned. The third part presents the materials and methods, introducing the study area, research methods and steps, selection of indicators, and their data sources. The fourth part is the statement of the results, which is the key component of this paper. This paper analyzes the evolution mode and influencing factors of urban industrial land change in the Yangtze River Delta in detail and measures the coordination of urban industrial land change with urban industrial economic development and enterprise performance change quantitatively to reveal the spatio-temporal effects of urban industrial land change. The fifth part is the discussion, which is the difficult section of the paper. On the one hand, the core point of this paper is compared with relevant literature to show their similarities and differences and possible reasons for these similarities and differences; on the other hand, based on the analysis results and the regional characteristics of the Yangtze River Delta, this paper puts forward the technical method of zoning management and supply governance of urban industrial land. The last part is the section of conclusions, which systematically summarizes and refines the main findings of this study, with an attempt to put forward the theoretical innovation, international value, and practical contribution of this paper, while explaining the shortcomings of this study, and giving a view of the future research direction.

2. Literature Review

2.1. Urban Industrial Land Change and Influencing Factors

Studies on the characteristics of urban industrial land change focus on the analysis of urban industrial land area, proportion, boundaries, use purposes, spatial forms and geo-graphical patterns, and its influencing factors. Zambon [17] found that the expansion of urban industrial land in the peri-urban areas of southern Europe is particularly intense and that industrial development is a principal factor driving the spatial spread of coastal cities. Debela [18] analyzed the impact of industrial investment and industrial land changes on smallholder livelihoods and food production in Ethiopia. Xiong [19] analyzed the process of industrial land expansion and its influencing factors in Shunde, China, finding that industrial land space is characterized by prominent "fragmentation" and that decentralization and marketization have the greatest influence on industrial land change while the influence of globalization and technological progress is not significant. Park [20] found that the loss of industrial land in the central urban area over time is closely related to the suburbanization of FDI manufacturing employment. Zhang [21] found that the significant reduction of industrial land in the central urban area of Hangzhou and the emergence of industrial clusters in the suburbs, active planning policies, controlled land prices, and market-based mechanisms have a great impact on the spatial restructuring and spatial pattern reconstruction of manufacturing industries. Ustaoglu [22] analyzed the lag effects between changes in industrial land and regional economic development in Dutch cities and found that GDP, employed population, and real estate prices are key influencing factors. Villarroya [23] and Pugh [24] analyzed the industrial land change in regions along highways in Spain and the United Kingdom, revealing the impact of industrial land change on spatial development, economic development, and job creation.

2.2. Socioeconomic Value of Land Use and Resource Management

Most papers are committed to the study of development intensity, input and output efficiency, land price management, functional validity, pollution and degradation degree, property ownership, operation mode, and the spatial effect of industrial land. Zhou [15] analyzed the characteristics of industrial land supply and its contribution to economic growth and found that over time, the supply of basic industrial land becomes increasingly concentrated while the supply of technology-intensive industrial land is gradually dispersed. Tonin [25] analyzed the effect of contamination and remediation schemes on industrial real estate properties and concluded that the effect of the size, location, accessibility, and other relevant economic indicators on the price differences of industrial land cannot be ignored. Chen [26,27] examined the spatial effect of industrial land diffusion on land price using a geographically weighted regression model and suggested that the government should guide the optimization of the manufacturing spatial layout through reasonable control of land prices. Lin [28] and Wu [29] found that the land price mechanism is an important way to control the expansion of urban industrial land through an empirical study in China, and Yang [30] further pointed out that the implementation of local industrial land price policies significantly improves the efficiency of industrial land use, and it plays a great role in promoting sustainable development of the regional economy. Li [31] proposed a model to measure the relationship between manufacturing input and output. Kumpula [32] analyzed the positive and negative impacts of industrial land changes on the social and ecological environment in the Arctic Russia region. Zhang [33] found that the productivity of urban industrial land has steadily increased and that capital density, labor density, urban population, economic growth, and industrial structure are key influencing factors.

2.3. Land Use Policy and Territorial Spatial Planning

To promote the rational and orderly development of industrial land, governments around the world have strengthened the management of industrial land development planning and policy design, prompting the study of industrial land planning techniques and policy effects to attract the attention of government policy makers and planners. Lee [34] analyzed the location patterns of knowledge-intensive industries and their determinants in the Seoul metropolitan area of Korea, with a focus on industrial land planning. Aktas [35] constructed a technical framework for industrial land planning suitability evaluation using the weighted linear combination technique and the analytic hierarchy process method and GIS tools to classify industrial land in Kemalpaa into five levels. Cheng [36] analyzed the decision-making process and mechanism of bottom-up industrial land redevelopment planning in China based on a case study of Shenzhen, explaining the roles, conflicting interests, and different stakeholders, such as landowners, developers, and the government, at different stages of industrial land redevelopment. Danilo [37] analyzed the evolution of industrial land policy in Chicago and explained the process by which industrial land planning and manufacturing reshape the urban space, society, and economy. Based on the combination of the multi-criteria decision-making method with the geographic information system, Salari [38] proposed an industrial land capacity and policy evaluation method in the three dimensions of the economy, society, and environment. Silva [39] and Ustaoglu [40] constructed a model for predicting industrial land area according to the level of urban economic development and applied it to industrial land policy design. Sun [41] found that the development zoning affects the use efficiency of urban industrial land through the selection effect, policy effect, cluster effect, and location effect, and suggested a policy design for high-quality development based on this. Galarza [42] analyzed the industrial land policy in Alava, summarized the theory and methods of incentivizing industrial land policy design, and proposed the establishment and effects of industrial parks and industrial land management agencies.

2.4. Literature Limitations and New Breakthrough Directions

In summary, as an emerging research hotspot, urban industrial land planning and policy research has achieved good results in a variety of fields, including urban industrial land planning methods and technical methods, industrial land development and redevelopment management policies, and research on industrial land supply and demand patterns and their impacts. Meanwhile, studies on the current conditions, change trends, problem diagnosis, spatio-temporal evolution of urban industrial land, and its influencing factors started early, with considerable literature and high maturity. These studies have better revealed the spatio-temporal evolution of industrial land and its driving mechanism, providing a basis for planners to carry out industrial policy design and urban development planning, and offering a reference for the government to promote industrial transformation and upgrading and urban function optimization.

However, the existing studies also have obvious shortcomings. As mentioned above, urban industrial land is generally increasing in scale, with great differences between different cities and regions. Such differences represent multi-dimensional spatial inequalities in economic, social, political, and ecological dimensions in different cities and regions, and ignorance of them in urban industrial land planning and management policy design will lead to a serious dilution of planning and policy implementation performance. The current papers are mainly based on regression analysis of time series and simulation, and there is insufficient analysis of spatial differentiation and correlation effects. In the new era of increasing spatio-temporal uncertainty and interaction, some studies have no integrated or specialized analysis of spatio-temporal coupling and fail to attract extensive attention from scholars and governments, although they have noticed the spatial differences in industrial land change and its utilization efficiency [43,44].

In addition, the research on the change dynamics, influencing factors, social and economic benefits, resource management policies, and spatial planning of urban industrial land is separated, lacking a technical framework to integrate different studies. At the same time, the urban industrial land use differentiation management method is still key and a difficult field in research and practice. Scholars such as Li [45], Meng [46], and Zirlewagen [47] proposed the concept of differentiated land management but did not address the workflow, technical methods, decision-making basis, or realization mechanism of differentiated urban industrial land management policies.

3. Materials and Methods

3.1. Study Area

The study area is the Yangtze River Delta of China, covering all administrative regions of Shanghai, Jiangsu, Zhejiang, and Anhui, including 41 cities such as Shanghai, Suzhou-JS, Changzhou, Nanjing, Hefei, Wuhu, Hangzhou, and Jiaxing (Figure 1). In this paper, Taizhou in Zhejiang province is abbreviated as Taizhou-ZJ, Taizhou in Jiangsu province is Taizhou-JS, Suzhou in Jiangsu province is Suzhou-JS, and Suzhou in Anhui province is Suzhou-AH to avoid confusion. The Yangtze River Delta is the region with the highest level of industrialization development in China, the core carrier used to implement China's manufacturing power strategy, and one of six world-class urban agglomerations identified by French geographer Jean Gottmann. Its urban industrial land changes are typical in China and the world.

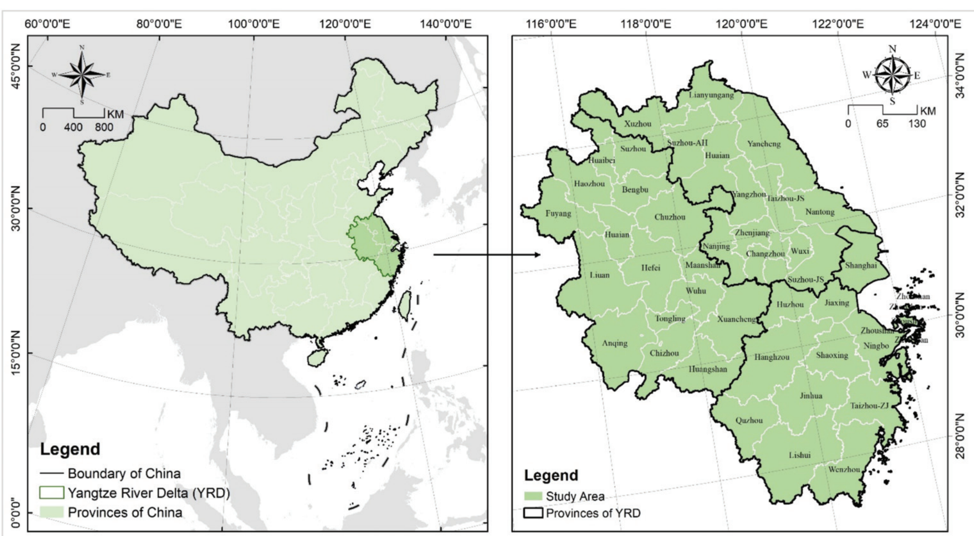

Figure 1. Study area.

Due to long-term high-intensity development, urban industrial land change in Yangtze River Delta is becoming increasingly complicated and the management needs are more diversified. In 2019, the urban industrial land in Yangtze River Delta covered an area of 2618.21 km^2, accounting for 22.62% of urban construction land; it created an industrial added value of 8,179.138 billion yuan, 34.47% of GDP. In the same year, the urban industrial land in Yangtze River Delta accounted for 22.81% of the total in China, and the industrial added value in Yangtze River Delta accounted for 25.87% of the total in China. An important goal of Yangtze River Delta spatial planning and urban planning is to enhance the protection and optimization of the use of urban industrial land in order to support and guarantee the development of the real economy. Therefore, it is of great significance to analyze the urban industrial land change and its interaction with economic growth in Yangtze River Delta to improve the industrial economic efficiency and effectively protect natural land resources.

3.2. Research Steps and Technical Route

The first step is to study the distribution and change spatial patterns of urban industrial land in the three dimensions of relative share, change speed, and evolution mode. In this process, GIS tools and the Boston Consulting Group matrix are used to analyze the key characteristics of urban industrial land change in the Yangtze River Delta. The second step is to analyze the main factors influencing the evolution of industrial land in the Yangtze River Delta cities and their intrinsic driving mechanisms using spatial econometric regression methods. First, exploratory spatial data analysis and the Gini Index are introduced to analyze the spatial correlation and heterogeneity of the industrial land distribution and changes in the Yangtze River Delta. Second, Geodetector is used to analyze the direct and interactive influences of different factors. The third step is to study the decoupling relationship between urban industrial land change and industrial economic growth from two perspectives of added value and enterprise assets to analyze the external economic performance of land resource consumption management. The fourth step is to design and study the zoning management policy. The technical method of planning zoning and supply governance is constructed, and specialized management policies for each zoning are proposed based on the overlay analysis of the research results reached in the previous steps, and the results are applied to spatial governance and urban planning (Figure 2).

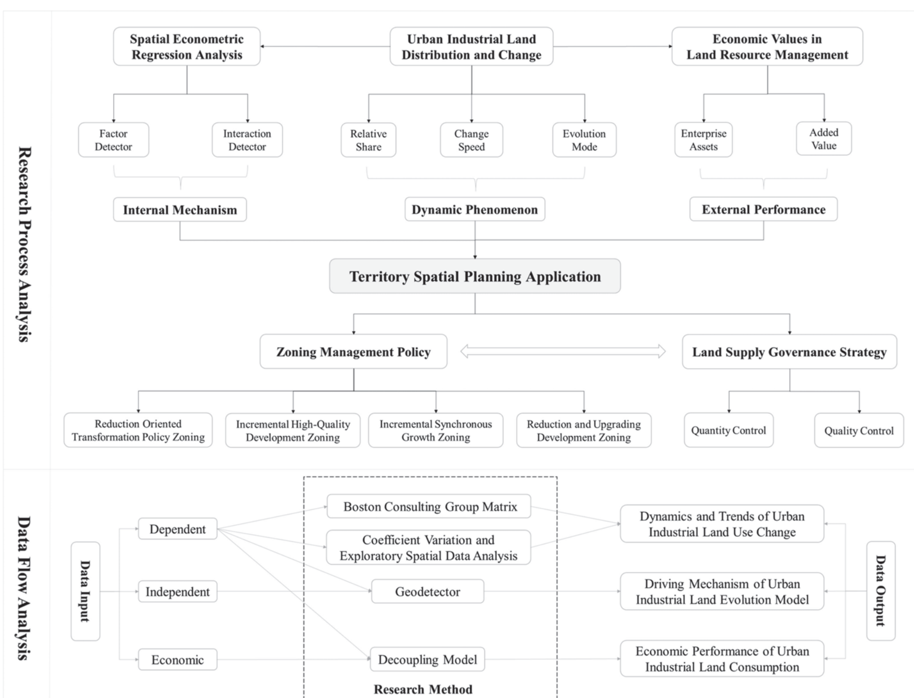

Figure 2. Research steps and technical route.

3.3. Variables and Data Sources

The study period of this paper is 2010–2019 and the variable types used include dependent, independent, and economic, with 15 indicators in total (Table 1). The urban industrial land in this paper coincides with the Code for Classification of Urban Land Use and Planning Standards of Development Land (GB50137-2011), referring to the land for independent factories, production workshops, handicraft workshops and their ancillary facilities. It includes production sites for construction and installation, slag (ash) discharge sites, and sites dedicated for railroads, docks, auxiliary roads, and parking lots. It is generally classified into three classes according to the degree of impact on the habitat. In Sections 4.1 and 4.3, the code of urban industrial land is L_i, which represents land area and is continuous data. In Section 4.2, the code is Y, which represents the evolution mode and is type data (integer with value range of 1–4).

Table 1. Description and analysis of the index system.

Variables	No.	Code	Indicators	Implication
Dependent	1	L_i/Y	Urban Industrial Land	Spatial Pattern/Evolution Model
Independent	2	X_1	Gross Domestic Product (GDP)	Government Demand
	3	X_2	Built-Up Area	
	4	X_3	Road Area	Environment
	5	X_4	Real Estate Investment	
	6	X_5	Per Capita GDP	Industrialization
	7	X_6	Tertiary Industry	
	8	X_7	Import	Globalization
	9	X_8	Export	
	10	X_9	Foreign Direct Investment	
	11	X_{10}	Patent Application Number	Innovation
	12	X_{11}	Higher Education Institution Number	
	13	X_{12}	Education investment	
Economic	14	Z_1	Secondary Industry Added Value	Government Value
	15	Z_2	Industrial Enterprise Assets	Market Value

The change in urban industrial land is a direct mapping of the synergistic development process of regional industrialization and urbanization, reflecting the real economic activities of cities and determining the main pattern of urban economic space. Industrial land is an important part of urban built-up area/construction land, and in the GDP-oriented performance appraisal system, the impact of a city government's pursuit of both economic growth and a larger city size on the change in industrial land must be considered first, which are represented by GDP and built-up area in this paper [48]. Industrial development is inseparable from the support of ancillary facilities, and their impact is measured by road area in view of the Chinese consensus that that transportation infrastructure is fundamental for a region's development [49,50]. As the industrial upgrading and urban renewal in the Yangtze River Delta has significantly accelerated in recent years, a lot of industrial land has been transformed into residential land, so the impact of real estate investment on the industrial business environment should not be ignored [51]. The supply and demand of urban industrial land are influenced by the industrialization stage and are also closely related to the economic structure. In this paper, per capita GDP and tertiary industry are adopted for measurement [52]. The Yangtze River Delta has been the frontier region of China's opening up to the outside world and has undertaken vast quantities of relocated international industries, so this paper chooses import, export, and foreign direct investment to analyze the impact of globalization on the evolution of urban industrial land [53]. The central government has put "innovation-driven" at the top of the "Five Development Ideas" and proposed in the *Development Plan for the Construction of Science and Technology*

Innovation Community in the Yangtze River Delta that the Yangtze River Delta should be fully established as a leading global science and technology innovation community by 2035. In this context, the influence of technology and education on land use and economic development in the Yangtze River Delta is becoming more important. In this paper, we choose patent application number, higher education institution number, and education investment to analyze the influence of innovation on industrial land in Yangtze River Delta cities [54].

The formation of production capacity in the manufacturing sector corresponding to industrial land will lead to a continuous increase in industrial added value and employment, thus promoting rapid economic and social development in the city. Therefore, the city government is strongly willing to keep expanding urban industrial land in order to attract manufacturing investment and boost the growth of the urban industrial economy. In this paper, we use the added value [55] of the secondary industry to represent government actions and concerns, and to reflect the economic value created by urban industrial land. In addition, the assets and operation status of enterprises, the direct users of urban industrial land, are the key factors affecting and reflecting the level of land use. Accordingly, enterprise assets [56,57] is used in this paper to represent the actions and concerns of enterprises, and reflect the economic benefits created by urban industrial land.

The data of urban industrial land are from the *China Urban Construction Statistical Yearbook* released by the Ministry of Housing and Construction of China. The other data are from the *China City Statistical Yearbook* issued by China's National Bureau of Statistics, and some missing data come from provincial and urban statistical yearbooks, statistical bulletins, and government work reports in the study area, with attention paid to the impact of adjustment of the administrative division in data collection and processing. Tables A1 and A2 show the analysis results of the evolution mode of independent variable factors, which are calculated by the Boston Consulting Group matrix. Tables A3 and A4 include the normalized data, and their source data are used by the decoupling model. The data of other years are integrated on the basis of the administrative divisions in 2019. For example, as Gaochun County and Lishui County were merged into Nanjing City in 2013, the data from 2010 to 2013 were directly included in those of Nanjing City; as another example, as the prefecture-level city of Chaohu in Anhui province was split in 2011, and the county-level cities of Chaohu and Lujiang under its jurisdiction were enclosed in Hefei City, Wuwei County was enclosed in Wuhu City, and Huangshan County and Hexian County (excluding Shenxiang Town) were enclosed in Ma'anshan City, the data of 2010–2011 were processed at a ratio of 2/5 for Hefei, 2/5 for Ma'anshan, and 1/5 for Wuhu when the data were integrated.

3.4. Research Methods

3.4.1. Boston Consulting Group Matrix

For companies that provide more than one type of product or service, their sustainability should be evaluated in an integrated way through portfolio analysis among their businesses since each business has different market positions and value advantages. The Boston Consulting Group matrix is based on a methodology pioneered by the Boston Consulting Group in the 1970s to analyze and optimize a company's business portfolio in the marketplace. In the Boston Consulting Group Matrix-based analysis, the horizontal coordinate represents the relative market share of the company's revenue, and the vertical coordinate represents the average annual growth rate of the revenue, with the average or set value (e.g., 0.5 or 10%) as the threshold to classify the company's business into four types: star, cow, question, and dog [58]. This division of business portfolio types facilitates the development of effective and appropriate strategies for different businesses and integration of corporate resources to improve competitiveness. Boston Consulting Group Matrix-based analysis aims to differentiate business by dividing the products or services into different quadrants to ensure that it continuously eliminates dog business with limited prospects and maintains a reasonable combination of star, cow, and question business, thus realizing a virtuous cycle of product, service, and resource allocation structure. The Boston Consulting Group Matrix has the advantage of improving the business analysis and strategic decision-making capabilities of corporate executives and providing a deeper understanding of the linkages between different business activities for them [59].

The Boston Consulting Group Matrix originated in the field of business management and is currently widely used in the fields of tourism management and foreign investment management and has also been tentatively applied in the field of land use change management [60]. In this paper, the Boston Consulting Group matrix is used to measure the spatial and temporal evolution trend of urban industrial land in Yangtze River Delta. It is also applied to analyze the spatial and temporal evolution trends of the independent variables, and the output results are then used as input variables for the Geodetector-based analysis. RS is defined as a relative share to reflect the position of urban industrial land stock in Yangtze River Delta. With L_i representing the area of urban industrial land in city i in a given year, L_{i-max} representing the maximum area of urban industrial land of 41 cities in Yangtze River Delta in a given year, L_{i-last} and L_{i-base} representing the urban industrial land area of city i in the base and end periods, t representing the time interval of the study period (t = 4 in 2010–2014, t = 5 in 2014–2019), and n being the number of cities, RS and AV are calculated as follows [61]:

$$RS = \frac{L_i}{L_{i-max}} \tag{1}$$

$$CS = \sqrt[t]{L_{i-last}/L_{i-base}} - 1 \tag{2}$$

According to Equations (1) and (2), the competition state of urban industrial land of the cities in Yangtze River Delta can be identified to reveal the spatial and temporal evolution trend of urban industrial land in Yangtze River Delta. With the average of CS and RS as a threshold, the 41 cities in Yangtze River Delta are divided into 4 types for analysis of the possible strategies for future management of urban industrial land in each city (Table 2). When both CS and RS are greater than or equal to the average value, it belongs to star-cities, and when both are less than the average value, it belongs to dog-cities. When CS is greater than or equal to the average and RS is less than the average, it belongs to cow-cities. When CS is less than the average and RS is not less than the average, it belongs to question-cities. At the same time, this paper also uses the method of the Boston Consulting Group matrix to deal with independent variables, which lays a foundation for the analysis of the driving mechanism.

3.4.2. Coefficient Variation and Exploratory Spatial Data Analysis

The spatial heterogeneity is analyzed by the coefficient of variation (CV), representing weak spatial heterogeneity when it is less than 0.15 or representing strong spatial heterogeneity if it is greater than 0.36 [62]. This paper uses the spatial autocorrelation analysis method to explore the correlation of the spatial distribution of urban industrial land. By calculating the global Moran's-I index, the overall spatial correlation and agglomeration degree of urban industrial land are measured [63]. The global Moran's I value ranges from −1 to 1, and a larger value indicates a higher degree of spatial correlation and agglomeration. When the global Moran's I index is greater than zero, it indicates a positive spatial correlation; on the contrary, if it is less than zero, it indicates a negative spatial correlation; if it is equal to zero, it indicates that the spatial distribution is random. The local Moran's I can reveal the similarity or correlation between spatial units and their neighbors, and further divide the spatial correlation mode into four types, including HH (High-High), HL (High-Low), LH (Low-High), and LL (Low-Low) [64]. This paper conducts the spatial autocorrelation analysis by Arcgis10.2 and GeoDa1.18 at the significance level of 0.1, with the spatial weight matrix based on the adjacent boundaries and all default parameters of the software. n represents the number of cities; M_i and M_j represent the observed values of cities i and j, respectively; $\overline{M}$ represents the average of the observed values; W_{ij} represents the spatial weight matrix in global spatial autocorrelation, or the row normalized value of spatial weight in local spatial autocorrelation; S_0 represents the sum of spatial weight matrices; and N_i and N_j represent the normalized values of the observations of cities i and j. The equations for global and local Moran's I are as follows [65]:

$$\text{Global Moran's } I = \frac{n}{S_0} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(M_i - \overline{M}\right)\left(M_j - \overline{M}\right)}{\sum_{i=1}^{n}\left(M_i - \overline{M}\right)^2},\ S_0 = \sum_{i=1}^{n}\sum_{i=1}^{n} = W_{ij} \tag{3}$$

$$\text{Local Moran's } I_i = N_i \sum_{i=1}^{n} W_{ij} NY_j \tag{4}$$

Table 2. Decoupling type and decoupling indicator range.

State	*RS*	*CS*	Characteristic	Future Alternative Strategies
Star-cities	$\geq \overline{RS}$	$\geq \overline{CS}$	High growth rate and relative share of urban industrial land, with great development potential and good opportunities.	They are at the stage of rapid growth and priority should be given to expansionary strategies and greater investment in urban industrial land to promote urban economic and social development.
Cow-cities	$\geq \overline{RS}$	$< \overline{CS}$	High relative share of urban industrial land but low growth rate, high regional status but low development potential.	They are at the stage of maturity, and priority should be given to harvesting strategies to control or even reduce investment in urban industrial land to maximize the return on investment in land resources.
Question-cities	$< \overline{RS}$	$\geq \overline{CS}$	Low relative share of urban industrial land, high growth rate, with possibility to become a new spatial growth pole for industrial economic development.	They are at the take-off stage and priority should be given to selective strategies. Due to the high uncertainty, it is necessary to be cautious and carefully analyze the real reasons for the increase in the growth rate, with a focus on cultivating cities that have the potential to become stars; otherwise, give up investment.
Dog-cities	$< \overline{RS}$	$< \overline{CS}$	Low relative share and growth rate of urban industrial land, and low regional status and development potential.	They are at the stage of recession and the priority should be given to withdrawal strategies. It is necessary to reduce the scale of land input to mitigate risks and avoid waste of resources due to blind investment.

3.4.3. Geodetector

When the geographical distribution of the research objects has spatial heterogeneity, correlation, and agglomeration, research on the driving mechanism needs to use the spatial econometric analysis method instead of the traditional regression model. Geodetector is a research-oriented (and still non-commercial) geostatistical analysis application developed by Prof. Wang Jinfeng in the Chinese Academy of Sciences, including both excel and R language versions, which can be downloaded for free at http://www.geodetector.cn/ (accessed on 20 July 2022). Geodetector software provides four functions: the first is for factor detection, applied to quantitatively measure the degree of spatial heterogeneity of the dependent variable and the influence of a single independent variable on the dependent variable; the second is for interaction analysis, applied to identify the compound influence on the dependent variable when different independent variable factors act together; the third is for risk analysis, applied to determine whether the differences between different classes of the independent variable factors are significant; and the fourth is for ecological analysis, applied to compare whether there are significant differences in the influence of different independent variable factors on the dependent variable [66,67]. The first and second functions are used in this paper.

In this paper, we use the *Factor−detector* function of Geodetector to analyze the influence of different factors on the evolution pattern of urban industrial land, and the *Interaction−detector* function to analyze the synergy between different factors. For the independent variable factors (e.g., X_i, X_j) and the dependent variable (Y), if they both have a similar evolution mode, Geodetector will determine that the factor has a greater influence on urban industrial land change [68]. With the input patterns of change in the independent and dependent variables, i.e., the results of the analysis using the Boston Consulting Group Matrix, Geodetector analyzes the influence of different factors on land use change by comparing the similarity of the patterns of change in the independent and dependent variables based on an internal algorithm. The influence size is represented by the index q, where $q\ (X_i)$ and $q\ (X_j)$ represent the direct influence of the two factors i and j in the independent stage, and $q\ (X_i \cap X_j)$ represents the interactive influence of the two factors i and j in the joint case. Their value range is [0,1], and a larger value implies a greater influence. In the Geodetector software, the independent needs to use type data instead of continuous data. With h representing the number of classifications of the independent variables (h = 4 in this paper), N_h and N representing the number of cities in stratum h and the study area, σ_h^2 and σ^2 representing the variance of the dependent variable in stratum h and the study area, respectively, SSW representing the within sum of squares, and SST representing the total sum of squares in the study area, the calculation equation for q is [69]:

$$q = 1 - \frac{\sum_{h=1}^{l} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST},\ SSW = \sum_{h=1}^{l} N_h \sigma_h^2,\ SST = N\sigma^2 \tag{5}$$

The interactive influence is classified into five types based on the relationship between $q\ (X_i \cap X_j)$ and the minimum (Min ($q\ (X_i)$, $q\ (X_j)$)), maximum (Max ($q\ (X_i)$)), $q\ (X_j)$)), and summation ($q\ (X_i)$ + $q\ (X_j)$) values of direct influence [70,71]. The nonlinear weaken ($q\ (X_i \cap X_j)$ < Min($q\ (X_i)$, $q\ (X_j)$)) and single nonlinear weaken (Min ($q\ (X_i)$, $q\ (X_j)$) < $q\ (X_i \cap X_j)$ < Max($q\ (X_i)$), $q\ (X_j)$)) represent the antagonistic effect between different factors, indicating that the driving forces of i and j cancel each other when they act together on Y, and that their influence is weakened or even disappears, so the pairing of the two factors should be avoided in policy design when possible. The bifactor enhancement ($q\ (X_i)$ + $q\ (X_j)$ > $q\ (X_i \cap X_j)$ > Max ($q\ (X_i)$, $q\ (X_j)$)) and nonlinear enhancement ($q\ (X_i \cap X_j)$ > $q\ (X_i)$ + $q\ (X_j)$) represent a synergy effect between different factors, indicating that the driving forces of i and j are mutually reinforcing when they act together on Y, and that the influence is enhanced or even significantly amplified, so the two factors should be paired in policy design when possible. Notably, when $q\ (X_i \cap X_j)$ = $q\ (X_i)$ + $q\ (X_j)$, it represents that the processes between the different factors are independent, and they do not interfere or relate to each other, a rare and special phenomenon requiring no consideration of the interactive influence (but the direct driving force) in policy design (Figure 3) [72].

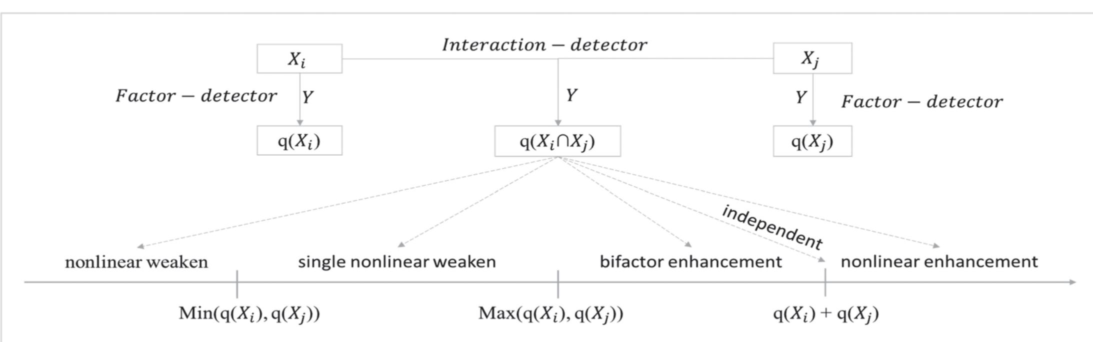

Figure 3. Analysis on the interaction between factors.

3.4.4. Decoupling Model

The decoupling model, proposed by Tapio [73], was originally used to analyze the connection of GDP with transport volume and carbon emissions in EU countries, and is now widely used in economics and ecology research. Analysis of the relationship between land change and economic growth based on decoupling models has emerged, mainly in the fields of urban construction land [74] and agricultural land [75], but it is still rare in urban industrial land studies. This paper analyzes the relationship between the urban industrial land change and the growth of the industrial economy (real economy) in Yangtze River Delta using the decoupling model, essentially analyzing the process of de-landing and materialization in the development of the real economy in Yangtze River Delta cities, i.e., the process of reducing the consumption of land resources by industrial economic activities [76]. With γ representing the decoupling index, $\Delta\alpha$ representing the growth rate of urban industrial land in Yangtze River Delta, $\Delta\beta$ representing the growth rate of industrial economic development-related indicators (including added value, total assets, gross profit, and employed population), X_i and X_{i+n} representing the annual values of economic development-related indicators in years i and $i+n$, respectively, and k representing the study period, the decoupling index is calculated as follows [77]:

$$\gamma = \frac{\Delta\alpha}{\Delta\beta} \tag{6}$$

$$\Delta\alpha = \frac{L_{i-last} - L_{i-base}}{L_{i-base}} \tag{7}$$

$$\Delta\beta = \frac{Z_{i-last} - Z_{i-base}}{Z_{i-base}} \tag{8}$$

The concept of “decoupling” emphasizes the long-term trending process. Based on the relevant research experience [78,79], the study period is divided into three stages of 2010–2014, 2015–2019, and 2010–2019, corresponding to short-term and long-term studies, in accordance with the length of the research data time series in this paper. The decoupling is classified into 3 types and 8 sub-types based on whether $\Delta\alpha$ and $\Delta\beta$ are positive or negative, with 0.8 and 1.2 as the thresholds for γ (Table 3) [80]. A remarkable fact is that strong or weak decoupling is ideal, which shows that the urban industrial land change is in high coordination with industrial economic growth, and the transformation of land investment into economic benefits has a nonlinear amplification effect. Cities in expansive coupling or expansive negative decoupling should improve their land use efficiency and intensity early while those in strong or weak negative decoupling or in recessive coupling or decoupling are unhealthy and they are question-cities of regional development, which should develop targeted policies and plans to reverse the development direction soon to achieve sustainable development.

Table 3. Decoupling type and decoupling indicator range.

Type	$\Delta\alpha$	$\Delta\beta$	γ	Implication
SD	≤ 0	≥ 0	≤ 0	It indicates the first best state, where the industrial growth is accompanied by a steady decline in urban industrial land; it has been a benchmark for regional high-quality development since the development of the real economy got rid of the expansion of urban industrial land.
WD	>0	>0	(0,0.8]	It indicates the second-best state, where the growth of the industrial economy is faster than that of urban industrial land with efficient use and intensive development of land resources.
EC	>0	>0	(0.8,1.2]	It indicates the state of steady incremental expansion, with the growth of industrial economy largely synchronized with that of urban industrial land, and the development still heavily depending on land resources.
END	>0	>0	$(1.2, +\infty)$	It indicates the state of incremental and extensive development, with the growth of the industrial economy being slower than that of urban industrial land, low utilization efficiency of land resources, and insufficient transformation of land investment into economic returns.
RD	<0	<0	$(1.2, +\infty)$	It indicates that the cities are in contraction, with both the industrial economy and urban industrial land in negative growth, land resources decreasing faster than the economy, and a high level of land use efficiency and intensity.
RC	<0	<0	(0.8,1.2]	It indicates the stage of steady reduction and contraction, where the industrial economy and urban industrial land are largely declining in a synchronous manner and development is still dependent on land resources.
WND	<0	<0	(0,0.8]	It indicates the second-worst state, with the industrial economy reduction occurring faster than that of urban industrial land, the added value of land output gradually decreasing, and the land reduction having an unhealthy effect of nonlinear amplification on economic development.
SND	>0	<0	<0	It indicates the worst state, where the urban industrial land continues to grow, but the industrial economy is declining gradually, the land investment has not transformed into economic returns, and there is a waste of resources, leading to unsustainable development.

Note: SD stands for strong decoupling, WD stands for weak decoupling, EC stands for expansive coupling, END stands for expansive negative decoupling, RD stands for recessive decoupling, RC stands for recessive coupling, WND stands for weak negative decoupling, and SND stands for strong negative decoupling.

4. Results

4.1. Dynamics and Trends of Urban Industrial Land Use Change

4.1.1. Relative Share

The average of the relative share of urban industrial land is 0.07. Shanghai is in first place and Lishui is at the bottom. The coefficient of variation has decreased from 2.19 to 2.09, indicating high-level but stable spatial heterogeneity. In 2014, high and higher cities were clustered in three agglomeration zones of Shanghai-Nanjing-Hefei, Shanghai-Huzhou-Hangzhou, and Ningbo-Wenzhou in a "finger-shaped" distribution, with Shanghai as the core while low and lower cities were mostly clustered in Anhui and western Zhejiang. In 2019, high and higher cities formed two "arc-shaped" agglomeration belts in Jiangsu and Zhejiang, and the agglomeration center of low and lower cities shifted further to the west of the study area, especially to western Anhui (Figures 4 and 5). In summary, the relative share of industrial land in the Yangtze River Delta cities is distributed in an "east-west" gradient and shows the characteristics of a belt-like agglomeration, with the status of cities in Jiangsu rising significantly and the cities in western Anhui remaining marginalized for a long time.

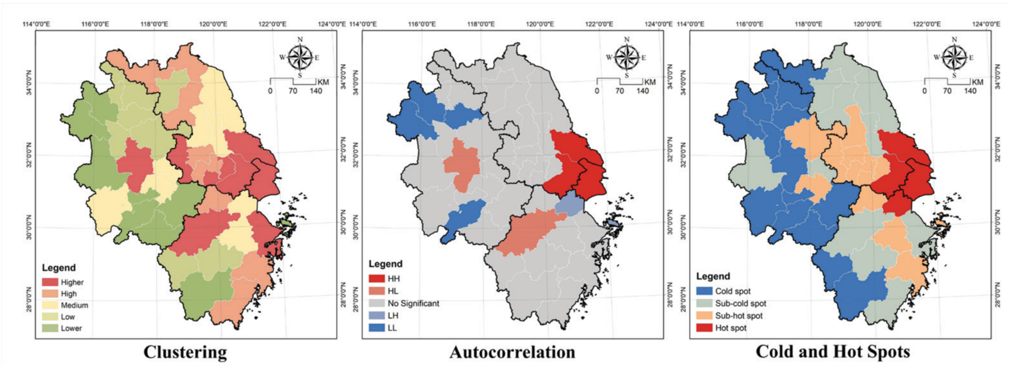

Figure 4. Spatial analysis of the relative share in 2010–2014.

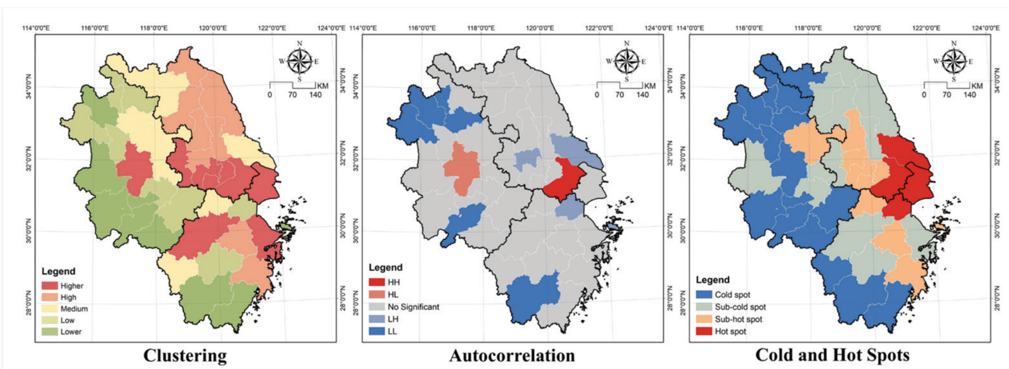

Figure 5. Spatial analysis of the relative share in 2015–2019.

The global Moran's I in 2014 was 0.072 ($p < 0.05$, Z = 2.28), indicating a spatially positive correlation between the relative shares of urban industrial land. HH cities were clustered in the Shanghai metropolitan area, including Shanghai, Nantong, and Suzhou-JS, while LL cities were clustered in Anhui, including Chizhou, Bozhou, Fuyang, and Bengbu. Hot spot cities were clustered in the Shanghai metropolitan area, with secondary hot spot cities extending to the Nanjing metropolitan area, while cold spot cities were clustered in a band in Anhui and western Zhejiang. Global Moran's I index in 2019 was 0.023 ($p > 0.05$, Z = 1.12), indicating that the spatial autocorrelation was significantly reduced and not statistically significant. Suzhou-JS was the only HH city, and there was one more LL city Lishui than in 2014. The cold hotspot cities remained largely unchanged in both geographic pattern and spatial structure.

4.1.2. Change Speed

The average change range of urban industrial land in Yangtze River Delta from 2010 to 2014 was 1.81 km^2, with the largest increase in Shaoxing of up to 35.71 km^2, and the largest decrease in Nantong of -37.81 km^2. The average change range of urban industrial land in Yangtze River Delta from 2015 to 2019 was -1.55 km^2, with the largest increase in Hangzhou of 44.76 km^2, and the largest decrease in Shanghai of -159.37 km^2. From the results of the quantile spatial clustering analysis, most of the highest and high cities were clustered in the Hangzhou-Ningbo development belt, and a few were concentrated in the junction between Jiangsu and Anhui; the lowest and low cities were mainly concentrated in the Shanghai metropolitan area, southern Zhejiang, and western Anhui, where urban industrial land has been experiencing active (e.g., Shanghai and Suzhou-JS, etc., making development strategic plans for active transformation) or passive (e.g., Wenzhou, Zhoushan, Huai'an, etc., subjected to the siphon effect of big cities) reduction (Figures 6 and 7). To sum up, urban industrial land in Yangtze River Delta experienced a small change on the whole, and the spatial pattern remained stable in general. However, it showed a tendency to shift from increment-led development to reduction-led development over time.

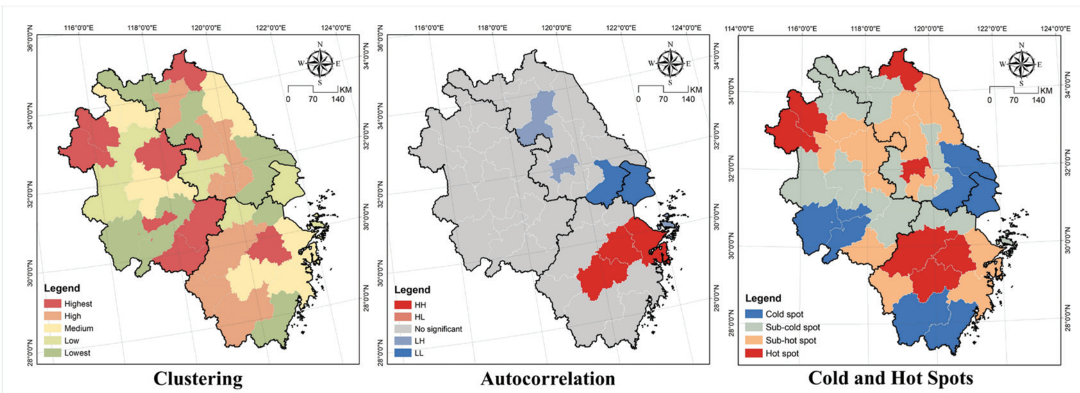

Figure 6. Spatial analysis of the change speed in 2010–2014.

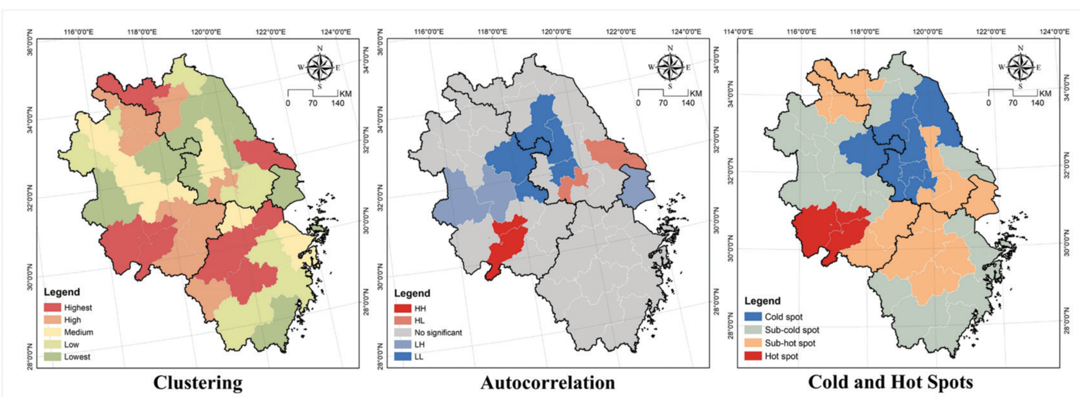

Figure 7. Spatial analysis of the change speed in 2015–2019.

The coefficient of variation decreased from 9.26 to 2.62, indicating that the level of spatial heterogeneity is decreasing but still high. It is worth noting that the global Moran's I index changed from 0.113 to -0.123, indicating that the change range of urban industrial land changed from positive to negative spatial correlation. In 2010–2014, HH cities clustered in Zhejiang province in a band shape but scattered in Zhejiang and Anhui provinces in 2015–2019. From 2010 to 2014, LL cities clustered in the Shanghai metropolitan area, and then all disappeared. There were no HL cities in 2010–2014, and most of them were concentrated in Jiangsu province in 2015–2019, especially in the peripheral areas of the Shanghai metropolitan area. The number of LH cities has been sparse for a long time and distributed randomly. From 2010 to 2014, hotspot cities were clustered in the Hangzhou metropolitan area and northern Anhui while cold spot cities were clustered in the Shanghai metropolitan area, Anhui, and southern Zhejiang. From 2015 to 2019, hotspot cities were clustered in southern Anhui, with secondary hotspot cities mostly clustered in the Anhui-

Zhejiang-Jiangsu junction area and Huaihai Economic Zone, and cold spots in central Jiangsu.

4.1.3. Evolution Mode

From the perspective of statistical distribution: The cities of the different types in 2010–2014 are ranked by number as stars = cows < dogs < question, and as stars < cows < question < dogs for the cities in 2015–2019. In the urban evolution mode, star-cities are in the best state and dog-cities are in the worst state while cow-cities and question-cities are in the middle between the two. The cities in different states evolve into three distribution structures by the quantity statistics: olive, pyramid, and dumbbell. The olive structure is the most stable, representing a small number of star-cities and dog-cities and a large number of cow-cities and question-cities, which is the best combination to adapt to the sustainable development of the region. In complete contrast to olive, dumbbell has a large number of star-cities and dog-cities and a small number of cow-cities and question-cities, indicating that the regional development is polarized at both ends, which is the least desirable combination. Pyramid is a structure between dumbbell and olive, with the number of star-cities, cow-cities, question-cities, and dog-cities increasing in that order. The distribution structure of the four types of patterns has changed from an "olive" shape to a "pyramid" shape, which indicates that the urban system in the region is becoming increasingly better.

From the perspective of geographical pattern: Except for question-cities, all types of cities were distributed randomly from 2010 to 2014, with star-cities being Wuxi, Hangzhou, Ningbo, and Hefei; cow-cities being Nanjing, Suzhou-JS, and Nantong; question-cities including Changzhou, Lianyungang, Yangzhou, Huzhou, Shaoxing, and Huangshan; and dog-cities including Xuzhou, Huai'an, Wenzhou, Jiaxing, Wuhu, and Bengbu. From 2015 to 2019, star-cities and cow-cities formed clustering zonings along the Shanghai-Suzhou-JS-Nanjing and Hangzhou-Ningbo axes while question-cities were mostly clustered in southwestern Anhui, and dog-cities were concentrated in a contiguous distribution in central Yangtze River Delta (central-northern Anhui and Jiangsu) and southern Zhejiang (Figures 8 and 9 and Table 4).

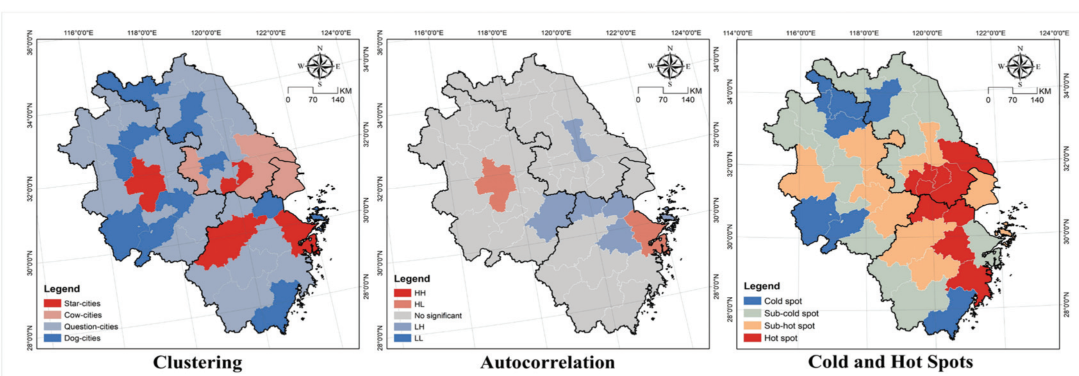

Figure 8. Spatial analysis of the evolution mode in 2010–2014.

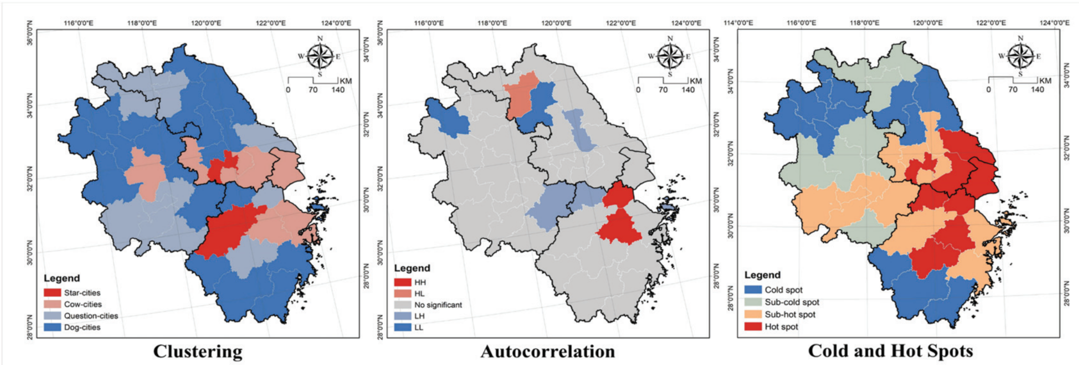

Figure 9. Spatial analysis of the evolution mode in 2015–2019.

Table 4. Analysis of the spatial heterogeneity parameters of urban industrial land in Yangtze River Delta.

	2010–2014	2015–2019
RS (%)	0.07	0.07
CS (%)	1.24	3.82
Star-cities	4	2
Cow-cities	4	7
Question-cities	22	11
Dog-cities	11	21

From the perspective of spatial effect: The coefficient of variation increased from 0.43 to 0.52, indicating that the spatial heterogeneity increased slightly and remained at a high level for a long time. The global Moran's I index changed from −0.129 to 0.080, indicating that the change trend of urban industrial land changed from a negative to positive spatial correlation. No cities belonged to HH and LL in 2010–2014, and HH cities were clustered in northern Zhejiang and LL cities were scattered in Jiangsu and Anhui provinces in 2015–2019. The number of HL cities has been sparse for a long time and distributed randomly. The LH cities were concentrated in northern Zhejiang in 2010–2014, and the spatial scope shrank significantly in 2015–2019. From 2010 to 2014, hotspot cities were clustered in the south of Jiangsu and extended to Zhejiang, with secondary hotspot cities in their periphery. Cold spot cities were clustered in Huaihai Economic Zone and southwestern Anhui. From 2015 to 2019, hotspot cities were clustered in the Shanghai metropolitan area and central Zhejiang, with secondary hotspot cities distributed in their periphery, while cold spot cities formed three clusters in northern Anhui, central Jiangsu, and southern Zhejiang.

4.2. Driving Mechanism of the Urban Industrial Land Evolution Model

4.2.1. Direct Influence

The results of the analysis of *Factor−detector* are shown in Table 5. Per capita GDP, export, and education investment had a low direct influence among the 12 factors, and they were not statistically significant from 2010 to 2014. The average direct influence of the remaining nine factors was 0.37, which was used as a threshold to classify the influence factors. The direct influence of real estate investment, tertiary industry, higher education institution number, and road area was greater than the average and they were important factors; import, foreign direct investment, built-up area, gross domestic product, and patent application number had a direct influence that was less than the average as auxiliary factors. Out of the 12 factors, only import had a low and non-statistically significant direct influence from 2015 to 2019. The average direct influence of the rest of the factors was 0.52. Export, built-up area, tertiary industry, patent application number, road area, real estate investment, education investment, and gross domestic product (GDP) had a direct influence that was greater than the average and they were important factors; while foreign direct investment, higher education institution number, and per capita GDP had a direct influence that was less than the average as auxiliary factors (Table 5).

Table 5. Analysis of the evolution mode of independent variables in 2015–2019.

Indicators	Code	2010–2014		2015–2019		Change
		q	*p*	*q*	*p*	*q*
Gross Domestic Product (GDP)	X_1	0.34	0.03	0.54	0.01	0.2
Built-Up Area	X_2	0.34	0.04	0.6	0	0.26
Road Area	X_3	0.38	0.01	0.57	0	0.19
Real Estate Investment	X_4	0.44	0.01	0.55	0.01	0.11
Per Capita GDP	X_5	0.09	0.98	0.31	0.02	#
Tertiary Industry	X_6	0.43	0.01	0.58	0	0.15
Import	X_7	0.36	0.01	0.34	0.26	#
Export	X_8	0.29	0.22	0.64	0	#
Foreign Direct Investment	X_9	0.35	0.01	0.44	0.02	0.09
Patent Application Number	X_{10}	0.28	0.04	0.57	0	0.3
Higher Education Institution Number	X_{11}	0.42	0.01	0.41	0.04	−0.01
Education investment	X_{12}	0.22	0.12	0.54	0	#

Notes: "#" represents that there were non-statistically significant phenomena in 2010–2014 or 2015–2019.

The comparison between 2010–2014 and 2015–2019 shows that the average growth of the factor influence exceeded 40%, and the factors insignificantly decreased from three to one, indicating a significant increase in their power to explain the evolution pattern of urban industrial land. Export and education investment showed the most significant change, transforming from non-statistically significant factors to important factors, and per capita GDP, despite a significant increase in the direct influence, still remained an auxiliary factor. Patent application number, gross domestic product, and built-up area experienced a great increase in direct influence and changed from auxiliary factors to important factors, playing a key role in the evolution of urban industrial land in the long term. Factors such as foreign direct investment, real estate investment, and tertiary industry experienced a small range of growth in their direct influence and their driving force remained stable over time. The influence of higher education institution number decreased but to a lesser extent and its driving force remained stable. It is notable that import shifted from an auxiliary factor to a non-statistically significant factor, with the steepest decline. The influence of industrial structure serviceization increased while the industrialization stage saw a significant decrease; the influence of foreign investment remained stable in the long term while the role of import and export was reversed; the driving force of applied innovation (patent) and education investment soared rapidly while the role of higher education institution number generally remained stable. The government demand, in general, is the key driving force of the evolution of urban industrial land, the influence of supporting facilities and business environment has long remained stable, and the mechanism of action of industrialization, globalization, and innovation is becoming more complex.

4.2.2. Interactive Influence

The results of the analysis of $Interaction-detector$ are shown in Tables 6 and 7. The interaction of factor pairs is dominated by bifactor enhancement, with only a few showing nonlinear enhancement effects found in 2010–2014, including $X_1 \cap X_9$, $X_1 \cap X_{10}$, $X_3 \cap X_{10}$, $X_9 \cap X_{12}$, and $X_{12} \cap X_{10}$. The difference between the interactive influence and the direct influence is calculated and defined as the enhancement range as the synergy effect in factor interaction. For example, the direct influence of X_1 was 0.34, and the interactive influence of X_1 with X_2, X_3 ......X_{11}, and X_{12} was 0.40, 0.69 ......0.54, and 0.51, respectively, with an enhancement range of 0.06, 0.35, and ......0.19, 0.17 and an average of 0.23 (Table 8). Education investment, per capita GDP, patent application number, road area, export, gross domestic product, and foreign direct investment experienced a large enhancement range from 2010 to 2014, and from 2015 to 2019, per capita GDP, import, higher education institution number, foreign direct investment, and patent application number experienced a large enhancement range, and they can be considered as super interaction factors. The maximum interaction forces were 0.76 ($X_3 \cap X_{10}$) and 0.84 ($X_1 \cap X_8$, $X_3 \cap X_{10}$, $X_8 \cap X_9$, $X_8 \cap X_{12}$, $X_{10} \cap X_9$), and the minimum values were 0.26 ($X_5 \cap X_{12}$) and 0.49 ($X_7 \cap X_{11}$) for 2010–2014 and 2015–2019, respectively. Notably, the interactive influence of $X_1 \cap X_3$, $X_1 \cap X_4$, $X_1 \cap X_9$, $X_1 \cap X_{10}$, $X_2 \cap X_3$, $X_3 \cap X_4$, $X_3 \cap X_6$, and $X_4 \cap X_{12}$ was close to or more than 0.7 from 2010 to 2014, and more than half of the factor pairs were close to or more than 0.7 from 2015 to 2019, including $X_1 \cap X_2$, $X_1 \cap X_9$, $X_2 \cap X_3$, $X_2 \cap X_4$, $X_2 \cap X_5$, $X_2 \cap X_6$, $X_2 \cap X_9$, $X_2 \cap X_{12}$, $X_3 \cap X_8$, $X_4 \cap X_8$, $X_4 \cap X_{10}$, $X_6 \cap X_8$, $X_6 \cap X_{10}$, and $X_{12} \cap X_{10}$, with an interactive influence of even more than 0.8, playing a pivotal role in the evolution of urban industrial land. Generally, the interaction of per capita GDP, foreign direct investment, and patent application number with other factors remained at a high level for a long time, and they must be given priority attention in urban industrial land management policy design and spatial planning.

Table 6. Analysis of the evolution mode of independent variables in 2015–2019.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
X_1	0.34											
X_2	0.40	0.34										
X_3	0.69	0.69	0.38									
X_4	<u>0.74</u>	0.53	<u>0.71</u>	0.44								
X_5	0.38	0.38	0.41	0.47	0.09							
X_6	0.49	0.47	<u>0.74</u>	0.66	0.45	0.43						
X_7	0.54	0.45	0.63	0.50	0.40	0.52	0.36					
X_8	0.53	0.55	0.64	0.53	0.34	0.56	0.50	0.29				
X_9	<u>0.75</u>	0.54	0.46	0.50	0.38	0.65	0.56	0.58	0.35			
X_{10}	<u>0.74</u>	0.51	**0.76**	0.50	0.32	0.64	0.42	0.53	0.49	0.28		
X_{11}	0.54	0.47	0.54	0.62	0.44	0.51	0.61	0.50	0.52	0.49	0.42	
X_{12}	0.51	0.48	0.63	0.69	**0.26**	0.58	0.53	0.52	0.67	0.54	0.51	0.22

Notes: Red represents the nonlinear enhancement relationship, bold represents the maximum and minimum values, and underline represents the significant high values.

Table 7. Analysis of the evolution mode of independent variables in 2015–2019.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
X_1	0.54											
X_2	<u>0.82</u>	0.60										
X_3	0.73	<u>0.81</u>	0.57									
X_4	0.57	<u>0.81</u>	0.74	0.55								
X_5	0.64	<u>0.81</u>	0.73	0.63	0.31							
X_6	0.64	<u>0.80</u>	0.74	0.60	0.73	0.58						
X_7	0.61	0.72	0.72	0.59	0.51	0.62	0.34					
X_8	<u>**0.84**</u>	0.77	<u>0.81</u>	<u>0.83</u>	0.79	<u>0.81</u>	0.75	0.64				
X_9	0.59	<u>0.81</u>	0.78	0.61	0.65	0.65	0.56	<u>**0.84**</u>	0.44			
X_{10}	<u>0.82</u>	0.74	<u>**0.84**</u>	<u>0.81</u>	0.71	<u>0.80</u>	0.78	0.69	<u>**0.84**</u>	0.57		
X_{11}	0.66	0.72	0.75	0.68	0.60	0.63	**0.49**	0.78	0.56	0.77	0.41	
X_{12}	0.56	<u>0.81</u>	0.73	0.56	0.62	0.60	0.61	<u>**0.84**</u>	0.60	<u>0.81</u>	0.66	0.54

Notes: Same as Table 6.

Table 8. Analysis of the evolution mode of independent variables in 2015–2019.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	Average
2010–2014	0.23	0.16	0.25	0.14	0.30	0.14	0.16	0.24	0.21	0.26	0.10	0.32	0.21
2015–2019	0.14	0.18	0.19	0.12	0.37	0.11	0.29	0.16	0.24	0.21	0.26	0.13	0.20

4.3. Economic Performance of Urban Industrial Land Consumption

4.3.1. Government: Secondary Industry Added Value

Changes in urban industrial land and industrial value-added growth are well coordination on the whole, with a stable spatial pattern in general, but there are more diversified decoupling types. More than 85% of the cities were in strong or weak decoupling from 2010 to 2014, with land consumption in good coordination with economic development. The cities of the former type were mainly found in the Shanghai metropolitan area and southwestern Anhui while those of the latter type were widely distributed in Yangtze River Delta. Other cities were decoupling, scattered in a random distribution. From 2015 to 2019, the cities in strong or weak decoupling decreased to about 70%, with the former clustered in the junction of three provinces and southeastern Zhejiang, including Shanghai, Suzhou-JS, Huzhou, Nanjing, Suqian, Wenzhou, Taizhou-ZJ, and the latter widely distributed in Yangtze River Delta. Zhenjiang, Jiaxing, Jinhua, Wuhu, and Bengbu were in expansive coupling. Cities in strong or expansive negative decoupling emerged, with the former being Huaibei and Tongling, and the latter being Xuzhou, Nantong, Hangzhou, and Anqing, all in the problem-space of Yangtze River Delta (Figure 10). The decoupling types were changing with increasing complexity. A total of 31.71% of the cities were in progressive decoupling, distributed in clusters in southwest Anhui and northwest Zhejiang; 36.59% remained unchanged in the decoupling state, clustered in northwest Jiangsu, southeast Zhejiang, and central Yangtze River Delta (in the junction of many provinces along Shanghai-Huangshan). Notably, 31.71% of the cities were in regressive decoupling, concentrated in Jiangsu and Anhui in a band. Measures should be taken in the future to prevent them from degenerating from decoupling to coupling or even negative decoupling.

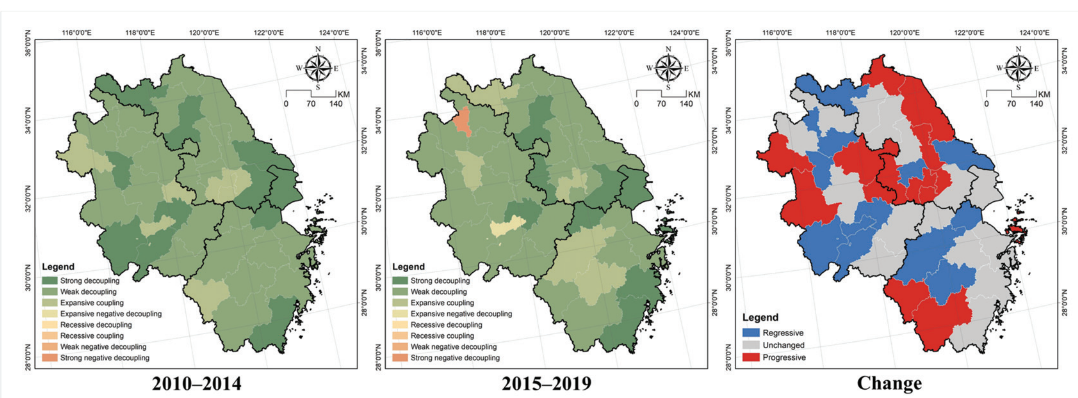

Figure 10. Spatial analysis of the decoupling relationship between urban industrial land and added value in Yangtze River Delta.

4.3.2. Market: Secondary Industry Enterprise Assets

The coordination between the urban industrial land change and industrial enterprise asset growth is acceptable on the whole and the decoupling types and spatial patterns are stable in general, with large changes in some areas of Anhui and Zhejiang. About 80% of the cities were in strong or weak decoupling from 2010 to 2014, including Changzhou, Ningbo, Fuyang, and Xuancheng in expansive coupling; Wuxi, Jinhua, and Taizhou-ZJ in expansive negative decoupling; and Wenzhou in recessive decoupling. The cities in strong or weak decoupling decreased to 56.10% from 2015 to 2019 while the cities in strong or expansive negative decoupling expanded to about 20%, with Huai'an and Zhoushan in recessive decoupling. From the perspective of de-coupling changes, 31.71% of the cities reached progressive decoupling, distributed in three clusters in southwestern Anhui, central Jiangsu, and northern Zhejiang; 24.39% remained unchanged, mostly concentrated in the Shanghai metropolitan area and central Zhejiang; Regressive decoupling was found in 43.90%, which were concentrated in southeastern Zhejiang, northeastern Jiangsu, western Anhui, Nanjing metropolitan area, and its sur-rounding areas (Figure 11).

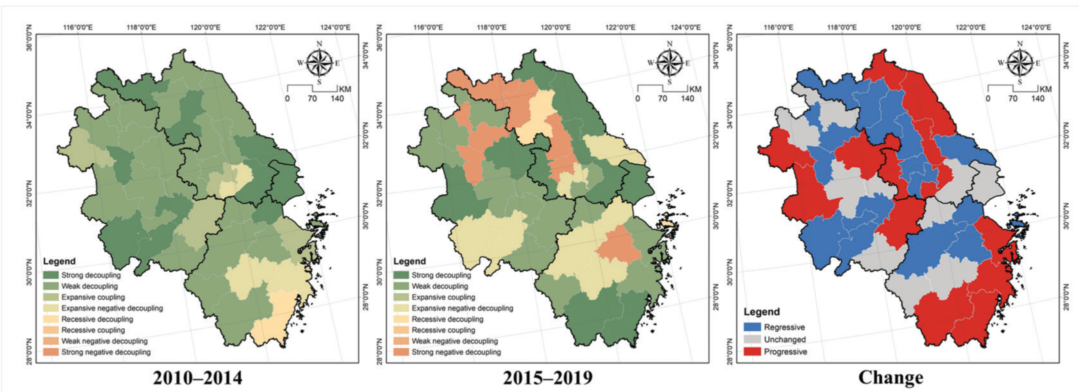

Figure 11. Spatial analysis of the decoupling relationship between urban industrial land and enterprise assets in Yangtze River Delta.

5. Discussion

The evolution model and spatial pattern of urban industrial land in the Yangtze River Delta are becoming increasingly more complicated, and the level of spatial agglomeration, heterogeneity, and relevance is decreasing. This complexity is shown in many areas. At the micro level, the evolution patterns, economic values, and driving mechanisms of different cities changed significantly in 2010–2014 and 2015–2019; at the macro level, the evolution pattern of urban industrial land changed from a "pyramid-" to an "olive"-shaped structure in the quantitative combination, with a shift from a random geographical distribution to geographical agglomeration, and from positive spatial correlation to negative spatial correlation. This conclusion confirms the views of other scholars. Louw [81] found significant spatial heterogeneity in the productivity of industrial areas in the Netherlands. Wang [82] and Cui [83] found that industrial land in China has in uneven spatial distribution with spatial convergence. A notable fact is that the viewpoints of some papers are not exactly the same or even opposite to the findings in this paper. Zhu [84] found, using a centrifugal model and contribution degree, that urban agglomerations in the middle reaches of the Yangtze River are significantly uneven in terms of the spatial distribution of industrial land, and that the spatial heterogeneity is increasing rather than decreasing over time, which is different from the conclusion reached in this paper. The possible reason for this discrepancy is that the study areas are different. Yangtze River Delta is located in the lower reaches of the Yangtze River as a developed region while the urban agglomerations in the middle reaches of the Yangtze River are located in the middle reaches and lag behind Yangtze River Delta in terms of development [85]. He found that the scale of urban industrial land in 38 counties of Chongqing changed repeatedly between regional imbalance and balance from 2009 to 2018, and there was no continuous decrease in spatial heterogeneity [86]. The scale may be a key factor leading to this discrepancy. This paper analyzed cities at the mesoscopic scale, compared to the microscopic scale at which he analyzed counties. These differences indicate that there are still controversies in the research on urban industrial land and its changing characteristics. More empirical studies and case studies are needed in the future to refine common patterns and identify individual characteristics through comparative analysis of new findings and the contributions of different papers to lay the foundation for establishing a characteristic industrial land management theory.

Due to the special background of land system and land management policies in China, where the primary market of industrial land supply is monopolized by the government, the city government tends to use land allocation as a policy tool to attract industrial investment and manufacturing enterprises [87]. Many city governments have adopted the development mode of boosting industrialization and urbanization by land supply, which, together with open-up policies and demographic dividends, did have a positive effect on urban industrial economic development. As for the value added, most cities remained in weak decoupling and strong decoupling, indicating that "seek-development-with-land" is still valid for city governments. However, from the perspective of enterprise assets, an increasing number of cities degenerated into the states of strong and expansive negative decoupling, with great variation in the type of decoupling between the two stages, indicating an unstable market performance and increasing challenges. This view is also supported by scholars in the field, Qi [88] found that the relationship between industrial land and economic growth is in weak decoupling in most Chinese cities, and there are a growing number of cities in negative decoupling. Against the background of increasingly strict land resource management and constraints, promotion of the transformation of the urban development mode from rough expansion to refined utilization through diversified land supply means such as expansion, contraction, and dynamic balance is becoming a new development trend. The impact of temporal and spatial evolution complexity and its driving factors must be considered for changes in the management system of urban industrial land supply, the development of spatial allocation schemes, and the design of planning and governance policies [89].

In the new era of high-quality development, it has become an important issue for the government and scholars to work together to improve the coordination between the change in industrial land and industrial economic growth, suppress the negative effect of land change, and reactivate the positive effect by reasonably controlling the scale of industrial land and optimizing the quantity, type structure, spatial layout, and development mode of industrial land supply through land spatial planning and land management reform [90]. There is a need to implement zoning management of urban industrial land changes in Yangtze River Delta, and to clarify the specialization and targeted strategies for different zonings, which are of great value to government decision makers. Based on the decoupling relationship between urban industrial land change and industrial economic growth and taking the land evolution model and its driving mechanism as constraints, the Yangtze River Delta is divided into four management zonings (Figure 2). In other words, the decoupling relationship between urban industrial land change and manufacturing economic growth should be the center, and cities in an ideal state should try to maintain the current evolution pattern while those in an unhealthy state should use a transformation strategy to change the unsustainable evolution pattern or trend by controlling the quantity and quality of urban industrial land supply.

Shanghai, Nanjing, Suzhou-JS, Lianyungang, Huai'an, Yancheng, Taizhou-JS, Wenzhou, Zhoushan, Lishui, Chuzhou, and Lu'an are in the best state of strong decoupling. In the future, a path-dependent strategy should be adopted to maintain land reduction development plans and policies, with these cities included in the reduction-oriented transformation policy zoning. Wuxi, Changzhou, Yangzhou, Suqian, Ningbo, Huzhou, Shaoxing, Quzhou, Taizhou-ZJ, Hefei, Huainan, Maanshan, Huangshan, Fuyang, Suzhou-AH, Bozhou, Chizhou, and Xuancheng are in weak decoupling, characterized by synergistic development between land and economy. The current land supply and management policies should be maintained in the future, with such cities included in the incremental high-quality development zoning. Moreover, Zhenjiang, Jiaxing, Jinhua, Wuhu, and Bengbu are in expansive coupling with low land use intensification, and the focus should be placed on improving land use efficiency in the future and these cities should be included in the incremental high-quality development zoning as well. Xuzhou, Nantong, Hangzhou, and Anqing are in expansive negative decoupling with extensive land use. In the future, strict control should be exercised over the land supply, with a focus on improving the quality of land use to ensure land consumption keeps pace with economic growth at least, and these cities are included in the incremental synchronous growth zoning. Huaibei and Tongling are in strong negative decoupling with serious land wastage. In the future, the focus should be on promoting industrial upgrading and reducing the land supply appropriately, with the inclusion of these cities in the reduction and upgrading development zoning (Figure 12).

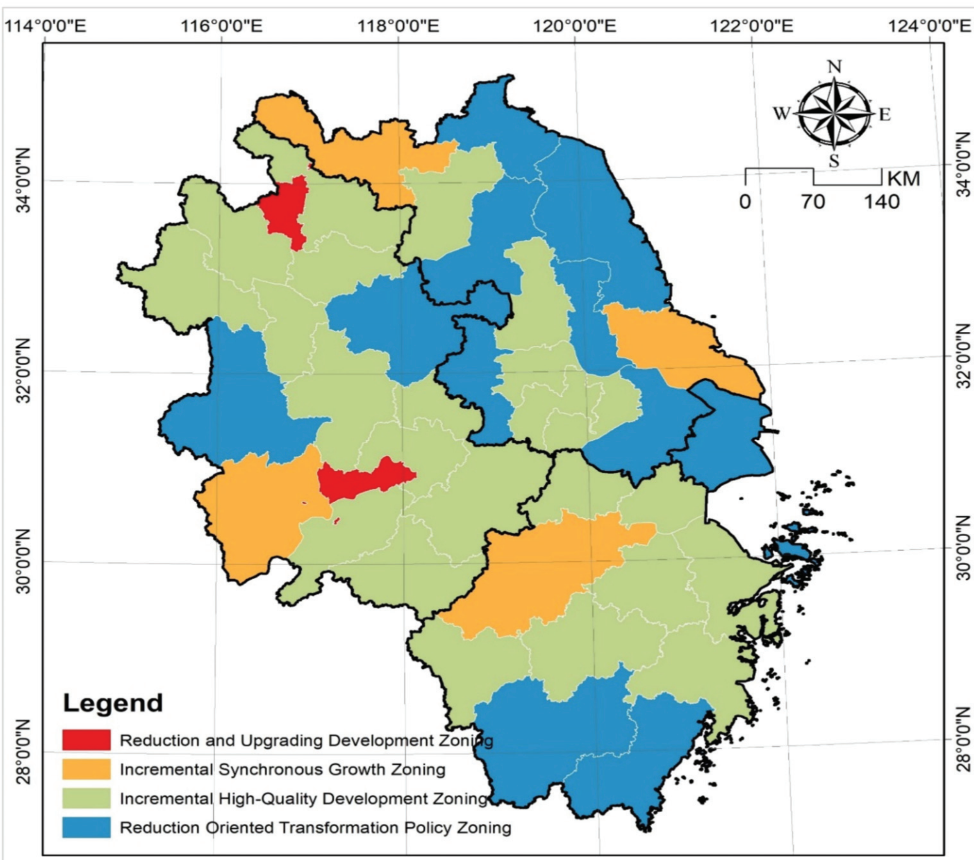

Figure 12. Analysis on the zoning management in Yangtze River Delta.

Additionally, differentiated governance strategies should be adopted for land supply in policy areas, with a combination of both quantitative and qualitative control methods. The government requires the coordination of territorial spatial planning and development planning and has announced the target of industrial added value (average annual growth rate) by 2025 in the 14th Five-Year Industrial Development Plan. The added value of the secondary industry is the core of the performance appraisal of city governments, and its decoupling from industrial land has long remained stable. Therefore, this paper predicts the industrial land area in 2025 based on the decoupling relationship between the change in industrial land and added value in urban areas, coupled with the objectives of the 14th Five-Year Plan and policy zoning, to provide a basis for controlling the quantity of land supply (Table 9). The cities in reduction-oriented transformation policy zoning should increase the input of capital, technology, talents, and other innovative factors per unit area of construction land; innovate the use model of industrial land; and promote industrial development transformation. These cities are in the stage of industrialization transition, in essence a process of optimizing and reconfiguring the relationship and combination of production factors such as land, natural resources, labor, capital, and technology. More efforts should be carried out to promote industrial parks [91], guide enterprises to enter industrial parks for development, and set up higher standards of investment access for manufacturing, trying to force the improvement of industrial land efficiency by means of the system in incremental high-quality development zoning [92].

For the cities in incremental synchronous growth zoning, relying on industrial land change to drive industrial economic growth is still an effective development mode. However, due to their low land use efficiency and unsatisfactory conversion of economic returns, measures should be taken to improve the quality of land use. Future work is increasing the supply of Class I and Class II industrial land, encouraging and supporting industrial upgrading and the development of new business models, and promoting the optimization of the urban industrial land structure in urban industrial land increment according to the development stage and characteristics of the city [93]. In the process of reusing industrial land, the government should be changed from the leading party to the guiding party to have a direct influence on psychological expectations and policy factors. Government-driven industrial land development and investment attraction are often disconnected from the market, leading to inefficient use of some industrial land, or even to it lying idle under the background of economic downturn and fierce competition between industrial parks. Therefore, reasonable incentive and penalty policies for the renewal of inefficient industrial land, such as floor area ratio awards, transfer of development rights, relaxation of planning controls, and land price reductions, should be formulated according to the land use needs and selection preferences of manufacturing and high-technology enterprises [94] to induce land-using enterprises to form their own willingness to renew and allow market forces to play a decisive role in the transformation of urban industrial land stock.

For the cities in reduction and upgrading development zoning, the scale of urban industrial land should be strictly controlled in the future, and the redevelopment of industrial land stock should be pushed hard in the process of reduction. First, it is necessary to carry out an evaluation of the suitability of urban industrial land reduction, identify spaces with reduction, and steadily promote and gradually explore the mode of withdrawal and redevelopment [95], renewal mechanisms [96], and reclamation programs [97] of urban industrial land stock. Second, the redevelopment of industrial land stock should be combined with the development of urban public space to promote the improvement of urban habitats and raise the quality of life of citizens. From the perspective of land planning, it is necessary to respect the change rules of urban industrial land, take into account the common and individual needs of different types of manufacturing enterprises [98], give priority to ensuring land for the development of new industries and new forms of business, support high-tech industries and environment-friendly enterprises, and drive the upgrading of industrial structures.

Table 9. Prediction of urban industrial land area based on the decoupling model.

City	Decoupling Index	Secondary Industry Added Value Growth Rate	Urban Industrial Land Growth Rate	Urban Industrial Land Area
Shanghai	−1.09	5.00	−5.46	383.95
Nanjing	−1.91	6.73	−12.87	41.08
Wuxi	0.11	6.79	0.74	74.67
Xuzhou	1.00	7.12	7.12	75.51
Changzhou	0.71	5.88	4.15	114.27
Suzhou-JS	−0.03	4.86	−0.15	127.66
Nantong	1.00	6.81	6.81	94.83
Lianyungang	0.00	10.00	−0.05	51.95
Huai'an	−0.92	10.42	−9.55	19.71
Yancheng	−1.40	7.79	−10.89	19.55
Yangzhou	0.66	5.94	3.90	48.86
Zhenjiang	0.40	2.52	1.01	42.70
Taizhou-JS	−0.80	7.78	−6.25	23.06
Suqian	0.59	10.00	5.92	41.67
Hangzhou	1.00	8.90	8.90	207.50
Ningbo	0.22	9.93	2.21	150.56
Wenzhou	−0.26	7.79	−1.99	5.96
Jiaxing	0.40	7.06	2.82	40.92
Huzhou	0.12	7.09	0.82	33.00
Shaoxing	0.05	9.90	0.51	67.52
Jinhua	0.40	7.72	3.09	30.02
Quzhou	0.43	9.47	4.07	35.49
Zhoushan	−3.71	10.00	−37.12	0.39
Taizhou-ZJ	0.08	5.83	0.44	35.42
Lishui	0.00	12.66	0.00	4.36
Hefei	0.55	10.38	5.66	119.35
Wuhu	0.40	6.48	2.59	19.22
Bengbu	0.40	6.36	2.54	30.52
Huainan	0.68	8.45	5.74	26.08
Ma'anshan	0.21	7.46	1.57	38.64
Huaibei	−0.15	13.40	−2.01	17.17
Tongling	−0.50	13.08	−6.54	15.93
Anqing	1.00	13.32	13.32	58.88
Huangshan	0.33	9.41	3.07	12.17
Chuzhou	−0.20	5.08	−1.03	24.17
Fuyang	0.08	7.62	0.58	21.45
Suzhou-AH	0.72	7.24	5.24	24.68
Lu'an	−0.01	9.36	−0.13	13.38
Bozhou	0.13	8.19	1.07	15.24
Chizhou	0.77	9.52	7.34	9.56
Xuancheng	0.34	6.49	2.24	20.18

6. Conclusions

(1) Behind the increasingly complex spatial and temporal evolution of urban industrial land dynamics, regular features of the process and spatial patterns of urban industrial land change are hidden. According to the Boston Consulting Group matrix, the spatio-temporal evolution model of urban industrial land can be divided into four types of stars, cows, dogs, and question, and the spatial agglomeration, heterogeneity, and correlation of different patterns have gradually decreased.

(2) The forces of different factors on the evolution of urban industrial land are increasingly differentiated, and their direct and interactive influences are significantly enhanced, with bifactor enhancement dominating the interaction of factor pairs. It should be noted that the government demand is the key driving force of the evolution of urban industrial land, the influence of supporting facilities and the business environment has

long remained stable, and the mechanism of action of industrialization, globalization, and innovation is becoming more complex.

(3) The match and synergy between changes in urban industrial land and industrial economic growth are fine in general, and the land resource management policy of "seek-development-with-land" is still effective for the government, but its effectiveness for enterprises (market) is declining rapidly. The progressive, unchanged, and regressive types of decoupling exist side by side, and the much higher long-term stability than that of assets makes the added value more suitable for future urban industrial land-scale projections.

(4) Based on the decoupling relationship, a technical framework for zoning management and classification governance of urban industrial land is constructed in this paper, with the land evolution pattern and its influencing factors taken into account. The Yangtze River Delta is divided into reduction-oriented transformation policy zoning, incremental high-quality development zoning, incremental synchronous growth zoning, and reduction and upgrading development zoning, and adaptive land quantity and quality control strategies are proposed for zonings.

The biggest innovation in this paper is the construction of a technical framework integrating "model evolution + driving mechanism + performance evaluation + policy design", which can be used for urban industrial land resources management and territory spatial planning based on the combination of GIS tools, Geodetector software, Boston Consulting Group matrix, and decoupling model. The technical framework and findings presented in this paper are not only applicable to China but also provide valuable references for decision making in countries undergoing rapid industrialization and re-industrialization. For countries in the early and middle stages of industrialization such as Vietnam, Indonesia, India, Malaysia, Iran, Uzbekistan, Brazil, and Egypt, and post-industrialized countries such as the United States, Japan, Russia, Germany, and France, which put forward re-industrialization strategies after the financial crisis, how to use land resources to attract large-scale investment in manufacturing, promote the development of the real economy or the return of manufacturing industries, and achieve scientific management of urban industrial land is becoming a new challenge for land management and spatial planning. The change in urban industrial land is a key manifestation of this urban industrial economic evolution. The two are showing an increasingly obvious non-linear, dynamic, and phased characteristic. Empirical studies and case studies of these countries based on decoupling models help to accurately capture and quantify the non-linear relationship and asymmetric effect between them, providing a scientific basis for government policy makers and planning designers.

Due to the limitation of data and information availability, this paper inevitably has some shortcomings in the selection of indicators and policy recommendations. For example, China's industrial land supply is monopolized by the government, and the system and policy have an important impact. However, because it is very difficult to obtain system and policy data, this paper did not include them in the analysis framework. If they can be incorporated into the analysis process in the future, it will help to improve the accuracy of the results. As another example, urban industrial land can be further subdivided into a variety of types, with some differences in the evolution mode and decoupling relationships between different types of industrial land, but there no detailed study of them was carried out in this paper. In addition, industrial land change creates economic benefits and social values while having some impact on both ecology and the environment. To gain a more comprehensive understanding of the combined effects of industrial land change, we call for future research to further focus on the social and ecological values of industrial land consumption.

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and F.Q.; funding acquisition, F.X. and F.Q. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: https://www.mohurd.gov.cn/index.html (accessed on 17 May 2022) and http://www.stats.gov.cn/(accessed on 21 May 2022).

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

Appendix A

Table A1. Analysis of the evolution mode of independent variables in 2010–2014.

City	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
Shanghai	3	3	3	3	1	3	3	4	3	3	3	3
Nanjing	3	3	4	3	1	3	3	3	3	3	3	3
Wuxi	3	4	3	3	1	3	3	3	3	3	3	3
Xuzhou	3	3	4	1	1	3	1	1	1	1	1	3
Changzhou	3	3	3	3	1	3	3	1	3	3	1	1
Suzhou-JS	4	3	3	4	1	4	3	3	3	3	3	3
Nantong	4	4	4	3	1	4	3	1	3	3	2	4
Lianyungang	2	2	1	1	1	2	1	2	1	2	1	2
Huai'an	1	2	4	1	1	1	2	1	1	2	1	1
Yancheng	4	1	2	2	1	2	1	2	1	2	1	4
Yangzhou	2	1	1	1	1	2	1	1	1	3	2	1
Zhenjiang	2	2	1	2	1	2	1	1	1	3	1	1
Taizhou-JS	2	1	1	2	1	2	1	1	1	4	1	2
Suqian	2	1	2	2	1	2	2	1	2	2	2	2
Hangzhou	3	3	3	3	4	3	3	4	3	3	3	3
Ningbo	3	3	3	3	1	3	3	4	3	3	3	3
Wenzhou	3	4	1	4	1	4	1	4	2	4	2	3
Jiaxing	2	1	1	2	1	2	2	4	4	4	1	2
Huzhou	1	2	1	2	1	2	1	1	1	1	1	1
Shaoxing	4	4	2	4	1	4	1	4	2	4	2	2
Jinhua	2	1	1	2	1	2	1	4	1	1	1	2
Quzhou	1	1	2	1	1	1	1	1	1	1	1	1
Zhoushan	1	1	2	2	1	1	2	2	2	1	2	1
Taizhou-ZJ	2	1	1	2	1	2	1	4	2	1	1	1
Lishui	2	1	1	2	1	2	1	2	2	1	1	2
Hefei	3	3	3	3	1	3	1	2	3	3	3	3
Wuhu	1	1	3	1	1	1	2	1	3	1	1	2
Bengbu	1	2	2	2	1	1	2	1	2	1	1	2
Huainan	1	1	2	1	1	1	2	2	1	1	1	1
Ma'anshan	1	1	1	1	1	1	1	2	1	2	1	1
Huaibei	1	2	1	1	1	1	2	1	2	2	1	1
Tongling	1	2	1	1	1	1	1	2	1	1	1	1
Anqing	2	1	1	1	1	2	2	1	1	2	2	2
Huangshan	1	2	1	1	1	1	2	1	1	1	2	1
Chuzhou	2	2	2	2	1	2	2	1	2	2	1	2
Fuyang	2	2	2	2	1	2	2	1	1	2	1	2
Suzhou-AH	2	2	2	2	1	2	2	1	2	2	2	2
Lu'an	2	1	2	2	2	2	2	1	2	2	1	2
Bozhou	2	2	2	2	1	2	2	1	2	1	1	2
Chizhou	1	1	1	1	1	1	1	2	1	2	1	1
Xuancheng	2	1	2	2	2	2	2	1	2	2	2	2

Table A2. Analysis of the evolution mode of independent variables in 2015–2019.

City	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
Shanghai	4	4	3	4	3	4	4	3	4	4	3	4
Nanjing	4	3	3	4	3	4	4	3	4	4	4	4
Wuxi	3	3	3	4	3	3	4	3	3	3	3	4
Xuzhou	1	3	3	2	4	1	1	2	2	4	1	1
Changzhou	4	3	3	4	3	4	1	4	4	3	1	4
Suzhou-JS	3	3	4	4	3	3	3	3	3	4	4	4
Nantong	1	4	3	1	4	1	1	4	1	3	1	1
Lianyungang	2	3	1	2	2	2	2	1	1	1	2	2
Huai'an	2	2	4	1	1	2	1	2	1	1	1	2
Yancheng	1	2	2	1	1	1	1	1	1	1	2	1
Yangzhou	2	2	1	2	3	2	1	2	2	4	2	2
Zhenjiang	1	1	1	1	3	1	1	1	1	1	2	1
Taizhou-JS	1	2	2	1	3	1	2	1	2	1	2	1
Suqian	1	2	1	1	1	1	1	2	1	1	1	1
Hangzhou	4	4	4	4	3	4	4	3	4	4	3	4
Ningbo	4	3	4	4	3	4	4	3	3	3	3	4
Wenzhou	1	3	1	1	1	1	2	3	2	4	4	1
Jiaxing	1	2	2	1	3	1	2	3	1	4	1	1
Huzhou	1	2	1	2	1	1	2	1	2	1	1	1
Shaoxing	2	4	2	2	3	1	2	3	1	3	4	2
Jinhua	1	2	2	1	1	1	2	3	1	4	2	1
Quzhou	1	1	1	2	1	1	2	1	2	2	1	1
Zhoushan	2	1	1	2	3	2	2	1	2	1	1	2
Taizhou-ZJ	1	1	1	2	1	1	2	1	2	4	1	1
Lishui	1	2	2	1	1	1	2	1	1	2	1	1
Hefei	4	3	4	3	4	4	2	2	4	4	3	4
Wuhu	2	1	3	1	4	2	1	2	3	1	1	2
Bengbu	2	1	2	2	2	2	1	1	1	1	1	1
Huainan	2	1	2	2	1	2	1	2	2	2	2	2
Ma'anshan	2	1	1	1	4	2	2	1	4	2	1	1
Huaibei	2	1	2	2	1	2	1	2	1	2	1	2
Tongling	2	1	2	2	1	2	2	1	2	1	1	2
Anqing	1	2	2	2	2	1	1	2	2	1	1	1
Huangshan	2	1	2	2	2	2	1	2	1	2	1	1
Chuzhou	1	1	1	1	4	2	2	2	1	1	1	1
Fuyang	1	2	2	2	2	2	1	2	2	1	1	1
Suzhou-AH	1	2	1	1	2	1	1	2	1	2	1	1
Lu'an	2	1	1	2	2	2	1	2	1	2	1	1
Bozhou	1	2	1	2	2	1	1	2	1	2	1	2
Chizhou	2	1	1	1	2	1	2	1	1	1	1	1
Xuancheng	1	2	1	1	1	1	1	2	1	1	1	1

Table A3. Index data based on the max-min standardization method in 2010 and 2014.

City	Industrial Land		Added Value		Enterprise Assets	
	2010	2014	2010	2014	2010	2014
Shanghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Nanjing	0.2151	0.2256	0.2803	0.4414	0.2447	0.3024
Wuxi	0.0721	0.0896	0.2161	0.2293	0.1859	0.1798
Xuzhou	0.0430	0.0310	0.1297	0.1683	0.0856	0.1289
Changzhou	0.0512	0.0719	0.1791	0.2219	0.1642	0.1961
Suzhou-JS	0.2083	0.1752	0.2687	0.4334	0.2356	0.3457
Nantong	0.0718	0.0195	0.0989	0.1152	0.0701	0.0879
Lianyungang	0.0415	0.0589	0.0240	0.0465	0.0378	0.0563

Table A3. *Cont.*

City	Industrial Land		Added Value		Enterprise Assets	
	2010	2014	2010	2014	2010	2014
Huai'an	0.0581	0.0503	0.0524	0.0726	0.0280	0.0415
Yancheng	0.0345	0.0404	0.0414	0.0635	0.0255	0.0367
Yangzhou	0.0329	0.0461	0.0723	0.1440	0.0539	0.0809
Zhenjiang	0.0437	0.0440	0.0616	0.0790	0.0473	0.0631
Taizhou-JS	0.0342	0.0466	0.0417	0.0840	0.0353	0.0549
Suqian	0.0175	0.0244	0.0199	0.0304	0.0141	0.0313
Hangzhou	0.0816	0.1027	0.2966	0.3885	0.2885	0.3430
Ningbo	0.1645	0.1992	0.2300	0.2805	0.2173	0.2199
Wenzhou	0.0423	0.0005	0.0764	0.0888	0.0537	0.0372
Jiaxing	0.0327	0.0201	0.0351	0.0367	0.0398	0.0463
Huzhou	0.0431	0.0453	0.0390	0.0404	0.0313	0.0342
Shaoxing	0.0332	0.0814	0.0234	0.1495	0.0344	0.1623
Jinhua	0.0170	0.0192	0.0184	0.0172	0.0220	0.0177
Quzhou	0.0203	0.0257	0.0168	0.0147	0.0146	0.0198
Zhoushan	0.0053	0.0045	0.0208	0.0264	0.0265	0.0293
Taizhou-ZJ	0.0581	0.0701	0.0514	0.0581	0.0445	0.0403
Lishui	0.0000	0.0000	0.0031	0.0002	0.0073	0.0077
Hefei	0.0843	0.0968	0.1387	0.2177	0.0854	0.1184
Wuhu	0.0330	0.0125	0.0711	0.1004	0.0519	0.0855
Bengbu	0.0240	0.0236	0.0177	0.0363	0.0119	0.0208
Huainan	0.0163	0.0144	0.0307	0.0257	0.0609	0.0633
Ma'anshan	0.0385	0.0442	0.0571	0.0514	0.0412	0.0445
Huaibei	0.0211	0.0235	0.0272	0.0337	0.0368	0.0428
Tongling	0.0078	0.0121	0.0333	0.0399	0.0281	0.0360
Anqing	0.0278	0.0018	0.0140	0.0110	0.0070	0.0111
Huangshan	0.0033	0.0059	0.0014	0.0000	0.0000	0.0000
Chuzhou	0.0214	0.0353	0.0073	0.0122	0.0060	0.0094
Fuyang	0.0075	0.0166	0.0056	0.0086	0.0048	0.0082
Suzhou-AH	0.0131	0.0141	0.0068	0.0152	0.0050	0.0060
Lu'an	0.0116	0.0121	0.0000	0.0080	0.0028	0.0070
Bozhou	0.0060	0.0108	0.0028	0.0029	0.0007	0.0036
Chizhou	0.0024	0.0001	0.0035	0.0042	0.0031	0.0062
Xuancheng	0.0093	0.0148	0.0006	0.0009	0.0027	0.0023

Table A4. Index data based on the max-min standardization method in 2015 and 2020.

City	Industrial Land		Added Value		Enterprise Assets	
	2015	2019	2015	2019	2015	2019
Shanghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Nanjing	0.2133	0.1678	0.4899	0.4833	0.2950	0.2981
Wuxi	0.0887	0.1258	0.2391	0.2495	0.1766	0.2088
Xuzhou	0.0319	0.0855	0.1728	0.1344	0.1236	0.0718
Changzhou	0.0905	0.1597	0.2640	0.2842	0.2196	0.2101
Suzhou-JS	0.1716	0.2334	0.4455	0.3947	0.3402	0.3634
Nantong	0.0266	0.1116	0.1271	0.1445	0.0876	0.0772
Lianyungang	0.0657	0.0895	0.0552	0.0712	0.0592	0.0630
Huai'an	0.0681	0.0593	0.0836	0.0959	0.0466	0.0291
Yancheng	0.0578	0.0650	0.1026	0.0860	0.0618	0.0571
Yangzhou	0.0412	0.0646	0.1583	0.1440	0.0803	0.0631
Zhenjiang	0.0455	0.0672	0.0889	0.0699	0.0633	0.0411
Taizhou-JS	0.0544	0.0555	0.0917	0.0942	0.0576	0.0539
Suqian	0.0273	0.0472	0.0380	0.0396	0.0334	0.0216

Table A4. *Cont.*

City	Industrial Land		Added Value		Enterprise Assets	
	2015	2019	2015	2019	2015	2019
Hangzhou	0.1033	0.2250	0.4034	0.4238	0.3437	0.3779
Ningbo	0.1619	0.2394	0.2988	0.3192	0.2209	0.2616
Wenzhou	0.0035	0.0044	0.1009	0.0844	0.0331	0.0358
Jiaxing	0.0215	0.0568	0.0392	0.0546	0.0447	0.0538
Huzhou	0.0346	0.0507	0.0455	0.0584	0.0359	0.0425
Shaoxing	0.0829	0.1146	0.1574	0.1466	0.1498	0.1121
Jinhua	0.0198	0.0387	0.0207	0.0188	0.0187	0.0186
Quzhou	0.0272	0.0442	0.0169	0.0173	0.0222	0.0239
Zhoushan	0.0045	0.0036	0.0317	0.0220	0.0280	0.0207
Taizhou-ZJ	0.0400	0.0565	0.0615	0.0691	0.0413	0.0419
Lishui	0.0000	0.0000	0.0029	0.0000	0.0072	0.0059
Hefei	0.1020	0.1526	0.2357	0.2096	0.1432	0.1887
Wuhu	0.0132	0.0227	0.1067	0.0916	0.0893	0.0947
Bengbu	0.0258	0.0410	0.0430	0.0354	0.0257	0.0192
Huainan	0.0167	0.0268	0.0232	0.0189	0.0616	0.0252
Ma'anshan	0.0392	0.0578	0.0487	0.0500	0.0441	0.0498
Huaibei	0.0194	0.0282	0.0304	0.0102	0.0474	0.0133
Tongling	0.0122	0.0366	0.0477	0.0278	0.0387	0.0321
Anqing	0.0020	0.0439	0.0134	0.0194	0.0134	0.0108
Huangshan	0.0060	0.0109	0.0000	0.0006	0.0000	0.0000
Chuzhou	0.0364	0.0400	0.0177	0.0358	0.0127	0.0216
Fuyang	0.0212	0.0307	0.0109	0.0166	0.0102	0.0094
Suzhou-AH	0.0143	0.0259	0.0205	0.0195	0.0065	0.0115
Lu'an	0.0126	0.0171	0.0117	0.0123	0.0067	0.0048
Bozhou	0.0118	0.0186	0.0074	0.0157	0.0049	0.0122
Chizhou	0.0003	0.0035	0.0078	0.0091	0.0060	0.0062
Xuancheng	0.0151	0.0250	0.0036	0.0041	0.0002	0.0057

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Article

The Value of Farmland and Its Determinants—The Current State of the Art

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Abstract: This article aims to perform a literature review on the topic of farmland valuation, covering the determinants of farmland value and the models that are used to price land. To do so, recent literature on the topic was combined with classical and well-known papers. All the factors considered in these papers to explain farmland prices and/or to model them were retrieved, presented, and compared. Then, the main models proposed in the literature are presented and their suitability and goals are explained. This study can help academics as it gives an overview of the current state of the art, summarizes the main factors proposed by researchers to explain farmland prices, and sheds light on new lines of research. Besides that, it is also relevant for policymakers because farmland valuation and its use have implications on society and on urban planning, which is a hot topic under discussion.

Keywords: farmland valuation; urban pressure; farmland price determinants; hedonic valuation models; econometric models

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1. Introduction

The existence of arable land has been galvanizing the development of mankind for generations. It is no coincidence that throughout time, major cities were formed in prosperous and fertile land, following the well-known Von Thünen model [1]. Indeed, in Ref. [2] it is argued that for a long time the main sources of wealth in the western world were property and agriculture. Presently, the agricultural land market is key for the sustainable development of rural areas [3]. In Ref. [4], it was observed that the agro-industry was hurt by COVID-19 because agricultural producers took losses due to their strong dependency on imported phytopharmaceutical products and equipment. Moreover, mankind's production of food and model of consumption needs areas available for agriculture and livestock and nationwide policies to manage agricultural soils [5]. In that study, it is also mentioned that it is important that human activity of hunting in wildlife areas and the wildlife commerce are controlled and have proper areas for their practice. Thus, it is also necessary to have public policies to manage soils.

Farmland is the livelihood of many people across the globe, such as agricultural and livestock producers, developers, and investors. These, and in due course, government officials, would all benefit from understanding what triggers farmland price volatility and knowing the factors that influence farmland prices [6]. Farmland accounts for 85% of the asset base of the USA's farm sector; consequently, any changes in farmland values have enormous implications for the financial health of this sector, in the biggest economy in the world [7]. Therefore, it becomes crucial in the modern world to appraise farmland accurately.

Traditional economic theory states that farmland values are determined by the discounted stream of future rents. So, in rural areas where agricultural land is only used for agricultural production, land prices are not influenced by the demand for its use in urban activities [6]. However, if there is the possibility of future development driven by urban necessities, then one needs to account for the expected return related to those changes in the current land value. Those necessities do not only include urban sprawl and expansion (e.g., [6]), but also the purchase of land for portfolio diversification (see [8]) and the push by urbanizations for developments capable of creating food and energy (see [9]). The market value of properties in areas where land-use changes are likely to occur intrinsically has an element of hope value [10]. Besides that, the amenity value of farmland is relevant. Not only are there natural amenities that influence the value of farmland, but also a land parcel itself may constitute a natural amenity for the surrounding properties. Furthermore, there is not enough liquidity in the real estate market to keep its players updated, and information asymmetry enhances the differences between the property's value and its sale price [11]. This fact threatens the concept of fair value. Hence, traditional economic theory is only able to partially value farmland, because agricultural land values are driven by a complex set of factors [12].

Although agriculture plays a big role in economic development and sustainability, agricultural producers are less keen to remain in the sector because of its increasingly challenging environment [13]. The continuity of the sector depends on the funding of their projects, preferably by using agricultural land as collateral [13]. Thus, farmland valuation becomes essential for all the people involved in the process: not only the farmers, but also financiers, investors, and ultimately consumers.

Farm real estate is a significant source of value in the farming sector and in the typical investment portfolios of families that live off agriculture [14]. Also, changes in the values of farm real estate have significant implications on the sector's health and the households' well-being because nearly a quarter of agricultural lands in the USA are subject to urban influences and consequently to the changes in the demand of residential markets [14]. Furthermore, real estate is often used in investment portfolios because it lowers risk while offering returns. In a study for New Zealand, it is confirmed that the risk-return trade-off of portfolios of financial assets can be improved if farm real estate is included in them since the diversification benefits are robust under high and low inflationary periods [8]. Moreover, farm real estate is a consistent part of risk efficient portfolios, as the risk reduction benefits of diversifying with farm real estate outweigh the risk enhancement benefits. The results show that farm real estate is more of a risk-reducer rather than a return-enhancer in a globally diversified portfolio [8]. However, there are some factors brought in by other researchers that are contrary to this view. For example, in a mixed-asset portfolio, the autocorrelation in the returns of agricultural land increases risk in the long run, which results in a lower diversification effect when compared to other traditional investment assets [15]. For the authors, given farmland's illiquidity, indivisibility, and high transaction costs, investors could select it for a longer retention period, but it is precisely during that period that autocorrelation and risk become significant.

Despite its relevance, in a study for Portugal, it is stated that the valuation of farmland is not popular among professionals and it is difficult to justify its different prices [16]. Since individuals rely heavily on experts to make decisions in the real estate market [11] and farmland valuation is difficult, the pathway for information asymmetry is formed. The lack of information, together with the differences in the search for land and bargaining costs in agricultural land impact price dispersion [17]. In the same study, it is claimed that information asymmetry causes an uneven playing field because when it is present institutional sellers can sell with markups whereas other sellers incur losses. Besides that, the authors also state that local farmers and buyers have an edge in the level of information they have on a property and take advantage of it, obtaining lower prices and search costs. So, it is suggested that other sellers could eventually halve their costs due to the lack of information if they were more professional and that tenant-buyers can benefit from informational advantages during the harvest season [17]. The significance of the characteristics of buyers and sellers in information asymmetry is also examined in [18], who determined that social and economic factors impact information asymmetry because realtors avoid making deals with clients who resort to credit, live far from the property, or look for cheap assets. Moreover, blindly trusting expert opinions to track the farm real estate conditions induces measurement errors labeled appraisal smoothing, which may negatively impact investment decisions and policy in agriculture [19].

Furthermore, at the time of the study in [20], the valuation of farmland was regaining interest because of tax adjustments, the purchase of land for public building and social purposes, and because it is necessary when the owners wish to claim EU grants. This last factor becomes even more pertinent today, as the EU's financial stimulus in reaction to the COVID-19 pandemic and subsequent crisis is the biggest ever in Europe [21]. Additionally, the growing demand for land for urban use impacts society as a whole. An example of that is the region of Flanders, where the remaining open spaces are being pressured by urbanization to deliver food and biomass, but not always with success for the society [9]. The societal impacts also include health. Residents of more compact urban counties show better health indicators because the urban environment encourages health-related good behaviors, while urban sprawl is often associated with obesity, hypertension, diabetes, and the low number of minutes walked [22]. Control in generalized urban sprawl is necessary, as it lacks accessibility and open spaces, and conveys exaggerated public spending and loss of resource lands [23]. However, there are ways to preserve farmland in the face of urbanization, according to [24]. In his article, the author provides a representative example of Oregon's policies, where there are exclusive farm use zones, boundaries for urban and exurban sprawl, and tax incentives for farmers to keep their activity. In a more recent article ([9]), it is mentioned that the optimal land use depends on the location and socio-economic context of the land and denotes the difference in regions with high and low population densities: in the former, cultural values are becoming more important for post-production rural development, while for the latter an exclusively production-oriented philosophy is preferred. For the authors, this is one of the aspects that shifts the preference toward more unconventional land-use alternatives, which integrate agro-ecological production with nature development. These shifts in the preference for land use and the aforementioned tax incentives are relevant for farmland valuation since policy changes impact land price because the prospects for that land are changed [25].

There is a gap in the literature on farmland valuation, according to [26]. The authors suggest that the current state of the art lacks sufficient detail on farm management and agronomic conditions, and the heterogeneity in behavioral constraints, and suggest incorporating learning and collective structures, and modeling complex adaptive systems. The literature, according to the authors, also needs articles that work on farm interaction and incorporate spatial dimensions: interactions should be modeled directly and established on empirical data, and researchers must use statistically sound methods to initialize the population, including its positioning in space. Moreover, land valuation can be inaccurate because of factors of a methodological, technical, and legal nature.

2. Materials and Methods

Considering the relevance of the topic, the aim of this literature review is to present the current state of the art on the topic of the value of farmland and its determinants. To do so, a literature review was conducted based on more than 50 research items, which are cited in this article. Following the lines of the present introduction, in Section 2, we delve into the factors presented in the literature that are utilized to explain the value of farmland, which are in line with the factors that researchers use in models they construct to value farmland. These factors will start by being exhibited, alongside the authors that mention them or use them in their valuation models. Then, the researchers' conclusions about those factors will be compared. This section is also meant to name the models used in farmland valuation and to see their limitations. Then, Section 3 is dedicated to the results and discussion. Here, the main results of the methodologies presented in Section 2 are presented and compared and some implications are discussed. Last but not least, in Section 4, the main conclusions on the topic of farmland valuation will be drawn.

It is known that valuing land can be a difficult task because many variables may influence farmland value. As previously mentioned, the value of land in rural areas goes beyond its discounted stream of agricultural rents or net returns. The literature on the topic of farmland valuation puts forward many factors which impact the value of farmland. While some researchers mention their effect, others build models to evaluate it. It is also possible to, for instance, measure the amenity benefits of farmland (e.g., [27]) and study the transfer of development rights (e.g., [28]).

However, in Table 1, our goal is to present the factors mentioned in the covered literature that are utilized to explain the value of the land. Therefore, no distinction is made between the methodology of the studies, as it is intended to go through the main factors in the literature first.

Table 1. Factors that impact farmland value and supporting literature.

Variables	**Sources**
A—Seller/Owner characteristics	[3,17,29–32].
B—Buyer characteristics	[17,30,31,33].
C—Location (including the characteristics of the neighborhood—industrial, commercial, agricultural, . . .)	[2,3,12,16,17,29,30,32–37].
D—Distance	[3,12,16,20,28,30,33,37–41].
E—Travel time	[12,33,35,42].
F—Farm income	[12,31,33,38,42–46]
G—Cultivated crops	[3,6,7,20,28,29,33,45].
H—Good access	[3,6,16,17,20,28,30,34–36,39,41,47].
I—Macroeconomic conditions	[7,32,38,42–44,48].
L—Land characteristics	
L1—Water rights	[7,16,30,34,36,45,47,49–51].
L2—Soil productivity	[2,3,6,17,20,28–30,33–37,41,45,50,52].
L3—Climate	[2,17,20,29,32,39,43,49].
L4—Tree cover	[12].
O—Other	Percentage of non-farm employment in manufacturing [6]; Percentages of people below the poverty line, agriculture in the state's GDP, and non-agricultural workers in the state [47]; Hunting licenses per square mile [12]; Debt to asset ratio and consumer distress [43]; Per capita income in each county [2,42]; Tenant farmer legislation [33].
R—Environment	[2,3,29,45].
S—Size	[6,12,16,17,28,33,34,37,41,45,49,50].
T—Date or time	[28,42].
U—Population	[2,6,12,33,38,45,47].
U'—Population growth	[6,42,49].
V—Property characteristics	
V1—Fence	[16,20].

Table 1. *Cont.*

Variables	Sources
V2—Infrastructure	[16,20,33,49].
V3—Geometry of the plot	[3,20,39,41].
V4—Unevenness of the plot	[3,20,39,50,52].
V5—Immediate and future development potential	[3,12,28,33,35,40,44,50].
W—Loss of farmland to sprawl	[6].
X—Government/Other subsidies	[17,29,32,38,43,44,53].
Y—Farm yields or production	[6,20,29,36,42,44,47,48].

Source: Own elaboration.

As for Table 1, it should be noticed that macroeconomic conditions include mentions of interest rates, annual returns on investment in the S&P 500 index as a proxy of the economy, and commodity price volatility. According to [43], the farmland option values per acre are positively related to inflation, commodity price volatility, weather, S&P500 annual return, and GDP; and are negatively related to the home price index and consumer distress index. On the other hand, although there is a consensus on the impact of inflation on the value of farmland, it was found to be irrelevant in the study [44]. Besides that, there are superscripts in the sources that correspond to [47] because this paper analyzes the Indian territory on two different levels: (1) corresponds to the study conducted for the district and village levels, and (2) to the all-India level. The authors discovered that the most important factors that influenced land prices on a village level were population density, road density, distance to the nearest town, percentage of people living below the poverty line, crop yield, non-agriculture share in the state's GDP, and workers in the non-agricultural sector as a ratio of agricultural workers. On a district level, the demand for more land from urban areas plays a big role in farmland prices, as industrialization and tourism drive the expansion of cities [47]. Interest rates are another macroeconomic factor that should be considered to explain real estate, and in particular, farmland prices [48]. Low interest rates allow investors to finance themselves at a cheaper price. Therefore, there is more demand and prices increase. On the other hand, with high interest rates, money becomes more expensive to borrow and demand decreases. Moreover, the increase in marked-to-market mortgages may increase the supply in the real estate market. So, in such a scenario, prices are expected to decrease.

An example of a paper that includes both the seller's and the buyer's characteristics is [17], as it was aforementioned. This subject is also tackled by [30], where the author states that farmland is exchanged at a lower price when both market participants are individuals (ceteris paribus) because when one of the parties is a corporation, due to its liquidity, the transaction occurs closer to the time of conversion to urban use. The authors of [31] introduce the characteristics of buyers and sellers in the model's equilibrium, in which the increase in a farmer's bid given a marginal increase in one of the characteristics must be equal to the increase in the market of the parcel's rent with a marginal improvement in that characteristic, or the farmer would profit by using land with different characteristics. Another condition is added in equilibrium: the farmer's total bid must equal the parcel's rental price. Since different farmers have different skills, the bid function is not equal to the hedonic price and locational preferences emerge [31].

Observing Table 1, it is important to note the characteristic called "T—date or time". The sale date was included, for example, in Ref. [28], as additional data that could impact selling prices. However, the authors do not mention any direct relation between it and selling prices. Furthermore, the discount stream of agricultural rents, which according to traditional economic theory determines farmland values, is mostly dependent on interest rates and/or inflation, so the impact of the transaction date on farmland prices is expected to be captured by other macroeconomic factors.

The location also impacts farmland value in different ways depending on its price range [29]. It is explained in Ref. [29] that at a higher price range of farmland, natural amenity heavily impacts the value because it is more "luxury" than "necessity". Attributes such as water area as a proportion of the total county area and high-value crop farms are also "luxury". At lower quantiles, land retirement programs positively impact farmland values [29].

The factor named distance generally comprises the inclusion of the distance to the nearest town, city, or metropolitan area in the study. However, in Ref. [12], the distance to services and recreational areas is also included. Curiously, the authors find that proximity to urban areas on land values is not statistically significant, as measured by the driving time to small and large town centers. Therefore, population interaction and development pressure can be more useful in explaining agricultural land values than simply the distance to an urban area [12]. This disagrees with the findings in [33], who conclude that farmland prices decrease steeply with distance when they are close to the city and then gently further away using an econometric approach. The authors were even able to study the gradient at which agricultural markets respond to distance from the city. The distance to technological centers and sales markets is also included in a study that uses fuzzy logic theory [3]. Furthermore, a peculiar finding in Ref. [42] is also included in the category of distance. The authors conduct a study where they include not only the distance to the nearest metropolitan area but also the second nearest metropolitan area, in the New York region. As expected, an increase in the distance to the closest metropolitan area is correlated with a decrease in land value, but land values increase when the distance to the second nearest metropolitan area increases, as is also the case for travel times [42].

Whether land has good access or not also impacts its value, according to the literature. For example, in Ref. [30] it is argued that the effect of distance to the nearest town on land price may be reduced in part by the location of parcels relative to the boundaries of incorporated towns, as closeness to such areas increases farmland prices by 40%. The author presented an example that considers the parcels located on non-township roads and with good access to motorways are also more expensive.

Logically, the value of farmland in the urban fringe is impacted by immediate and future development potential. The urban fringe is defined in Ref. [30] as the areas that border central cities and that consist of the surrounding close-in suburbs and non-contiguous nearby towns, extending into the adjacent, open countryside. However, apart from distance, location, and travel times, other characteristics measure immediate and future development potential, which is the reason why there is also a category named after that factor. For example, the per-acre premium related to entitlements: one-home-site entitlement increases the value of an agricultural parcel by 130,000$ [28]. The expectation of future development can go beyond the distance to the closest city or metropolitan area, and that expectation influences the farmland price [40,50].

The main task when valuating land is to identify the variables, which affect its value [20]. So far, some variables which are present and common in the literature are identified alongside their sources. Having checked those variables, some studies build models to value land. The following subsections are intended to ascertain the models that are utilized in the literature and their applicability, performance, and shortcomings.

2.1. Hedonic Valuation Models

The hedonic methodology can be traced back to 1939 and became widely used in the 1960s, according to [31]. The author also states that the hedonic methodology received a theoretical model that consolidates the empirical techniques in 1974. Economists started using the hedonic price method to value farmland amenities in the late 1990s [54]. Hedonic pricing can be used to estimate the values of individual farmland characteristics [6] and allows for a more explicit model of the complex set of attributes that form the basis for farmland valuation [12]. Therefore, hedonic valuation models are widely used in the literature, due to the fact that they are well-established and easily applied.

An example of such a model is the one developed in Ref. [16] for farmland valuation in Portugal. The hedonic valuation model shows that there are factors that impact the farmland's value, besides the factors which include the quality of the soil and other characteristics that generate a certain cash flow for that land [16]. The authors explicitly included those factors, such as proximity to highly populated areas, population density, and possible land use, in the hedonic pricing model, and they could explain why asking square meter prices change so much, for all the studied land sizes (up to 100.000 square meters).

In Ref. [6], farmland values are also modeled as a hedonic function of factors that include the location (proximity to metropolitan areas), physical land characteristics, and the potential of converting farmland to alternative uses. The authors included dummy variables to measure the influence of urban access on farmland prices for sales in non-metropolitan areas and the natural logarithm of the land's price per square meter as the target.

In Ref. [12], the authors decided to take a slightly different approach to the hedonic price model. Since the authors intended to model both the agricultural and non-agricultural determinants of farmland values, they think of the portion of farmland's market value not attributed to agricultural use as a "residual" value. This regression shows the degree to which non-agricultural factors explain the portion of land values not attributed to agricultural returns [12]. To account for spatial dependence and spatial autocorrelation, the authors use spatial fixed effects and spatial error clustering. Another study [34] used the same methodology, achieving results in agreement with the aforementioned study; the hedonic price model is also utilized to estimate the impact on the price of Chilean farmland of the following variables: size, soil quality, water rights, connectivity (distance to the nearest paved road) and location.

The hedonic price model is also used in [30] to ascertain the natural and man-made factors that impact farmland prices in an urban fringe market. This model is adequate because it identifies the specific characteristics of different parcels, accommodating the heterogeneous qualities of land [30].

Although hedonic price models generally include a simple linear regression in their methodology, a different approach is carried out in Ref. [31]. In the article, the author starts with a hedonic price model for land rents and mentions that it does not need to be linear. Then, the bid function (payment the farmer is willing to pay for the use of a parcel) is derived and it depends on the characteristics of the parcel, the prices of outputs and other inputs, the desired profit level, and the farmer's production skills. The authors then proceed to derive conditions for equilibrium: the increase in a farmer's bid given a marginal increase in one of the characteristics must be equal to the increase in the market of the parcel's rent with a marginal improvement in that characteristic, and the farmer's total bid must equal the parcel's rental price. Since different farmers have different skills, the bid function is not equal to the hedonic price and locational preferences emerge [31].

2.2. Econometric Models

Econometric models, on the other hand, have been widely used in this subject, namely regarding the incidence of USA agricultural subsidies on farmland rental rates, according to [46]. In their study, the authors apply a general spatial model that combines a spatial lag and a spatial error model and justify that it is necessary to obtain consistent results. An econometric model is also built in [42], now for the price of farmland, using the average per-acre net return from agricultural land, the population change in the two nearest metropolitan areas, the travel times to those areas, and the per-capita income of the county. Essentially, what the authors were able to grasp was the impact of urban pressure on farmland values. An interesting approach to ascertain the urban influence on farmland prices is also undertaken in [33]. The utilized methodology is also an econometric model, which was revealed to be suitable for this task.

In a study for Midwest [48], the authors use an econometric approach and state that farmland has grown in value due to low interest rates, an increase in the demand for grains and lower stocks. These authors conclude that there is some speculation, especially for high and medium-quality land, which is in agreement with the warnings made in [33].

2.3. Other Alternative Models

So far, the literature on farmland valuation using hedonic pricing models and econometric models has been addressed. However, other valid and adequate models should also be presented. For instance, multiple correspondence analysis (MCA) is widely used in social sciences, and the authors of [20] state that it is an adequate method for farmland valuation in Spain due to the possibility of multicollinearity and redundant information. Using this method, followed by a linear model with the variables that resulted from MCA, the authors managed to build a simple model with R-square values greater than 0.92.

A semi-parametric quantile regression was used in [29], which according to the authors has advantages over the conventional ordinary least squares method. Namely, it provides a more complete picture of the conditional distributions of a dependent variable given a set of regressors, it is more robust to outliers, it can be more efficient when the error is non-normal, and heteroskedasticity can be conveniently analyzed by estimating quantile regressions. This method allowed the authors to group explanatory variables into "luxury" or "necessity" factors and to verify spatial differences in farmland values.

A Samuelson-McKean model is proposed in [10], which is an option pricing model, to determine the hope value of farmland. In this article, the authors prove its efficacy in the valuation of land plots with development potential. The application of an option pricing model is also seen in [43], a study that uses a real options approach for the farmland market of Illinois.

Furthermore, the authors of [3] propose the application of fuzzy logic theory to valuate agricultural lands. This method is cheap, efficient, and transparent throughout the entire valuation procedure; thus it is useful in a limited market with an insufficient number of sales transactions or in underdeveloped regions.

In Ref. [54], a literature review work on amenity values generated by farmland, the authors indicate that contingent valuation studies were widely used in the 1980s to estimate willingness to pay to protect farmland. In Ref. [27], the authors estimated the amenity value of horse farmland in Kentucky using the contingent valuation and the hedonic pricing model methods. A different approach is taken in [38], using a so-called gravity model, based on the idea from Marketing research that the attraction of retail between two cities is proportional to their populations and inversely proportional to the square of the distance between both cities. The authors successfully grasp the urban impact on land prices of farmland located in the rural-urban fringe, as their model explains more than 95% of the variations in farmland prices. A classic and simple methodology is proposed by the authors of [6], who state that according to economic theory, farmland values are based on the expected economic returns. Thus, net present value models are usually used to evaluate farmland values. In these models, the net present value of farmland represents the sum of all future income streams from farming, accounting for the difference between the value of money today and at some future date [6]. The authors of [6] also note that farmland values are based on expected returns, not necessarily historical revenues. These observations are backed by another study [42], which states that in a competitive land market, the price for land equals the present discounted value of the stream of future rent.

3. Results and Discussion

3.1. Results of the Methodologies

In this subsection, we list the main conclusions and results of farmland valuation using the aforementioned methodologies.

Something that is a result of many studies is the impact of urban necessities on farmland value. For instance, using a hedonic valuation model, the authors of [12] state that development potential and population interaction are significant determinants of market value, as a 1% increase in the land area subject to immediate development potential has a

0.43% increase in cropland values and a 0.74% increase in pastureland values. Moreover, future development potential shows similar premiums [12]. In fact, with a similar methodology, in Ref. [34] it is seen that the most important attribute is the location of farmland and the second most important attribute is the quality of the land, and that both have a double-digit percent impact on the price of farmland. The importance of the location of farmland reflects the market's preference for places where non-farm profits can be obtained from a future real estate development, while the remaining variables are of little impact, according to the authors. The distance to paved roads and the parcel's size slightly decrease the value of land, while the impact of water rights on farmland prices is only marginally positive [34]. However, according to a previous study [35], farmland values tend to be higher near urban areas for more reasons, apart from susceptibility to development pressures. Those reasons, according to the authors, include the soil's productivity, as many urban centers initially grew among particularly fertile soils, greater access to markets and ports and therefore lower transportation costs, and recreational opportunities and lifestyle amenities offered at the urban fringe to the nearby population. As a consequence, farmland values are higher in urban-influenced areas with a premium at the median of approximately USD 2000 per acre [35]. A hedonic valuation model [30] also allows concluding that neighboring waters impact farmland prices negatively because they increase the risk of floods or present unacceptable levels of water quality, and the uses of neighboring land significantly impact urban fringe farmland prices. The insertion of land in an industrial/commercial zone increases its value by 28% over agriculturally zoned land [30].

Econometric approaches validate the previous methodology's conclusions on the impact of urban pressure on farmland value. For instance, in a study for New York [42], the authors found that since land development is perceived as imminent due to higher rates of population change, land values increase. An increase of 1000 people in the rate of population change in the nearest metropolitan area increases the land value by USD 97 per acre; similarly, the corresponding number for the second-nearest metropolitan area is USD 101 per acre [42]. The conclusions in Ref. [42] are backed by another study where an econometric model is used [33]. According to the authors, in peri-urban areas, since farmland is expected to be converted to urban uses which are translated into potential capital gains from such development, farmland prices decrease with distance to cities. More specifically, in Ref. [33] it is found that farmland prices are only determined by agricultural factors far from urban influence, approximately 35–40 km away from the closest city. It is also stated that for land for residential use, the land price decrease per kilometer is -12.8% at the urban pole boundary, -3.3% at 20 km from the boundary, and almost flat at 35 km. Land rents were also studied by the authors, who concluded that the main determinant of land rent is the trade-off between commuting costs and land rent and that its impact is bigger than that of development expectations because once there is residential use, we are dealing with actual conversion instead of expectations. The limitation of urban sprawl caused by the ideas and policies of urban planners is the main driver of the farmland prices bubble, according to [33]. Thus, cities must be dense and surrounding rural areas must be preserved, and consequently, expectations of demand for new residential land will disappear [33]. Rental prices are also an object of study in Ref. [46], where it is seen that farmland rental prices are mainly influenced by the rental prices in the parcel's neighborhood and by regional livestock density, which are heavily influenced by agricultural policies.

Moreover, an option pricing method in Ref. [43] led to the conclusion that rising farmland values are primarily dependent on agricultural commodity prices and interest rates and that the farmland market value is also influenced by uncertainty about future growth and capital gains. Furthermore, the farmland option values per acre are positively related to the inflation rate, commodity price volatility, weather, S&P500 annual return, and GDP; and are negatively related to the home price index and consumer distress index [43].

A combination of hedonic pricing models and contingent valuation in Ref. [27] allowed concluding that Kentucky's residents feel that horse farms are a positive amenity, because of their cultural heritage, prettiness, and their service as an impediment to gentrification. Farmland itself generates positive externalities, and that is shown in both methods [27].

Like the authors of [33], who took on an econometric approach, the authors of [38] found that expectation adds more value to farmland than actual present returns, with a gravity model: a one-dollar increase of the net real returns to land from farming adds USD 0.74 to the value of farmland, while the expectation of a one-dollar growth in real capital gains increases farmland value by USD 1.27.

3.2. Comparison of the Methodologies

Hedonic pricing methods are arguably the most straightforward models to conceive and implement. In most standard cases, the researcher collects in the literature a set of impactful characteristics in farmland valuation and builds a simple regression model.

An example of a successful application of such a model is found in [6]. The model was significant at the 0.001 level, with an R-square value equal to 0.46, condition indices below 30, and no variable had two or more variance proportion values greater than 0.5 [6]. Therefore, multicollinearity was assumed not to be a problem and the methodology was appropriate, according to the authors. Hedonic pricing methods also allow for the usage of supplementary statistical treatment of the data. As was mentioned before, an example of that is found in Ref. [12], where the authors use cluster analysis to account for spatial autocorrelation.

A good alternative when there is a possibility of multicollinearity and redundant information is multiple correspondence analysis [20]. As seen in the previous section, in Ref. [29] a semi-parametric quantile regression is used, which is useful when the error is non-normal and to analyze any potential case of heteroskedasticity.

Spatial econometrics is a very robust way of seeing the impact of proximity to urban centers, for example. This variable is no ordinary example; across all the studies reviewed that include it, its impact was always measured to be positive. Since spatial econometrics is capable of grasping the spatial correlations and including them in the model, it is a strong and classical candidate to measure the impact of these factors, in particular.

3.3. Discussion

As for the determinants of farmland value, there is an agreement in some of the determinants, although the literature covered in this article often disagrees about the effects of some factors on farmland value.

Soil productivity is an example of a factor in which there is agreement about its positive impact on the farmland's value (see, for example, [6,29,41]). However, there is some disagreement about to which extent it is significant. On one hand, the types of soil and their diversity is the most important characteristic when valuing farmland, according to the authors of [41], and soil productivity's double-digit percent impact on farmland price is outlined in [34]. On the other hand, the authors of [30] observed that the soil productivity index is not statistically relevant because farmland transactions are mainly for speculative and urban purposes. Therefore, it is concluded that when valuing farmland, it is important to keep in mind its future use. The productivity of the soil is important if the land is used for agricultural purposes; on the contrary, if there is a potential for urban development, the impact of soil productivity on the farmland's value will be diluted.

Urban development pressure and potential are also driving factors of farmland prices, according to the literature. In this article, it was shown that, given a land parcel, researchers propose different measures of urban influence on it [20]; in Ref. [47], for example, the authors utilize the distance to the nearest urban center and observe its significant and positive impact on land prices. Distance to the urban fringe is also investigated by the authors of [33], who put a timespan for the conversion of farmland to urban use of roughly 30–50 years for parcels 5–40 km away from the urban fringe, in a non-linear form. An urban influence index that relates the size of the nearest urban pole and the distance to it was proposed by the authors of [38], who found out that a one-unit increase in the numerical value of that index will increase per acre real land value by $132.60. However, the authors of [12] warn that measuring population interaction can be more effective in explaining land prices than simply the distance to an urban area, and the authors of [54] state that there is no evidence to attest to the impact of distance on farmland amenity values. Furthermore, the proximity of farmland to urban centers affects both the development component of farmland values and agricultural rents, because places with better access to population centers have a larger share of high-value crops, which is consistent with the von Thünen formulation [55]. Moreover, when there are policies that prevent the conversion of farmland from agricultural to urban uses, farmland prices are not influenced by distance to the city [33]. This evidence indicates that each land plot must be attentively considered and looked into along with the existing legislation. Thus, researchers must be cautious when using distance when trying to measure the urban influence in a plot, as there can potentially exist multicollinearity issues, as the aforementioned observation in Ref. [55] points out.

The literature review conducted in this work shows the difficulty in developing a method for valuing and determining the factors that impact farmland value that can stand across time and different regions. Another example of such a factor is water rights or water irrigation. It is stated in a study [50] that the prices of irrigated lands, regardless of their productive orientation, are approximately twice the prices of dry lands. The authors of [29] have a different view, stating that the water area as a proportion of the total county area positively impacts farmland value because it is viewed as a "luxury" factor. On the other hand, it is observed in [30] that neighboring waters impact farmland prices negatively because they increase the risk of floods or present unacceptable levels of water quality. This example illustrates the necessity of integrating a factor with a variety of others that influence it. It is expected that irrigated lands are more valuable if they are located in an area where the climate is usually propitious to draughts, for example, so the climate should be taken into account.

Due to some characteristics of the farmland market, such as high transaction costs and low turnover, they have characteristics of inefficient markets [43]. That explains why plattage value (the value of breaking one larger parcel into several smaller parcels) exists in the market because of subdivision costs, the liquidity of the buyers, and the lack of market information held by the sellers [30]. The real estate market is not efficient and information asymmetry is a particular problem that buyers must face, as it is crucial to find both the positive and the negative aspects of a property [56]. If information asymmetries are correlated with hedonic characteristics, not acknowledging their implications can lead to inefficient estimation and biased coefficients for the hedonic function [17]. For example, heterogeneity is extremely common in Spanish orography, as geographically close districts do not share their main land features [20], which reveals how spatial autocorrelation might not always be as strong as expected. For buyers and sellers, this means that knowing the prices of properties sold in geographically close areas may not be a reliable source of information about the fair value of a given plot.

Therefore, appropriate and fair farmland valuation serves individuals and society as a whole. The urban fringe is a delicate problem because the remaining space must be used innovatively [9]. Moreover, with the urban development sprawl, conflict regarding land use in rural communities has grown [6]. The grassland ecosystems are in danger due to the expansion of their conversion to row crops, driven by commodity price increases, technological improvements, and agricultural policy [57]. Today, land use is a central concern in evaluating agri-environmental policies and the role of the government in agriculture is a major source of uncertainty affecting agricultural production and farmland markets [43]. This often leads to contradictory views by urban planners and policymakers. The process of the demand for the expansion of urban land increases the interest in single-family detached homes, which also require land for household support services (e.g., schools and shopping centers) [28]. Private investments must be channeled transparently and with a long-run vision for the implementation of sustainable urban land development, according to [58]. The author also reinforces the idea that the government must be involved to support this objective and achieve economic sustainability, providing funds to socially and environmentally sustainable realms.

4. Conclusions

The objective of this work was to highlight the importance of farmland valuation, break down the determinants of farmland prices and valuation, and describe some of the models and methodology used in the literature to value farmland.

Furthermore, this work is relevant for policymakers. At this point, it is important to remember that there is more to the value of farmland than simply the value of the land itself. From a social point of view, farmland is crucial to the people who live off it and to the industries that depend on it. Public policymakers and stakeholders must weigh both potential uses and returns: urban development and rural use. Therefore, in a certain region, it becomes essential for policymakers to know the value of farmland if it is exclusively used for urban development and if it is used to create jobs and value via farming. The topic of farmland valuation and the relationship between urban and rural poles must be studied together by academia and decision-makers because of the reasons stated above. As for academia, this topic of research is still open because this study must often be conducted on a micro-level for there to be an agreement about the determinants of farmland prices. Any future lines of work can use this article to ascertain which land features to use, as well as to see the models covered and their suitability to the work that is intended to be carried out. It is our belief that this article can be a good starting point for such studies due to the extensive amount of articles reviewed, the explanatory factors presented (which are extracted from those articles), and the introduction to several valuation models and their suitability for the desired research direction.

Starting from this literature review, in future work we intend to develop a multiple linear regression model through which we can test the dependent variables that impact the value of farmland. That model will allow the verification, in practical terms, of the value of the different agricultural properties, which, by comparing to the market prices, will allow inferring if the price is below or above the model's reference value.

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Article

Spatio-Temporal Evolution, Spillover Effects of Land Resource Use Efficiency in Urban Built-Up Area: A Further Analysis Based on Economic Agglomeration

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Abstract: The Chinese "New Normal" economic model is a national strategy for adapting to sustainable development and offers important implications for the development of new economies. The "New Normal" economic model aims at improving the use efficiency of land resources in the framework of sustainable development. A discussion of the spatio-temporal evolution of land resource use efficiency (LRUE) in urban built-up areas can help in better assessing LRUE. In this paper, the super-efficiency slack-based measure (Super-SBM) method and spatial econometric models are used to study 281 prefecture-level cities in China between 2004 and 2020. Further, this paper explores the relationship between economic agglomeration and LRUE, which is of great value in managing land resources. The results show that there is a spatial spillover in LRUE and a U-shaped relationship between it and economic agglomeration.

Keywords: economic agglomeration; urban built-up area; urban land resource; spatial econometric analysis

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1. Introduction

Since China's reform and opening-up policy was established in 1978, China's economy has been growing rapidly, the level of economic agglomeration has been continuously improving, and industries and population have shown a trend of concentration [1]. Despite the brilliant achievements in the economy, many problems such as resource depletion [2], low land utilization rate [3], serious environmental pollution [4,5], and uneven regional development [6] have arisen. After the 18th National Congress of the Communist Party of China, Chinese President Xi Jinping has brought forth a concept of the "New Normal" on various occasions. As China's economy is gradually entering the new normal stage of a medium to high rate of growth, sustainable development has become one of the core policies of the Chinese government for the environment and the economy [7]. The extensive economic development model of the past has had difficulty promoting the sustained and healthy development of China's economy or has even caused huge losses [8]. Therefore, solving the distribution issues and environmental problems in the process of economic development has become a major strategic goal of China's sustainable development.

The increase in land resource use efficiency (LRUE) should not solely be bounded by improving the economic output of land resources, but it should include ecological protection measures as part of the evaluation. The perspective of development at the cost of land resources loss and urban ecological environment pollution has been facing difficulties in meeting the requirements of high-quality economic development under the era of the "New Normal" [9]. Land resource use efficiency has become a key indicator for formulating economic and environmental development policies in many countries and regions, and it has begun to play an increasingly important role in measuring the efficiency of economic activities in relation to natural resources and the environment [10].

The rapid growth of China's economy in the past is closely related to economic agglomeration. According to the seventh national population census in 2020, compared with the sixth national population census in 2010, China's floating population has increased beyond expectations in the past ten years, and the population has continued to flood into big cities and metropolitan areas. However, while promoting economic growth, economic agglomeration, as a compact economic behavior, also has some negative externalities. For individuals at the micro level, the advantages brought by agglomeration such as productivity increase and economic aggregate growth can be barely felt in the short term, while it is very intuitive to feel the environmental pollution, traffic congestion, and other problems. Therefore, exploiting the relationship between economic agglomeration and urban land resource utilization not only is an action serving the needs of national development strategies, but also has important guiding significance for developing countries rationally allocating land resources and guiding the agglomeration of production factors and ecological construction [11].

In the past, a large number of studies have focused on the formation factors of economic agglomeration and the measure of land use efficiency, and there are few related studies for the relationship between both in China. On top of summarizing the existing economic agglomeration and land use efficiency-related theory and research, this thesis conducts an analysis of economic agglomeration under the influence of various scales for land use efficiency to establish a framework for theoretical connections. Based on the comprehensive use of the location theory, externality theory, new economic geography theory, and economic growth theory, through the study of the effect on post-economic agglomeration formation, this thesis analyzes the intrinsic mechanism between economic agglomeration and LRUE and tries to clarify the transmission pathway of economic agglomeration toward LRUE to provide important theoretical support for ecological environment facilitation, social equality, and economic development coordination.

The possible marginal contributions of this paper are as follows: (1) This study examines the spatial effects of economic agglomeration on LRUE in urban built-up areas at different scales, which enriches the relevant studies on LRUE. Moreover, the study passed the Moran's I test, robustness test, and IV method test, which made the results more reliable. (2) This study clarifies the transmission paths through which economic agglomeration improves LRUE, i.e., the scale effect, the knowledge spillover effect, and the crowding effect. In addition, this paper further examines the regional heterogeneity of economic agglomeration and LRUE.

In the next section, we review relevant studies and bring forward research ideas of our own. Section 3 describes the method, variable design, and data sources. Section 4 reports the regression results of the spatial econometric model and a series of tests. Section 5 discusses the spatio-temporal evolution characteristics of LRUE and the spatial spillover phenomenon and proposes corresponding policy recommendations.

2. Literature Review

2.1. Basic Concept

2.1.1. Economic Agglomeration

Scholars already have a relatively full understanding of the reasons for the formation of economic agglomeration. Early literature holds the view that agglomeration usually occurs in areas with superior geographical environments and abundant resource endowments [12–14]. Krugman took spatial factors into the category of economics and changed the assumption of a constant return to scale in traditional economics into that the return to scale is increasing instead [15]. The positive externalities brought by economies of scale are an important factor attracting similar enterprises to gather together in one place, tempting a greater labor force and more industries to enter [16–18]. In addition to the increasing return to scale, transportation cost is also an important factor affecting agglomeration in the new economic geography theory [19,20]. Increasing return to scale and transportation cost saving are both from the perspective of the supplying side when it comes to the formation of economic agglomeration, as well as market demand [16,21]. Meanwhile, knowledge spillover is also an endogenous and important factor [22–24].

In addition, some scholars mention that institutional factors also play certain roles in promoting the formation of economic agglomeration. After the emergence of the new economic geography, the study of the correlation between geography and economic factors continued for a long time, which lead to the ignorance of how the policy system may have an impact on economic development. In addition, due to various national conditions, in some countries (such as the United States), the impact of trade protectionism among regions on regional trader protection policy is not severe [25]. In China, however, the impact of policies and regulations is quite obvious [26,27].

2.1.2. Land Resource Use Efficiency

Considerable research on LRUE has been conducted by scholars, mainly on the following two aspects:

Measurement and evaluation of LRUE. Conventional measurement of LRUE is mainly based on the single-factor evaluation method, which is simple and efficient, but it cannot reflect the efficiency relationship among multiple inputs and multiple outputs in the process of urban land resource use. The data envelopment analysis (DEA) model is a common method that can better deal with the relationship between input–output factors. Based on this, the DEA-SBM model [28,29] and the Super-SBM model [30,31] further remedy the problem that the efficiency of multiple DMUs had. At the level of research objectives, it contains the usage of watershed [9], provincial [32], city [33], and county [34] objectives. The Super-SBM model can solve the comparison and sequencing problems that appear to be in the forefront of the study of the efficiency of multiple land resource uses.

Driving-factor analysis of LRUE. Existing studies have focused more on the economic benefits generated by land resources, and less on their impact on ecosystems. This impact is worthy of attention [35], and the inclusion of undesired outputs in the LRUE evaluation system would lead to more valid conclusions [31]. In terms of research models, the traditional linear regression model was gradually shifted to the spatial measurement model based on spatial factors, and the Tobit regression model and spatial lag model [36] were used to explore the driving factors of LRUE.

2.2. The Effects of Economic Agglomeration on Land Resource Use Efficiency

The idea of the crowding effect argues that economic agglomeration will worsen types of environmental pollution such as water pollution [37,38] and carbon pollution [39]. It is considered that the agglomeration process inevitably generates production and domestic waste, leading to increased pollution. From the perspective of the "pollution heaven hypothesis", different regions place different emphases on environmental management, resulting in different levels of pollution from economic agglomeration. To reduce the cost of pollution control, pollution-intensive firms prefer to move to areas with weaker environmental controls, thus creating agglomerations [40–42]. From a "race to the bottom" perspective, local governments may selectively relax environmental regulations for the sake of fiscal revenue. This has led to environmental degradation in the surrounding area and a vicious cycle process that has led to region-wide environmental degradation [43–46].

On the other hand, some scholars argue that economic agglomeration contributes to green development. Economic agglomeration will link the upstream and downstream of the industrial chain, increasing the efficiency of resource use and indirectly reducing energy consumption and pollution. At the same time, a dense population will reduce the marginal consumption of resources [47,48].

Through the literature review, we have identified three main routes through which economic agglomeration has an impact on LRUE. (1) Production cost saving effect: Economic agglomeration leads to the gradual improvement of certain industries in terms of information transfer, infrastructure sharing, and service systems, thus significantly reducing transaction costs (in terms of management, financing, and marketing) [49,50]. (2) Scale economy effect: The scale economy effect is an important element of the new economic geography and spatial economics [15]. It emphasizes that the division of labor and regional differentiation contribute to the formation of economic agglomerations, which in turn generate multiplier effects. In this process, land resources will gradually reach their optimum value in terms of economies of scale. (3) Knowledge spillover effects: On the one hand, the clustering of similar enterprises helps them to exchange and share knowledge and information, thus creating spillover effects [51]; on the other hand, the clustering of different industries in the same region helps to form a pattern of industrial diversification, thus stimulating knowledge and technology spillover effects [52]. In addition, excessive agglomeration may also lead to resource scarcity, which increases production costs and reduces LRUE [53,54].

2.3. Review and Hypotheses

In summary, although a large number of studies focused on economic agglomeration and its mechanism of influence, little attention has been paid to the issue of whether China's economic agglomeration improves LRUE. There is no unified conclusion about how economic agglomeration influences LRUE. Specifically for land resources (urban land in built-up areas), the carrier of urban development, research on how economic agglomeration affects LRUE is still in the exploratory stage. Urban economic agglomeration directly affects the intensity and direction of resource input (Figure 1): when more of the agglomeration area is devoted to economic development while the ecological environment is ignored, the production of industrial and domestic wastes is facilitated, thus restraining the ecological efficiency of land. However, when the economy develops to a certain stage, the technological innovation ability will be stronger in the region and the industrial structure will be optimized; under the guidance of policies and regulations, the land utilization rate and ecological environment will be gradually improved. In addition, previous studies mostly used a single model on the relationship between economic agglomeration and LRUE, ignoring that there may be both linear and nonlinear, direct and complicated relationships. Based on the above analysis, this thesis puts forward the following hypotheses:

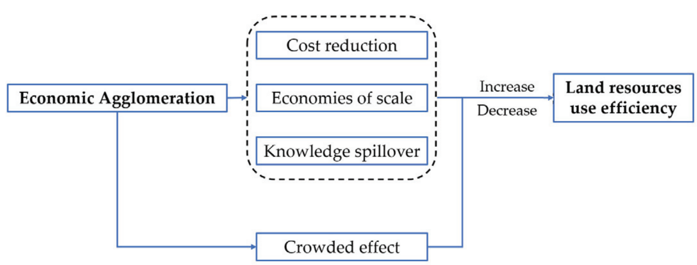

Figure 1. Influencing path of economic agglomeration on land resource use efficiency.

Hypothesis 1. *LRUE has spillover effects.*

Hypothesis 2. *There is a U-shaped relationship between economic agglomeration and LRUE.*

3. Methods and Research Data

3.1. Methods

3.1.1. Moran's I Index

The spatial autocorrelation test is the precondition of spatial econometric models, which determine whether variables are spatially dependent. Spatial autocorrelation tests are divided into overall autocorrelation experiments and partial autocorrelation experiments to analyze whether there is an overall spatial autocorrelation [55]. The range of Moran's

I index is [−1,1]. A Moran's I index in the range of (0,1] indicates that each variable has a positive correlation over the whole region; otherwise, the variable has a negative correlation over the whole region. If Moran's I index is equal to 0, the variable is not correlated over the whole region. The Moran's I index is calculated as follows:

$$\text{Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}}, \tag{1}$$

x_i represents the observed value of each region; $\overline{x}$ represents the mean of the sample; s^2 represents the variance of the sample; W_{ij} represents the binary spatial weight matrix (whether the region i borders with region j).

3.1.2. Spatial Econometric Model

According to the first law of geography, the closer the distance, the stronger the correlation is. There are interactive effects on the economic behavior of each region: the closer the distance is among regions, the stronger the interactions are. Therefore, when studying the relationship between the regions, the assumption that the economic variables of each region are independent of each other will cause deviation in the results. The spatial measurement model fully considers spatial dependence and spatial heterogeneity and can more accurately measure the correlation between economic variables in regional areas. The basic expression form of the spatial panel model is as follows:

$$Y_{it} = \rho \sum_{j=1}^{n} W_{ij}Y_{jt} + \beta X_{it} + \theta \sum_{j=1}^{n} W_{ij}X_{jt} + \gamma_t + \mu_i + \varepsilon_{it}, \tag{2}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{n} W_{ij}\varepsilon_{it} + \xi_{it}, \tag{3}$$

In Equation (2), Y_{it} *and* X_{it} represent the explained variables and explanatory variables in the region period, respectively; Y_{jt} *and* X_{jt} represent the explained variables and explanatory variables in the region period, respectively; W_{ij} is the spatial weight matrix; $W_{ij}Y_{jt}$ and $W_{ij}X_{jt}$ are the spatial lag terms of the lag effect of the adjacent region; ρ is the spatial autoregression coefficient; β is the regression coefficient of the explanatory variable; θ is the spatial lag term coefficient; γ_t is the temporal effect; μ_i is individual effect; ε_{it} represents the random disturbance term; λ represents the correlation coefficient of the spatial lag factor; and ξ_{it} represents a random disturbance term that follows an independent distribution.

When $\rho \neq 0,\ \theta = 0,\ and\ \lambda = 0$, the model is a spatial lag model (SAR), that is, the model contains the spatial lag term of both the explanatory variable and the explained variable, and the error term does not contain the spatial autocorrelation, so the spatial lag model (SAR) is selected to test the spatial spillover effect. Considering that the LRUE has interactive effects among regions and that the ecological efficiency of the current period is affected by the previous period, the dynamic spatial lag model is adopted to investigate the relationship between economic agglomeration and the LRUE. The dynamic spatial lag model is set as follows:

$$Y_{it} = \rho \sum_{j=1}^{n} w_{ij}Y_{it} + \sum_{j=1}^{n} \beta X_{it} + \gamma_i + \mu_t + \varepsilon_{it}, \tag{4}$$

The spatial weight matrix represents the network structure matrix of the relationship among various regions. This paper uses the geographic and economic nested weight matrix, and it uses the adjacent weight matrix as a comparison.

- The adjacency weight matrix is $w_{ij} = \begin{cases} 1,\ i \neq j \\ 0,\ i = j \end{cases};$
- The geographical distance weight matrix is $w_{ij} = \begin{cases} \frac{1}{d_{ij}^2},\ i \neq j \\ 0,\ i = j \end{cases};$
- The economic distance weight matrix is $w_{ij} = \begin{cases} \frac{1}{|GDP_i - GDP_j|},\ i \neq j \\ 0,\ i = j \end{cases}.$

3.2. Variable Design

This paper uses a spatial econometric model to conduct an empirical study. Table 1 shows the explained variable, explanatory variables, and control variables. See below for details.

Table 1. Description of all variables in the econometric model.

Type	Full Name	Labels	Description
Explained variable *	Labor input	LRUE	Sum of the employment rate of the workplace and the self-employed individuals.
	Capital input		Fixed capital stock calculated by perpetual inventory method.
	Energy input		The annual electricity consumption.
	Natural element input		Urban built-up area.
	Expected output		Real GDP deflator based on 2003.
	Undesired output		Environmental pollution (indicators of industrial waste); Social distribution (ratio of urban to rural disposable income); Social development opportunities (registered urban unemployment rate).
Explanatory variable	Economic agglomeration	Agg	Natural logarithm of non-agricultural output per unit area.
	Square of economic agglomeration	Agg^2	The square term of Agg.
Control variable	Production rate of labor	Lp	Natural logarithm of average labor output.
	Degree of openness	Op	The total volume of import and export/GDP.
	Local industrial structure	Stru	The ratio of the secondary industry output value against the GDP.
	Environmental regulation	Rglt	Comprehensive utilization rate of industrial waste.
	Scientific and technological innovation level	Te	Civic expenditures on urban science and technology/GDP.

* This variable is a composite indicator and is therefore represented by only one label.

3.2.1. Explained Variable

The explained variable is the LRUE. The measure of the LRUE needs to be structured through appropriate methods. Constructing a set of production possibilities that contain the expected output and the undesired output is the first step. Assuming there is a total number of N decision-making units, in each period when $t = 1, 2, \cdots, T$, each $DMU_n (n = 1, 2, \cdots, N)$ uses many values of x as M, $\mathrm{x} = (\mathrm{x}_1, \mathrm{x}_2, \cdots, \mathrm{x}_\mathrm{M}) \in \mathrm{R}_+^\mathrm{M}$, and produces various types of expected output as P, $y^g = (y_1^g, y_2^g, \cdots, y_P^g \in R_+^P)$, and various types of unexpected output as Q, $y^b = \left(y_1^b, y_2^b, \cdots, y_Q^b\right) \in R_+^Q$, the input and output values of DMU_n at period t can be written as $\left(x_n^t, y_n^{gt}, y_n^{bt}\right)$. To meet the conditions of the strong disposability of the cluster, bounded set, input, and expected output, the possible production set under the production technology condition in period t can be expressed as follows:

$$P'(x') = \left\{ \begin{array}{c} \left(y^{gt}, y^{bt} : \sum_{n=1}^N \lambda_n^t y_{np}^{gt} \geq y_p^{gt}, \forall p; \sum_{n=1}^N \lambda_n^t y_{nq}^{bt} = y_q^{bt}, \forall q;\right) \\ \sum_{n=1}^N \lambda_n^t x_{nm}^t \leq x_m^t, \forall m; \lambda_n^t \geq 0, \forall n \end{array} \right\}, \tag{5}$$

Here, λ_n^t is the density varable, representing the observed value weight in each cross section. Equation (5) is the constant-scale reward condition; when $\sum_{n=1}^N \lambda_n^t = 1, \lambda_n^t \geq 0$ is added, and then Equation (5) is the variable-scale reward condition. Because the DEA method measures the relative efficiency, the different inspection periods cannot be directly compared due to the variation of production frontiers. The overall comparison method utilizes all of the DMUs within the production possibility set during the whole sample investigation period to structure the overall production possibility set $P^G(x) = P^1(x^1) \cup P^2(x^2) \cdots P^T(x^T)$. Based on the stability of the unified production frontier and the input–output factors and development objectives of the sample in each period, the overall efficiency values of DMU are comparable across different sections of periods [56].

The slack-based measure (SBM) model is a non-radial distance function; it meets the requirements of including pollutants as one of the non-expected outputs during the measurement of green development efficiency, and it also solves the problem of variables' slackness, but as an index assessing relative efficiency, when multiple LRUE values appear to be in the forefront (i.e., many LRUE values are 1), the SBM model will fail in the comparison and sequencing of the efficiency of these cities, which will also affect the accuracy of the subsequent empirical results. The Super-SBM model can solve this problem very well. For this reason, the Super-SBM model is used to structure the LRUE index for years from 2004 to 2020 as follows:

$$min\rho = \frac{\frac{1}{M}\sum_{m=1}^{M}\frac{\overline{x_m^t}}{x_{n_0m}^t}}{\frac{1}{P+Q}\left(\sum_{p=1}^{P}\frac{\overline{y_p^{gt}}}{y_{n_0p}^{gt}}+\sum_{q=1}^{Q}\frac{\overline{y_q^{bt}}}{y_{n_0q}^{bt}}\right)}, \tag{6}$$

$$\overline{x_m^t} \geq \sum_{n=1,\neq n_0}^{N} x_{nm}^t\lambda_n^t, \overline{x_m^t} = x_{n_0m}^t + s_m^-, \forall m, \tag{7}$$

$$\overline{y_p^{gt}} \leq \sum_{n=1,\neq n_0}^{N} y_{np}^{gt}\lambda_n^t, \overline{y_p^{gt}} = y_{n_0p}^{gt} - s_p^+, \forall p \tag{8}$$

$$\begin{aligned} \overline{y_q^{bt}} &\geq \sum_{n=1,\neq n_0}^{N} y_{nq}^{bt}\lambda_n, \overline{y_q^{bt}} = y_{n_0p}^{bt} + s_p^+, \forall p \\ \text{s.t. } \overline{y_q^{bt}} &\geq \sum_{n=1,\neq n_0}^{N} y_{nq}^{bt}\lambda_n, \overline{y_q^{bt}} = y_{n_0p}^{bt} + s_p^+, \forall p \\ \text{s.t. } \lambda_n^t &\geq 0, \forall n(\neq n_0). \end{aligned} \tag{9}$$

where s_m^- and s_p^+ are the slack variables indicating input redundancy and insufficient output, respectively.

1. Labor input: the number of employees at the end of the year in each of the selected cities is the labor input index, that is, the sum of the employment rate of the workplace and the self-employed individuals; the unit is ten thousand.
2. Capital input: "perpetual inventory method" is used to calculate the fixed capital stock, as the capital input index, and the unit is CNY 10,000. The index is formulated as follows:

$$K_{it} = I_{it} + K_{it-1}(1-\delta), \tag{10}$$

K_{it} represents the fixed capital stock amount in the t year of the prefecture-level city numbered as i; I_{it} represents the total fixed capital amount in the year of the prefecture-level city; δ represents the depreciation rate, given as 9.6%. Taking 2003 as the base period, the initial fixed capital stock is defined as $K_{i0} = K_{i1}/(\delta + g_i)$, where g_i represents the average growth rate of investment. Similarly, I_{it} is calculated according to the fixed asset investment price index based on the year 2003, and the fixed asset price index is directly adopted using the fixed asset price index of each province of China.

3. Energy input: the use of energy is related to the national economic construction as well as social and ecological environment. Due to the fact that there are no specific energy consumption data available at the prefecture level, this thesis takes the annual electricity consumption as the proxy variable as the energy input index with the unit of 10,000 kilowatt-hours.
4. Natural element input: applied land in urban built-up areas.
5. Expected output: the actual GDP of each urban area is used as the expected output index, and the provincial GDP deflator in 2003 is used for deflation, with the unit of CNY 10,000.

6. Undesired output: (1) Negative impacts of economic development on the ecological environment selected are industrial wastewater emission, industrial sulfur dioxide emission, and industrial smoke and dust emission for the "environmental" aspect, and the units are ten thousand tons, tons, and tons, respectively; the annual average density of PM2.5 is selected for the "ecological" aspect, in micrograms/cubic meter. (2) Economic development is going to have a negative impact on social distribution. This thesis selects the income and expenditure gap among urban and rural residents as "social distribution results" (income gap = urban residents' disposable income/disposable income of rural residents; the expenditure gap between urban and rural residents = the expenditure of rural residents) and selects the registered urban unemployment rate for the "social development opportunity" aspect.

3.2.2. Explanatory Variables

Economic agglomeration (Agg) is a process and phenomenon of regional concentration of various economic activities. Based on relevant literature, the study of economic agglomeration is mostly based on analyzing GDP production per unit area.

3.2.3. Control Variables

Considering the influencing forces of LRUE, we take labor productivity (Lp), degree of openness (Op), local industrial structure (Stru), environmental regulations (Rglt), and scientific and technological innovation level (Te) into consideration as control variables.

3.2.4. Data Sources

This thesis takes the panel data of prefecture-level cities in China from 2004 to 2020 as the research object. As of 2022, there are a total of 293 prefecture-level cities[1] in China, among which some of them were canceled and re-grouped under others during the observation period (e.g., Chaohu City, Laiwu City), some of them ranked up or were re-established during the observation period (e.g., Bijie City, Tongren City, Sansha City), and some places in the west region of China do not have full statistical data and the quality of accessible data is low (e.g., Lhasa City, Nyingchi City, Naqu City, Xigaze City, Zhongwei City, Haidong City). Due to the conditions mentioned above, 281 prefecture-level cities were finally selected as samples for the land use eco-efficiency measurement and the subsequent empirical analysis. Data are mainly from the Statistical Yearbook of Chinese Cities from 2005 to 2021, the Statistical Yearbook of each city, the Statistical Bulletin of National Economic and Social Development, the wind database, China's economic and social big data research platform (https://data.cnki.Net/, accessed on 20 December 2022), the Atmospheric Composition Analysis Group, the official website of the University of Washington (https://sites.wustl.edu/acag/datasets/surface-pm2-5/, accessed on 20 December 2022), NTL data, statistical data, and administrative boundaries. Missing data values were replaced by linear interpolation or mean supplementation. Table 2 reports the descriptive statistics of variables.

Table 2. Descriptive statistics of variables.

Variable	Observations	Mean	STDEV	Min	Max
LRUE	4777	0.3526	0.1809	0.0915	1.8263
Agg	4777	6.3964	1.4408	1.5439	11.3351
Lp	4777	3.0461	0.5633	1.0897	5.2671
Op	4777	0.1929	0.3142	0.0016	1.8364
Stru	4777	46.7327	11.0458	17.1000	73.8000
Rglt	4777	79.9185	21.9035	4.5400	100.0000
Te	4777	0.0109	0.0330	0.0000	0.2431
Ups and Downs	4777	0.6734	0.7557	0.0013	3.8138
DN	4777	0.8690	1.8967	0.0027	22.1829

4. Results

4.1. Precondition: Spatial Autocorrelation Test

The precondition for the use of spatial econometric models in this study is the existence of spatial dependence of land resource use efficiency (LRUE), as determined by the spatial autocorrelation test. GeoDa software was used to calculate the global Moran index of land use ecological efficiency and economic agglomeration in China following the geographic distance weight matrix (Table 3). The results show that the Moran's I index values of land use ecological efficiency value and economic agglomeration are all greater than 0 and are significant at a 1% significance level within the sample period, indicating that land use ecological efficiency and economic agglomeration have significant space autocorrelation and that land use ecological efficiency and economic agglomeration are not independent among cities but affected by surrounding areas. Therefore, a spatial econometric model can be used in this study.

Table 3. Results of global Moran's I test.

Year	Land Resource Use Efficiency		Economic Agglomeration	
	Moran's I	**Z Statistics**	**Moran's I**	**Z Statistics**
2004	0.060 ***	3.904	0.253 ***	14.984
2005	0.094 ***	6.004	0.254 ***	14.991
2006	0.065 ***	4.024	0.255 ***	15.073
2007	0.076 ***	4.634	0.257 ***	15.202
2008	0.065 ***	4.138	0.257 ***	15.148
2009	0.061 ***	3.851	0.254 ***	14.975
2010	0.114 ***	7.305	0.251 ***	14.783
2011	0 112 ***	7.092	0.244 ***	14.371
2012	0.119 ***	7.411	0.241 ***	14.206
2013	0.108 ***	6.953	0.245 ***	14.410
2014	0.093 ***	5.996	0.248 ***	14.593
2015	0.083 ***	5 249	0.250 ***	14.670
2016	0.067 ***	4.261	0.251 ***	14.744
2017	0.123 ***	7.689	0.254 ***	14.911
2018	0.106 ***	6.642	0.253 ***	14.892
2019	0.103 ***	6.331	0.251 ***	14.781
2020	0 086 ***	5.108	0.255 ***	14.971

*** indicates statistical significance at the 1% level.

4.2. Regression Results of the Spatial Econometric Model

We used MATLAB R2021a software to conduct an empirical analysis based on three spatial weight matrices (geographic distance weight matrix, adjacency weight matrix, and economic distance weight matrix). These results are reported in Table 4. The coefficient under both the static spatial lag model and the dynamic spatial lag model for the spatial lag term W*LRUE of the explained variables is significantly positive, indicating that the LRUE has a positive spatial correlation. The spatial lag term coefficient of Agg^2 is significantly positive, initially indicating that economic agglomeration may have a positive spatial spillover effect on the LRUE. However, merely relying on the regression coefficient of the spatial lag model to analyze the local impact of economic agglomeration on the LRUE and its spatial spillover level may lead to deviation [57,58]. The direct and indirect effects of independent variables on dependent variables should be broken down further.

Table 4. Regression results of the spatial econometric model.

	Explained Variable: LRUE		
	Adjacent Weight Matrix	**Geographic Distance**	**Economic Distance**
Agg	−0.4629 *** (−18.82)	−0.2252 *** (−10.42)	−0.4997 *** (−20.45)
Agg2	0.0370 *** (29.03)	0.0179 *** (15.33)	0.0392 *** (30.90)
Lp	0.1414 *** (17.03)	0.0880 *** (12.31)	0.1421 *** (16.99)
Op	0.0110 (0.77)	0.0036 (0.30)	0.0068 (0.47)
Stru	−0.0003 (−0.87)	0.0002 (0.66)	−0.0002 (−0.65)
Rglt	−0.0006 *** (−5.27)	−0.0003 *** (−2.65)	−0.0007 *** (−5.28)
Te	0.0000 *** (2.65)	0.0000 *** (3.12)	0.0000 *** (2.92)
W*LRUE	0.1555 *** (7.43)	0.0523 *** (3.31)	0.0657 * (1.92)
R-sq	0.7075	0.7900	0.7034

* and *** indicate statistical significance at the 10% and 1% levels, respectively. Z statistics in parentheses.

Table 5 reports the results of the effect decomposition for Table 4. In both the direct and the indirect effects, the Agg and Agg^2 terms pass the 1% significance test under all three spatial weight matrices, indicating that there is a significant spatial spillover effect of economic agglomeration on LRUE and that the effect of economic agglomeration on LRUE has a U-shaped trend. The above results suggest that Hypothesis 1 and Hypothesis 2 of this paper hold true.

Table 5. Results of the effect decomposition of the spatial econometric model.

Types	**Variable**	Explained Variable: LRUE		
		Adjacent Weight	**Geographic Distance**	**Economic Distance**
Direct effect	Agg	−0.4636 *** (−19.07)	−0.2253 *** (−10.23)	−0.4992 *** (−20.50)
	Agg^2	0.0371 *** (29.75)	0.0180 *** (15.01)	0.0391 *** (31.18)
	Control	YES	YES	YES
Indirect effect	Agg	−0.0833 *** (−6.16)	−0.0122 *** (−3.14)	−0.0370 *** (−1.84)
	Agg^2	0.0067 *** (6.49)	0.0010 *** (3.21)	0.0029 *** (1.84)
	Control	YES	YES	YES
Gross effect	Agg	−0.5469 *** (−18.40)	−0.2374 *** (−10.45)	−0.5361 ** (−17.36)
	Agg^2	0.0438 *** (28.75)	0.0189 *** (15.58)	0.0420 *** (23.16)
	Control	YES	YES	YES

** and *** indicate statistical significance at the 5% and 1% levels, respectively. Z statistics in parentheses.

4.3. Robustness: Judgment of Spatial Econometric Model Types

Spatial econometric models exist in many forms. The previous section uses a spatial fixed-effects spatial lag model based on common sense. This section goes through a series of validations to re-establish that this model is the most appropriate one for this paper.

Using MATLAB R2021a software, through the Lagrange multiplier (LM), we can test the spatial lag model, spatial error model, and LM model to find out which is the best for the study of the thesis. The test results are shown in Table 6. The results of the LM test and robust LM test are both significant, fully confirming that the spatial measurement model is the suitable model for the analysis of the impact of economic agglomeration on land use eco-efficiency. Given that the spatial lag model can reflect both the spatial effect of the explanatory variable and the spatial effect of the explained variable as a more general model, the spatial lag model is selected to expand the analysis. Through the Hausman test, whether the model has a fixed effect or a random effect can be determined. Results show that the p-value is less than 0.01, and a fixed effect should be used. Lastly, the maximum likelihood ratio (LR) test is used to decide if the spatial factor, the temporal factor, or both should be fixed. The results show that both spatial and temporal factors are significant, but the spatial fixed effect coefficient was significantly larger than the temporal fixed effect coefficient. Therefore, the model used in this study is the most appropriate.

Table 6. A series of tests of the spatial econometric model.

Test Object	Statistics	p-Value
LM rest no spatial	34.1785	0.000
Robust LM test no spatial lag	27.2021	0.000
LM test no spatial error	16.0945	0.000
Robust LM test no spatial error	9.1181	0.003
Hausman test	−99.6930	0.000
LR-test joint significance spatial fixed effects	4280.9887	0.000
LR-test joint significance time-period fixed effects	119.7880	0.000

4.4. Robustness: Instrumental Variable (IV) Method

Firstly, the empirical results of the three spatial weight matrices (the geographic distance weight matrix, adjacent weight matrix, and economic distance weight matrix) are generally consistent, indicating that the findings are somewhat robust. Further, in order to alleviate the endogeneity problem of the model, the IV method is used for robustness testing.

The first instrumental variable is the topographic relief (Ups and Downs). Topography is closely related to population agglomeration. Areas with low topographic fluctuations are more likely to form population clusters than areas with high topographic fluctuations, which satisfies the first condition of IV—correlation with the explanatory variables. Topographic height is related to the elevation and area of the region, but not to the LRUE [59]. Using ArcGIS software, the digital elevation model (SRTM 90 m) data were resampled and reformed into a grid of 1 km*1 km, using a grid size of 10 km*10 km as the manipulating unit; the dataset of the topographic grid by kilometers was gradually extracted by using the formula.

The second instrumental variable was the number of night lights (DN) in Chinese cities, which was satellite-derived night light data [60,61].

Table 7 shows the results of the above. As shown in Table 7, the values generated by the F test in Stage I are all greater than 10, which complies with the rule of thumb, indicating that the instrumental variables selected in this paper are not weak instrumental variables. The terrain fluctuation rate is significantly correlated with the regression coefficient of economic agglomeration in a negative way; that is, when the terrain fluctuation rate is high, the degree of economic agglomeration is low, which is also consistent with reality. In the plateau region, the natural conditions are poor, the soil is not suitable for crop planting, the terrain is rugged, and the traffic costs are high, and these factors lead to a small population and labor force. The night lighting data showed a significant positive correlation with the quadratic term of economic agglomeration, which showed frequent economic activity and a high degree of agglomeration in the economically developed area. The regression results of Stage II confirm that the results of the benchmark regression are robust, on top of the consideration of endogeneity; the impact of economic agglomeration on land use eco-efficiency continues to be U-shaped.

Table 7. Regression results of the spatial econometric model.

	Stage I		Stage II
	Agg	**Agg^2**	**LRUE**
Ups and Downs	−0.4139 *** (−20.78)	−4.612 *** (−21.41)	
DN	0.2352 *** (18.85)	4.0846 *** (21.77)	
Agg			−0.2715 *** (−8.95)
Agg^2			03.022 *** (10.53)
Control variables	Yes	Yes	Yes
Constant items	−1.3372 *** (−5.66)	−51.0338 *** (−16.26)	1.2915 *** (13.07)
F	448.31	586.56	
Adjusted R-sq	0.7603	0.7986	0.2586
Cragg–Donald Wald F statistic			318.57

*** indicates statistical significance at the 1% level.

5. Discussion and Policy Recommendations

5.1. Temporal Evolution Trend of Land Resource Use Efficiency

With the help of MaxDEA 8Ultra Software, we examined the overall LRUE evolution trend for 281 prefecture-level cities in China from 2004 to 2020 (Figure 2). It can be found that both nationally and locally, LRUE shows an increasing trend. The upward trend is most obvious in the eastern region, while the upward trend is weakest in the western region. The outcome of this result is different from most of the previous studies as in those an upward trend or a development trend of first rising and then falling is observed [10,31]. Therefore, it is necessary to include energy inputs and undesired outputs in the LRUE evaluation system. This is also related to the importance China has placed on energy conservation and emission reduction in the last 20 years. The importance attached by local governments to energy conservation, emission reduction, and sustainable development is the main reason for the steady rise in LRUE in all regions of China.

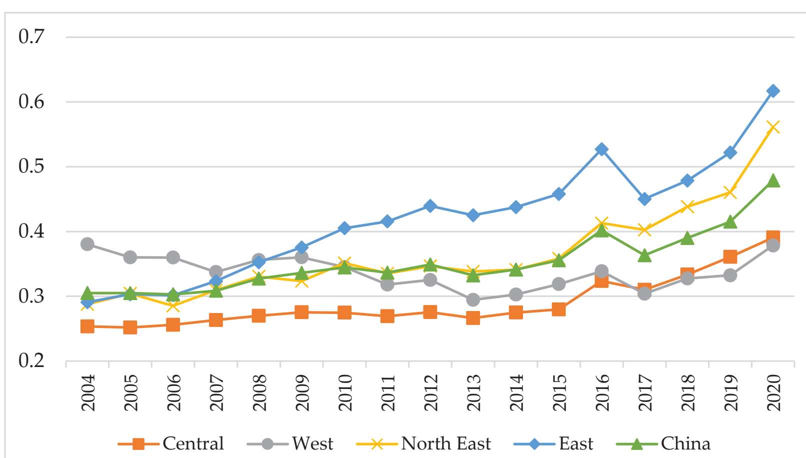

Figure 2. Trends of land resource use efficiency by region in China from 2004 to 2020.

The LRUE of prefecture-level cities is found to go from large to small in eastern, northeast, central, and western China. This distinctive distribution is related to the topography, the economic level, and the policy orientation. The western region, which has many plateaus, mountains, and deserts, is taken as an example. Due to topographical constraints, the cities in this region lack the labor force and consumer base to supply industrial development, thus reflecting a lower LRUE value. At the same time, it can be found that with the exception of the eastern region, the rise in LRUE mainly occurred after 2014, which may be related to the many energy-saving and emission-reduction policies enacted in China during this period, such as carbon emission trading scheme and forestry carbon sink policies. These policies prompted local governments to guide enterprises in their emission reduction efforts, which in turn reduced the marginal consumption of their output. In terms of LRUE value, the level remains low in all regions except for the eastern region. This suggests that there is still ample room for upward mobility in China's use of land resources.

5.2. Spatial Evolution Trend of Land Resource Use Efficiency

Using ArcGIS 10.4 software, we mapped the LRUE distribution in China for 2004, 2006, 2016, and 2020 (Figure 3). Based on the distribution of LRUE values, we classified them into five categories: low efficiency ($\leq$0.6), medium-low efficiency (0.61–0.1–0.7), medium efficiency (0.71–0.8), medium-high efficiency (0.81–1.0), and high efficiency (>1.0). Previous studies focus more on evaluating land resource use efficiency without too much consideration of the relationship between economic agglomeration and LRUE. High use efficiency (LUE) in these agglomerations demonstrates that "the more intensive the city is, the higher is its use efficiency" [62]. However, our study presents different results after considering the ecological factors.

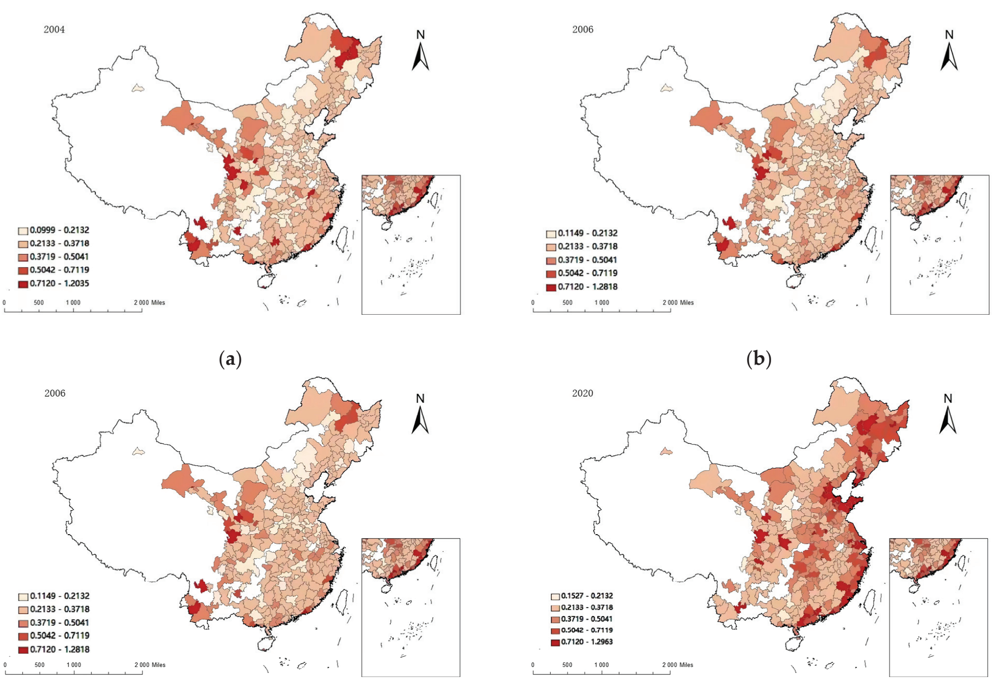

Figure 3. Distribution of land resource use efficiency in 4 years: (**a**) land resource use efficiency in 2004; (**b**) land resource use efficiency in 2006; (**c**) land resource use efficiency in 2016; (**d**) land resource use efficiency in 2020.

During the observation period, the distribution area of high efficiency changed: In 2004, the high-efficiency areas are mainly distributed in the northern region and a few are scattered around southwest regions. This was not due to the realization of an increased LRUE among these regions, but because of the underdeveloped economy, unexploited ecological environment, and relatively fair social distribution, so comprehensive efficiency is high because of a combination of low input and low undesired output. After 2006, the disadvantages caused by extensive development in these regions gradually appeared. Some cities have shifted from the high-efficiency areas, while a dramatic increase in the efficiency value among other cities is not observed. After 2016, the spatial distribution characteristics of "high in the east, low in the west" appear to be obvious, and the high efficiency values are gradually concentrated in the eastern and northeastern regions and provincial capitals of China. These regions have a decent economic foundation and pay more attention to the improvement of human capital accumulation and technical level, which leads to a continuous increase in the LRUE. The spatial spillover effect is one of the factors that affect the spatial and temporal evolution trend of LRUE. However, there are other reasons that LRUE is probably influenced by the policy implementation efficiency, economic foundation, technological conditions, and environmental awareness in the different regions. Moreover, high land prices force the cities in eastern regions to use land resources more effectively, and the urban built-up area there expanded rapidly.

5.3. Spatial Spillover Phenomenon

This subsection focuses on the spatial spillover phenomenon (direct and indirect effects) of LRUE, as shown in Table 5. The direct effect reflects the impact of economic agglomeration in the region on the LRUE, while the indirect effect reflects the impact of economic agglomeration in other regions (depending on the spatial weight matrix) on the LRUE of the region.

In terms of direct effects, economic agglomeration has a U-shaped relationship with LRUE; i.e., in the early stages of economic agglomeration, the crowding effect is greater than the agglomeration effect, making factors such as high pollution and inequitable distribution worsen LRUE. The economic agglomeration, after a long period of "agglomeration–diffusion–agglomeration", optimizes the allocation of resources, improves regional knowledge and technology, and reduces distributional inequalities. This leads to a reduction in the undesired output of the LRUE, which in turn increases the LRUE.

In terms of indirect effects, there is still a U-shaped relationship between economic agglomeration and LRUE. In the early stages of economic agglomeration, the rapid transfer of economic activities to other regions reduces the production factors in the region, while the pollutants generated in other regions (especially in neighboring regions) will spread to the region, resulting in a reduction in its LRUE. However, when the economic agglomeration of other regions reaches a mature stage, it achieves the optimal allocation of resources and generates knowledge spillover effects. This helps the region to improve its LRUE level through exchange, cooperation, and learning by imitation.

5.4. Policy Recommendations

Based on the above findings, this paper makes the following recommendations:

(1) Reasonably guide economic agglomeration and improve its scope and quality in order to contribute to positive externalities. The U-shaped relationship between economic agglomeration and LRUE shows the following: when the development level of economic agglomeration is low, externalities cannot be revealed; when economic agglomeration develops too fast, it generates a crowding effect, leading to a waste of resources and social injustice, making LRUE decrease; when economic agglomeration develops maturely, resources are fully utilized and LRUE improves. Therefore, the negative effects of economic agglomeration are temporary and can be avoided. Local governments should apply this law of development in a reasonable manner.

(2) Mitigate the problem of over-agglomeration. Some regions in China have the problem of over-agglomeration, which is detrimental to the development of both the region and neighboring regions. Therefore, local governments should use policy tools to guide the level of agglomeration in a reasonable manner.
(3) Develop an economic agglomeration strategy with local characteristics. Currently, China's economic agglomeration and LRUE show great differences in spatial distribution, which implies that localities should tailor their economic agglomeration policies to guide high-quality economic agglomeration behavior according to their own strengths and weaknesses as well as the stage of agglomeration.

6. Conclusions

Based on the panel data of 281 prefecture-level cities in China from 2004 to 2020, this study explores the impact of economic agglomeration on LRUE by using the spatial lag model. After performing a series of tests, we obtained robust conclusions: (1) there is a positive spatial spillover effect on LRUE, and an increase in LRUE in the region helps to improve LRUE in neighboring regions; (2) there is a U-shaped relationship between economic agglomeration and LRUE.

There are still some shortcomings in this research due to the limits of time, energy, and length. First, the heterogeneity of economic agglomeration can be further discussed. As far as different regional economic developments are concerned, it is possible to discuss China's eastern, central, and western regions separately. Secondly, in this study, we used prefecture-level city data; the sample size could be larger if county-level city data are used. Thirdly, the transmission mechanism of economic agglomeration and LRUE can be further studied.

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Notes

1 A prefecture-level city refers to a city that ranks below province and above county as an administrative division of China, which usually governs a couple of subordinated areas including some county-level cities.

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Article

Proprietary Varieties' Influence on Economics and Competitiveness in Land Use within the Hop Industry

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Abstract: To evaluate changes to hop industry concentration and competitiveness the Herfindahl-Hirschman Index (HHI) was used. The ownership of hop proprietary varieties, their acreage and production were compared with public varieties. Market share for each proprietary hop variety acreage and production was calculated between 2000 and 2020. The quantity of land under centralized control in the U.S. hop industry due to increased proprietary variety acreage between 2000 and 2020 was quantified. Assuming tacit collusion between the participants in the oligopoly, the HHI enabled us to quantify the portion of land under oligopoly control. The HHI analysis of hop acreage and hop production demonstrated that market concentration rose rapidly between the years 2010 (0.0376 and 0.0729) and 2020 (0.4927 and 0.5394). This resulted in decreasing business competitiveness within the market during this period caused primarily by rapid consolidation of ownership during increased proprietary variety acreage and production increases. Calculations revealed that in 2016 a tipping point had been reached concerning market concentration, which resulted in higher sustained season average prices of hops—a key raw material in brewing.

Keywords: hop industry; varieties; market concentration; intellectual property; prices

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1. Introduction

Hops, along with malt and water, are the basic raw materials used for beer production. The basic role of hops is to provide beer with a pleasantly bitter taste and a hoppy aroma [1–3]. Between 2000 and 2020 the proportion of privately owned patented U.S. hop varieties increased. Other countries experienced increases in patented varieties, but these were owned by national associations. In the United States during that time, one variety development company, the Hop Breeding Company, grew to the point where its varieties enjoyed significant market share. The agglomeration of hop farms in Washington, Oregon, and Idaho (i.e., the Pacific Northwest (PNW)) facilitates the exchange of information by reducing monitoring costs thereby increasing market transparency among participants [4]. The increase in proprietary variety acreage and production has a causal effect on hop prices [5]. Tacit collusion results from competitors independently realizing their collective best interests to adjust prices or quantities [6]. The exchange of production-related information including anticipated yields and current prices among farmers may lead to a similar outcome [7].

Since 1913, the United States Department of Agriculture (USDA) has collected and published statistical data regarding the U.S. hop industry. The publication of intellectual property (IP) necessitates the use of symbols for registered trademarks, unregistered trademarks, and copyright, (i.e., "®", "™" and "©") respectively. The USDA complies with these requirements. Proprietary variety ownership is publicly available through the U.S. Patent and Trademark Office (USPTO). The introduction of proprietary varieties, therefore, enabled the calculation of hop market share by acreage and production for the first time. Market share regarding sales of these varieties to brewers remained unavailable but was not important for calculating influence within the U.S. hop industry.

We used the Herfindahl-Hirschman Index (HHI) to measure changes in hop industry competitiveness by way of measuring market concentration. A similar methodological approach was used to measure market concentration in the airline industry [8]. According to the 2020 U.S. Federal Register, HHI was used to evaluate the acquisition of the Craft Brew Alliance, Inc. (CBA) by Anheuser-Busch InBev SA/NV ("ABI") and Anheuser-Busch Companies, LLC ("AB Companies"). The results of such analyses can provide insights into industry behavior. Markets with relatively high HHI values, market share inequality, and the presence of major firms are imperfectly competitive. Under such circumstances, market imperfections are vulnerable to exploitation [9].

The presence of IP introduced constraints into the market where none had previously existed and affected farmer planting decisions on that acreage. More constrained varieties were planted at a faster pace than those that were unconstrained [10]. Changes in market concentration and price-cost margins can be used to determine the direction of competitiveness [11]. The greater degree of specificity, control, and profit incentivized private hop breeding companies to invest further in the development of new intellectual property. Their owners are incentivized by the ability to protect and enforce their rights [12]. Patent law also enabled IP owners to determine production and distribution via licensing agreements.

In 2021, Germany and the U.S. produced 32.91 and 40.87 percent of global hop acreage respectively. These are the two largest hop-producing regions, but each operates under different business models. In 2020, patented and trademarked varieties in the United States represented 70.19% of PNW acreage and 73.44% of PNW production. Between 2009 and 2019, the annual farmgate value of American hops increased by 282% [13]. According to the country reports of the International Hop Growers' Convention (IHGC) between 2009 and 2019, 70 hop farmers in the PNW received approximately $4.7 billion in farm revenue, $2.88 billion more than the $1.87 billion the 1087 German hop farmers received during the same period [14].

Between 1998 and 2020, USDA data recorded U.S. proprietary variety acreage and production soaring from zero to over 70 percent. Publicly available information regarding proprietary variety ownership enabled us to calculate the U.S. hop market share for the first time in history. One variety development company, the Hop Breeding Company (HBC), owned the varieties responsible for over 50 percent of U.S. acreage and production by 2020 [13].

The objective of the study was to evaluate changes to the hop industry area and production concentration and competitiveness with respect to the changes in proprietary varieties of hops relative to public varieties. Comi [15] refers to farmers who euphemistically described this process as "decommodification" implying only positive added value for the good of all. Using the Herfindahl-Hirschman Index (HHI), the concentration of acreage-producing proprietary varieties between 2000 and 2020 under the control of a cartel-like structure with strict production and sales licensing agreements was quantified. Proprietary variety owners used their IP to create competitive advantages for their companies and those farmers allied with them. Consequently, they denied their competitors and farmers they did not favor primary access to their IP. This research analyzed publicly available industry data to determine the market effects resulting from the increased use of branded proprietary varieties by the craft brewing industry during this time and compared it with other periods possessing unique characteristics dating back to 1948.

2. Materials and Methods

2.1. Proprietary Hop Variety Supply and Market Share

The United States Department of Agriculture lists each branded proprietary variety together with their respective intellectual property symbols in their publications [16]. The details of patents and trademarks are public information. By tracking the ownership of these varieties in patent and trademark records with the U.S. Patent and Trademark Office

(USPTO) and through the Google Patent Search website, we discerned the influence of individuals and entities over proprietary varieties. Data reported by the USDA included season average prices (SAP), inventory levels, production, and acreage. Wright and Williams [17] suggest that when supply is elastic and demand inelastic (as is the case with hops), the accumulation of stocks is typically damped by a compensating production response. The hop industry suffers from something called the Delayed Surplus Response (DSR). Production is highly elastic when prices and demand increase, but there is a delay of several years when prices and demand decrease. This results in surplus production that negatively affects global prices for hops through recurring boom-and-bust cycles [18]. Data published by the USDA enabled us to calculate the accumulation of aggregate stock levels and the annual market share of acreage by variety. We restricted our research to USDA National Hop Report (NHR) data between 1998 and 2022. That represented the period during which branded proprietary varieties were first reported by the USDA and included the most recently available industry data at the time of our calculations.

The companies that developed proprietary hop varieties own and license the production of multiple proprietary varieties to growers (for production) and sales and distribution of those varieties to merchants in their supply chain, thereby facilitating the management of production and distribution. We calculated the percentage for each proprietary variety produced within the Pacific Northwest (PNW) by the total acreage for the PNW i.e., the total market share. We calculated the market share for each entity owning IP listed by the USDA NASS in the USDA National Hop Report (NHR) by grouping those with common ownership of patented and trademarked products [16].

We expanded the variety-specific acreage market share calculations to group together those varieties that share common ownership to get a better picture of the influence of the five largest variety development companies. One company, the Hop Breeding Company, LLC (HBC) enjoyed increased influence within the industry as its proprietary varieties increased to occupy 51% of the acreage in the PNW. According to the company's website (www.hopbreeding.com, accessed on 18 July 2022), it is a joint venture between John I. Haas, Inc., a hop merchant company, and Yakima Chief Ranches, L.L.C., a company owned by the Smith, Carpenter, and Perrault families. These three families are also shareholders of Yakima Chief Hops, Inc., a hop merchant company. This complicated ownership structure effectively created a duopoly through which the proprietary varieties of the HBC were processed and distributed. Production was handled first through the farming resources to which each of the merchant companies had access. In the case of John I. Haas, Inc., that included the company farm and entities such as Roy Farms Inc., who touts on their website (http://royfarms.com/hops/roy-farms-citra/, accessed on 15 November 2022) their production and direct sales of one popular proprietary HBC variety, Citra®. In the case of Yakima Chief Hops Inc., those resources belonged to their farm owners. According to an article in the beer industry news outlet, Brewbound [18], that number expanded in 2019 from 11 to 15 farms. These varieties created a competitive advantage for the shareholders of the HBC and the other companies with whom it shared common ownership. How the owners of the HBC managed acreage between the two merchant companies to maintain equitable market share remains unknown. Proprietary varieties were distributed worldwide via licensing agreements with select merchants. The influence over such substantial acreage afforded the individuals involved with the HBC a disproportionate amount of influence in the industry. Their patents enabled them to decide via licensing agreements who would produce and sell their varieties. The MacKinnon Report, a hop market report published on Substack.com (https://mackinnonreport.substack.com, accessed on 26 January 2023) detailed that in 2023 the patent owners must reduce proprietary variety acreage by at least 8328 acres (3371 ha.) in response to a massive surplus that began in 2016. Those decisions have the power to create inefficiencies for some farms. How the decisions to reduce acreage will be coordinated by the two companies and which farmers will be told to reduce acreage remains to be seen. Some will be less efficient producers and not be able to compete in the future market.

Data demonstrated that the difference between depletion rates (i.e., the quantity of hops shipped from U.S. warehouses) and the total available supply increased by 54 million pounds between 2016 and 2022 (Figure 1). What we could not ascertain, however, was the degree to which inventories managed by the same companies were growing in warehouses located outside the purview of the USDA NASS surveys (i.e., every country other than the U.S.). Other countries do not publish similar data, which limited the completeness of this study.

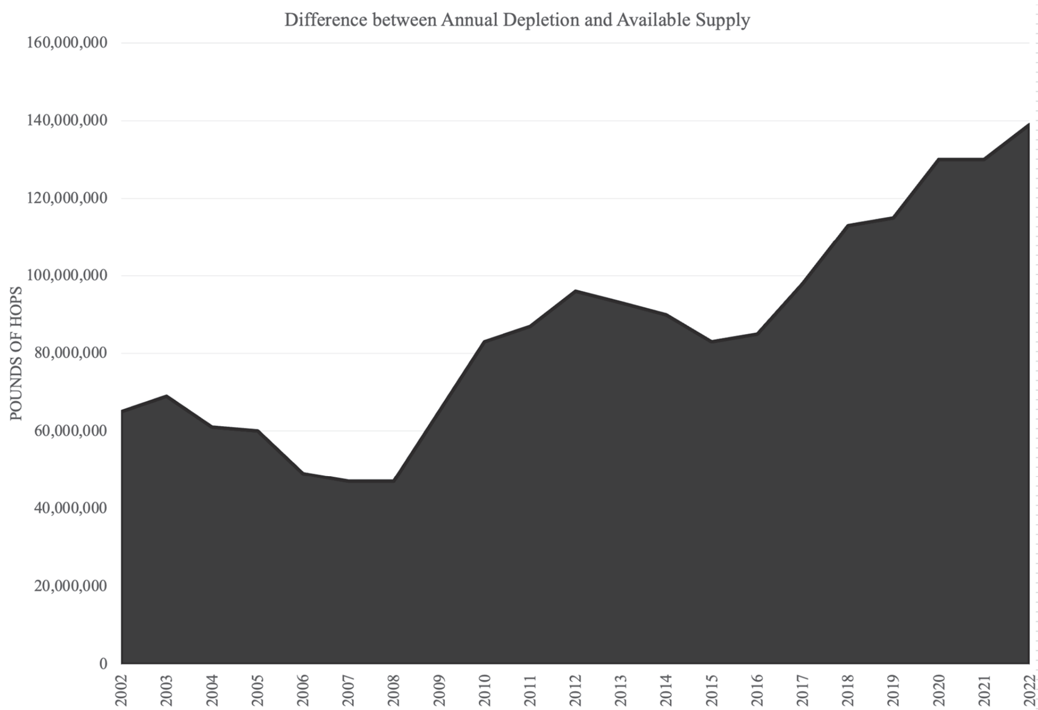

Figure 1. Annual Depletion (Sept n–Sept n-1) Relative to Total Available Supply (Crop (n-1) and Inventory (n-1)) (own study based on [16]).

2.2. Calculating HHI

We used the Herfindahl-Hirschman Index (HHI) to evaluate changes to hop industry concentration and competitiveness with respect to the changes in proprietary varieties of hops relative to public varieties. A significant portion of PNW acreage appears in two aggregate categories called "other" and "experimental". USDA data show that in 2022 7.12% of total acreage was categorized as "other" or "experimental". The categories are used to report acreage and production for varieties that do not meet the three-independent-grower threshold set by the USDA. Based on historical data, we believe at least half of this acreage was proprietary.

The HHI is a method used also by the United States Department of Justice (USDOJ) to measure market concentration during mergers or acquisitions, to evaluate one competitor's position relative to another, and to uncover potentially anti-competitive practices. The HHI values of zero to 0.1500 mean a low market concentration. Values of 0.1500 to 0.2500 are considered a moderate concentration. Values of 0.2500 and above count as high concentration. The HHI value will be low when market shares among participants are equal. The value will be high when one firm has a disproportionate share of the market [19]. The value of the HHI decreases as the number of firms in the market increases. Market concentration is inversely proportional to competitiveness [20]. The HHI is responsive to the asymmetry of market shares and is used to evaluate changes in the competitiveness within a single industry over time or to compare one industry to another [19]. In our research, we adopted this method for the first time in the hop industry for the measurement of its market concentration.

The HHI Formula

$$HHI = S1^2 + S2^2 + S3^2 + \ldots\ Sn^2 \quad (1)$$

where:

n refers to the number of varieties in the market;
S refers to the percent market share for a variety.

3. Results and Discussion

3.1. Acreage and Production Linked to Proprietary Hop Varieties

Calculating the Herfindahl-Hirschman Index (HHI) of the U.S. hop industry based on the market share of hop sales to brewers was a hopeless endeavor as information regarding market share based on sales of hops by merchants to breweries was proprietary information and never shared. We discovered an alternative method for measuring market share. The USDA NASS restrictions related to the reporting of proprietary U.S. acreage and production (i.e., that three or more independent producers must list acreage or production for the corresponding statistics to be reported in aggregate form) to meet the needs of this research.

Acreage, and the infrastructure necessary to harvest that acreage, was the scarcest and most valuable commodity in the hop industry in 2020, not the hops themselves. Acreage was the asset for which there was the greatest competition. The primary method for harvesting hops was via fixed picking machine facilities. Mobile combines exist that harvest cones from the vines in the field. Combines, when they were used, operated in conjunction with the more traditional fixed-picking facilities that could process at least 600 acres (242 hectares) of hops in a season. Combines returned cones harvested in the field to the picking facility to separate leaves, stems, and foreign material from the cones themselves through the picking facility's recleaning equipment. Due to the time-sensitive nature of the harvest, high ambient air temperatures, which could reach over 100 degrees Fahrenheit (37.78 °C) in Washington and Idaho states during harvest, hop growers sought to grow hops on land that was in close proximity (not more than 10–15 min driving time) to their fixed picking facilities to reduce the incidents of hops dehydrating prior to going through the picking machine, which increases cone shatter and reduces quality.

Five companies comprised approximately 70 percent of proprietary U.S. hop acreage and production in the Pacific Northwest in 2022 (Table 1). These variety development companies can license hop merchant companies to sell their varieties. They can license hop farms to produce their varieties. In some cases, the variety of development company ownership and the licensed merchants and farms shared common ownership. Licenses extended beyond companies in which they shared ownership. Previously independent farms were transformed into contract growers. The decision-makers for the five largest variety development companies, therefore, enjoyed a disproportionate influence in the industry and upon the market. The acreage on which a company's proprietary varieties were produced represented the market share of influence of the owners of each variety development company. The market share of influence represented a new and significant measurement possible within the industry all made possible by the growing demand for and reporting of proprietary varieties of hops.

Table 1. Five largest U.S. hop variety development companies and the market share of U.S. acreage and production of their proprietary varieties in 2022.

	Variety Development Company	Market Share of U.S. Total Acreage in 2022	Market Share of U.S. Total Production in 2022
1	Hop Breeding Company (HBC)	49.05%	49.12%
2	HopSteiner	7.71%	10.78%
3	Association for the Development of Hop Agronomy (ADHA)	3.27%	3.35%
4	Virgil Gamache Farms (VGF)	3.20%	2.88%
5	CLS Farms	2.06%	2.02%
	TOTAL	65.30%	68.15%

Calculating the market share for each ownership group based on their ownership of proprietary hop varieties enabled the calculation of the market share of influence over the scarcest resource in the hop industry, acreage. Branded proprietary varieties are products that enjoy monopoly control by their very nature as patented and trademarked products. Seventy percent of the acreage, therefore, was governed by the decision-makers of five entities. Public varieties, in contrast, are available for any grower to produce.

We calculated the market share for each proprietary variety production and acreage relative to total U.S. acreage for the years 2000 through 2020. During this time, market concentration moved from low to high according to the standards set by the U.S. Department of Justice when evaluating mergers and acquisitions between competitors.

Using the HHI market share data by variety, we calculated the market share for all proprietary varieties collectively as the U.S. hop industry resembles what is referred to as a complex monopoly in the U.K. [21]. We calculated the increase in market concentration between 2000 and 2020 of publicly reported U.S. proprietary hop varieties. The increasing HHI values between 2000 and 2020 demonstrated the changes in the degree of competitiveness in the industry (Table 2).

Table 2. HHI Values for U.S. Total Proprietary Varieties by Acreage and Production 2000–2020.

Crop Year	HHI Values for Proprietary Varieties by Acreage	HHI Values for Proprietary Varieties by Production
2000	0.0376	0.0729
2001	0.0900	0.1474
2002	0.0961	0.1709
2003	0.0755	0.1416
2004	0.0898	0.1586
2005	0.0904	0.1425
2006	0.0948	0.1791
2007	0.1200	0.2100
2008	0.1533	0.2441
2009	0.1642	0.2593
2010	0.1393	0.1903
2011	0.1496	0.2050
2012	0.1149	0.1618
2013	0.2024	0.2882
2014	0.1822	0.2700

Table 2. *Cont.*

Crop Year	HHI Values for Proprietary Varieties by Acreage	HHI Values for Proprietary Varieties by Production
2015	0.1841	0.2500
2016	0.1832	0.2292
2017	0.2661	0.3170
2018	0.3094	0.3628
2019	0.4058	0.4371
2020	0.4927	0.5394

The U.S. proprietary hop varieties used to calculate market concentration relative to public varieties between 2000 and 2020 listed in alphabetical order: Ahtanum ™, YCR 1, Amarillo ® VGXP01, Apollo ™, Azacca ™ ADHA-483, Bravo ™, Calypso ™, Chelan, Citra ®, HBC 394, Columbus/Tomahawk®/Zeus (also known as: C/T/Z®), Ekuanot ™, HBC 366, El Dorado ®, Eureka ™, IDAHO 7™, Idaho Gem™, Jarrylo ™, ADHA-881, Loral ™, HBC 291, Millennium®, Mosaic ®, HBC 369, Pahto ™, HBC 682, Palisade ®, YCR 4, Pekko ™, ADHA-871, Sabro™, HBC 438, Simcoe ®, YCR 14, Strata™ OR 91331, Summit ™, Super Galena ™, Talus®, Warrior ™, YCR 5, Zappa® (own study based on [13]).

The HHI analysis demonstrates that the market concentration due to the increasing proportion of proprietary varieties rose from a low to a moderate concentration between 2000 and 2010. It remained in the moderate zone until 2016 when it rapidly began to increase through 2020 when a tipping point had been reached (Figures 2 and 3). Official government data documented that in 2017 proprietary varieties represented greater than 50% of U.S. hop acreage [13].

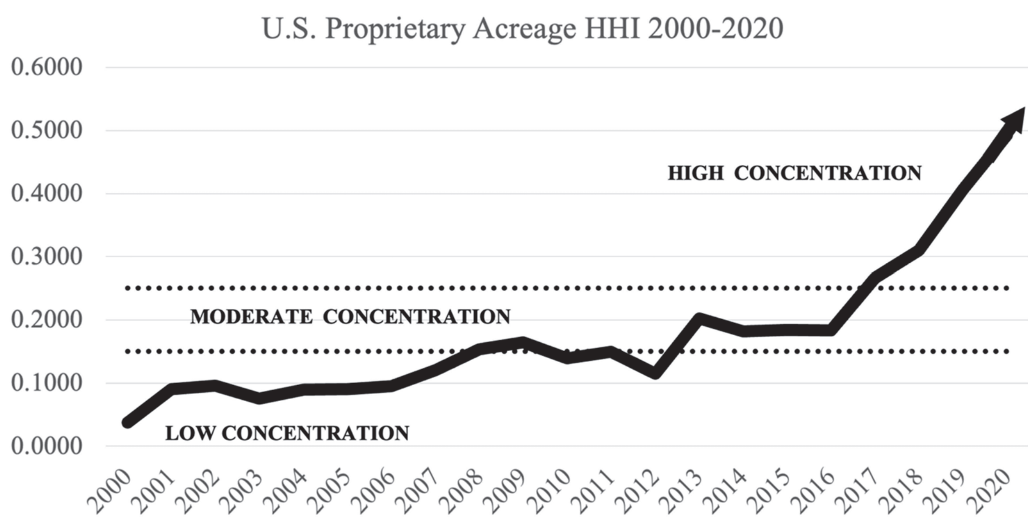

Figure 2. The HHI for total U.S. branded proprietary variety acreage 2000–2020 (own study based on [13]).

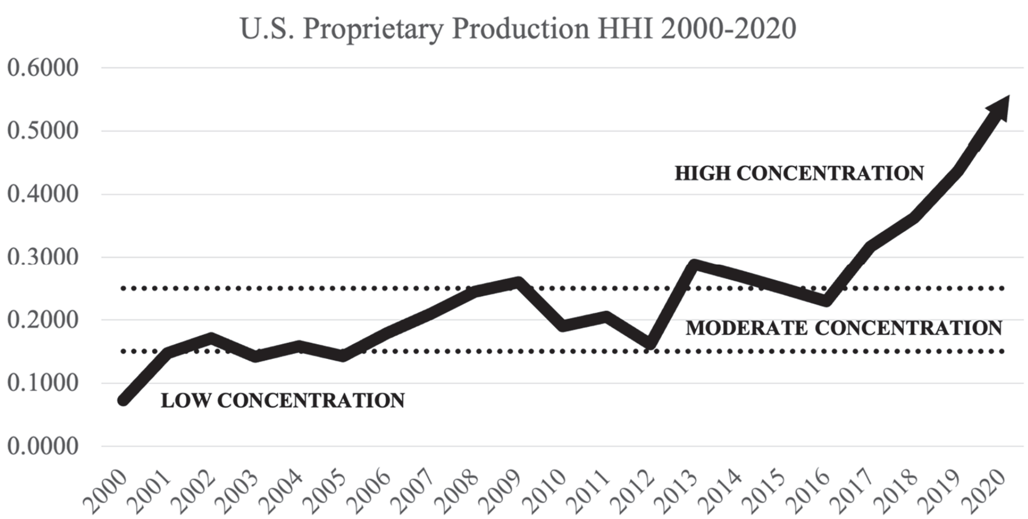

Figure 3. The HHI for total U.S. branded proprietary variety production 2000–2020 (own study based on [13]).

3.2. Prices of Hops Linked to the Intellectual Property

In the measurement of the effects on price over time, it was necessary to adjust for inflation. No appropriate Producer Price Index existed that could be applied to the U.S. hop industry. Therefore, we decided to use the Consumer Price Index (CPI) as it reflects changes in the economy and the purchasing power of the U.S. dollar over time. Vermeulen [22] suggests that U.S. producers adjust their prices as often as retailers. This suggested that the use of the CPI for adjusting prices for inflation would be an appropriate strategy.

Between 2016 and 2022, U.S. season average prices for hops as reported by the USDA remained stable at 75-year record high levels as acreage and production of proprietary varieties surpassed 50%. This suggested the existence of a tipping point facilitated by proprietary varieties that had been reached with regard to industry influence and its effect on price control. Prices when adjusted for inflation rose rapidly following 2016. The rapidly increasing HHI values post-2016 represented rapidly decreasing competitiveness. Reduced competitiveness was both a symptom and a consequence of the predominance of patented products where five entities captured 70% market share. As a result, prices increased to two standard deviations above the 75-year average of inflation-adjusted prices of $4.56 per pound (Figure 4). The parameter of long-term season average prices of hops during that time was chosen because it demonstrated lower price variability than the previous 36-year period for which data was available [13], a period that included World War I, the Great Depression, U.S. Prohibition, and World War II.

Rhoades (1995) concluded that the results of such analyses can yield useful insights into industry behavior. Concentration and the degree of competitiveness within an industry can impact price. MacAvoy [11] identified a general hypothesis regarding changes in market concentration and price-cost margins used to determine the direction of competitiveness.

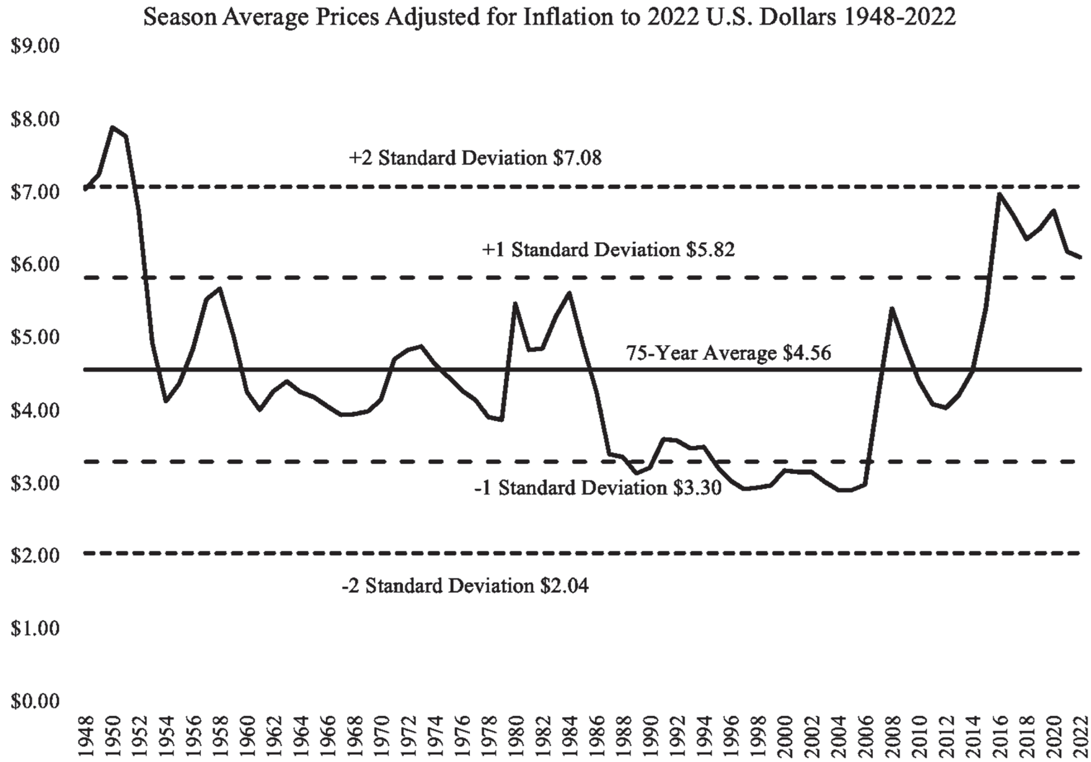

Figure 4. U.S. Season Average Prices 1948–2022 Adjusted for Inflation Using CPI (own study based on [16,23,24]).

Industry concentration reduced price competition as licensing agreements centralized decisions regarding production, sales, and marketing. Standardized quality by controlling harvest timing by IP owners was another result [25,26]. Patents grant the inventor control over the production, sales, and licensing of their invention without government involvement or oversight. Quantity or volume regulation and producer allotments of hops through Federal Marketing Orders have previously led to monopolistic policies [27].

3.3. Discussion

The Herfindahl-Hirschman Index calculations revealed that increases in proprietary variety acreage resulted in increased concentrations of power within the industry. This resulted in reduced competitiveness. Reduced competition in an oligopoly such as that which existed in the hop industry between 2016 and 2022 resulted in inflation-adjusted prices remaining stable at levels between one and two standard deviations higher than the 75-year average of U.S. season average prices, which was $4.56 per pound of hops i.e., $2.06 per kg of hops despite the existence of a growing surplus of hop inventory [13]. This was contrary to the normal tendency for prices to revert to long-term mean values or lower within 2–3 years following a price spike.

Reduced competitiveness within the hop industry during the period 2000–2020, enabled season average prices to remain at elevated levels for a prolonged period as they did between 2016 and 2020. The intrinsic homogeneous traits of branded proprietary varieties of hops such as oil production, which would typically result in symmetrical marginal costs, are overshadowed by extrinsic heterogeneous characteristics such as the perceived value of a brand and the urgency created by artificial scarcity. These characteristics create the perception of additional value for which the brewing industry has been prepared to pay handsomely [28]. The premium price and royalties warranted by proprietary varieties can be considered a deadweight loss ultimately born by the beer consumer.

We expanded the variety-specific acreage market share calculations to group those varieties that share common ownership to get a better picture of the influence of the five largest variety development companies. One company, the Hop Breeding Company, had a much greater share than the rest. Common ownership between the entities that create branded proprietary varieties, individual hop farms and hop merchant firms further increased market concentration. The individuals who own the entities that create proprietary varieties have created a competitive advantage for the merchant companies and farms in which they share a financial interest. We concluded that branded proprietary varieties, when their ownership is concentrated in few hands, reduced competition within the market, encouraged market segmentation and created opportunities for potential anti-competitive behavior.

According to data available between 2009 and 2020 from IHGC economic reports and the Hop Growers of America Statistical Packets, the farmgate value for contracted American hops was $2.88 billion greater than German growers. That does not represent the added value that processing, packaging, and reselling add to the price paid by brewers and beer consumers. During this same period, the USDA reported that proprietary variety acreage increased from 40.52 percent to 70.19 percent in the PNW [13].

4. Conclusions

The Herfindahl-Hirschman Index calculations offered a glimpse of changes in proprietary variety market share and the impact these changes have had upon market concentration and competitiveness within the U.S. hop industry between 2000 and 2022. During that short time, the industry went from one dominated by publicly available varieties to one managed product controlled by a duopoly.

The most relevant of the consequences of increased market concentration of reduced competitiveness was the greater ability of proprietary variety owners to manage the perception of scarcity of supply for their proprietary products on the market. Artificial scarcity created fear among brewers, which led to them signing long-term contracts at high prices (terms dictated by the farmer/merchant entities). Through their efforts, they could reduce or eliminate surplus inventory thereby enabling sustained premium prices indefinitely. A return to a system based on free market competition rather than one controlled by oligarchs would return market-based pricing and eliminate prices set at artificially high levels.

Additional data now suggest a surplus of contracted proprietary varieties developed and grew between 2016 and 2022. Artificially high prices were sustained since free market forces were not allowed to act. In the face of oversupply, these higher prices artificially increased the cost of production not only for American brewers but for brewers around the globe. The effect of proprietary varieties on the DSR remains to be seen as it is underway in 2023. It appears at the time of this writing the additional opacity created by private management of approximately 70 percent of the U.S. crop delayed the initial signaling period for the DSR to begin.

The effects of such supply management efforts affect not only proprietary U.S. varieties but public varieties in the U.S., too. The relationship between hop varieties (i.e., hop varieties may be substituted with other varieties) extends the effects of proprietary variety management upon farmers in countries where they are not produced. Additional research regarding the complementary relationship between the U.S. and German production regions is recommended to understand price movements, the disparity of pricing, and perceived value. The reduction in competitiveness within the U.S. industry this research provides is an important step in furthering the understanding of hop market dynamics and the interrelatedness of world markets. Further research might include an examination of the methods owners of proprietary varieties may use to cooperate with other related entities to alter supply to determine where the border exists for anti-trust violations. Further investigation into acreage management strategies is warranted.

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The Driving Role of Food and Cultivated Land Resource in Balancing the Complex Urban System of Socio-Economy and Environment: A Case Study of Shanghai City in China

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Abstract: Food is increasingly seen as a vehicle to address complex sustainability challenges, where the quantitative driving role in balancing the complex urban system of socio-economy and environment is still a gap. To fill this gap, taking Shanghai city as an example, this paper utilizes system dynamics to innovatively set three policy scenarios that aim at adjusting food security and cultivated land resources. The results confirm their positive role in socioeconomic and environmental improvement and coordinated development. In the high-rate grain yield growth scenario, the labor force ratio of the primary industry increases back to the size of 2012 (4.1%), the proportion of the primary industrial investment grows at twice the rate of the current trend, the grain yield per unit area increases back to the capacity of 1997 (798.154 t/km^2), and simultaneously, the occupation of cultivated land resources by the secondary industry and the negative impact of environmental pollution on productivity are mitigated. In that case, the coordination level between the socio-economy and the environment can keep increasing. The results indicate that future urban planning should increase the input of labor force and assets in the primary industry, improve food productivity per unit area through technical means or person training, alleviate the occupation of cultivated land resources by the secondary industry, and mitigate the negative impact of environmental pollution on cultivated land productivity.

Keywords: role of food and cultivated land resource; sustainable development; coordination development; socio-economy and environment; Shanghai city

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1. Introduction

Humans have entered the urban century [1]. The scale of the urban population worldwide reached 4.22 billion in 2018 and will keep growing to 6.68 billion in 2050 [2]. Urban development simultaneously creates more than 75% of the global GDP and contributes to 75% of energy-based carbon emissions [3]. Therefore, the urban population is the protagonist in the challenge for achieving sustainable development, as it carries most human activities connected with environmental crises and resource depletion. The New Urban Agenda at the Habitat III conference emphasized the role of cities as engines for sustainable development [4]. The knowledge about a sustainable future from an urban perspective should be central, and building a global urban science is essential [5]. Therefore, research on urban-scale development is of great significance for sustainable goals and science.

Further, realizing sustainable goals is not only the independent progress of each goal but, more importantly, to combat undesirable interactions, conflicts, and impacts, which can exactly be reflected in system analysis [6]. The urban system is a complex system and seeks systematic thinking [7]. System approaches can reduce negative surprises and promote integrated planning, management, and governance [8]. Therefore, it has been a research priority for some scholars to fully connect the urban socioeconomic and environmental systems and understand their dynamic interplay and feedback [9].

Among elements in different subsystems of complex urban system models, the resource mainly covers water resources [10,11], energy resources [12], nonrenewable and renewable resources [13], land use [14,15], and land development [16]. However, rapid urban development and sprawl are also threatening agricultural sustainability [17]. Although making cities sustainable is a global determination, little attention has been paid by the government to agriculture due to the belief that the highest benefit use of land is not on agriculture; this may result from a lack of the literature on the precise role of urban agriculture in building sustainable cities [18]. Therefore, considering the cultivated land elements in the complex urban system is of great theoretical significance.

A few studies on urban development take cultivated land resources and grain output into account [19]. Tapia et al. evaluated urban sustainability in Arhus based on an indicator framework that includes urban agriculture and food security [20]. Nigussie et al. analyzed the capacity and suitability of urban farmland in Ethiopia to contribute to sustainable development [21]. Tong et al. explored the manner to optimize urban food production in Tucson, a semi-arid region [22]. Xia et al. quantified the dynamics of green infrastructure in agriculture in Zhengzhou from the perspective of ecological security and food security [23]. Clerino et al. examined the practices for the sustainability assessment of professional urban agriculture [24]. Gozdziewicz-Biechonska et al. analyzed theoretical frameworks and practices for protecting agricultural land use [25]. These studies consider the element role of cultivated land and grain in sustainability. However, there is still a gap in their driving role in the coordinated development of complex urban systems.

Indeed, food is increasingly being regarded as a vehicle to simultaneously address economic, social, and environmental dilemmas [26]. Urban agriculture is recognized as a potential contributor to more sustainable development at the city level as it promotes food security and food sovereignty [27]. It is also lauded for its potential positive impacts on all three pillars of sustainability [18]. However, the effect of agriculture on the urban scale can be conflicting as good or bad [28]. The positive impacts include enhancing dietary diversity and improving ecosystem services and social quality [18,29,30], while the negative impacts are also stressed by some critics [27,31]. These arguments make it urgent to identify the role of food and cultivated land resources in the coordinated development of complex urban systems. In addition, although food resources for a metropolis can basically be supplied through trade with neighboring regions, the risk of public health events and natural disasters should be considered, and urban farming should be emphasized to increase food safety [32].

To sum up, this paper aims to fill the gap of the quantitative driving role of food and cultivated land resource in balancing the complex urban system of the socio-economy and the environment. Taking Shanghai city as an example, the system dynamics model is applied to simulate complex urban system development. Different scenarios are set to adjust the conditions of food and cultivated land resource and forecast the coordination level. According to the simulation results, suggestions for more sustainable and coordinated development are proposed from the perspectives of food security and cultivated land protection.

2. Methods and Study Area

2.1. System Dynamics Model

This paper applies system dynamics, which is an effective method for developing an understanding of complex systems [33]. This method can incorporate various elements of different subsystems in an integrated model, and the feedback loop can quickly seize the complex interactions [13]. In addition, scenario simulation is a good tool for policy or scheme analysis [10,34]. Due to these advantages, system dynamics has been applied in broad fields, including the urban system analysis, such as urban water–energy–food system [32], urban economy–resource–environment system [19], green urban system [35], urban social economy–water environment system [11], urban economy–society–resource–environment system [36], etc. Accordingly, this paper takes advantage of system dynamics to analyze the food role of urban agriculture in the urban system for coordination development between the socio-economy and the environment.

2.1.1. Model Conceptualization

This paper establishes an urban system, as shown in Figure 1. Firstly, this paper focuses on the food role in the coordination development of the urban system, reflected in 77 loops. For example:

Grain security→Total population→Labor force→Output of the primary industry→Grain security (a positive loop);
Grain security→Total population→Labor force→Output of tertiary/secondary industry→natural land→Grain security (a negative loop);
Grain security→Total population→Air/Water pollution→Pollution index→Output of the primary industry→Grain security (a negative loop);
Grain security→Total population→Labor force→Output of the tertiary/secondary industry→GDP→Output of the primary industry (a positive loop);
Grain security→Total population→Air/Water pollution→Pollution index→Output of the tertiary/secondary industry→GDP→Output of the primary industry (a negative loop).

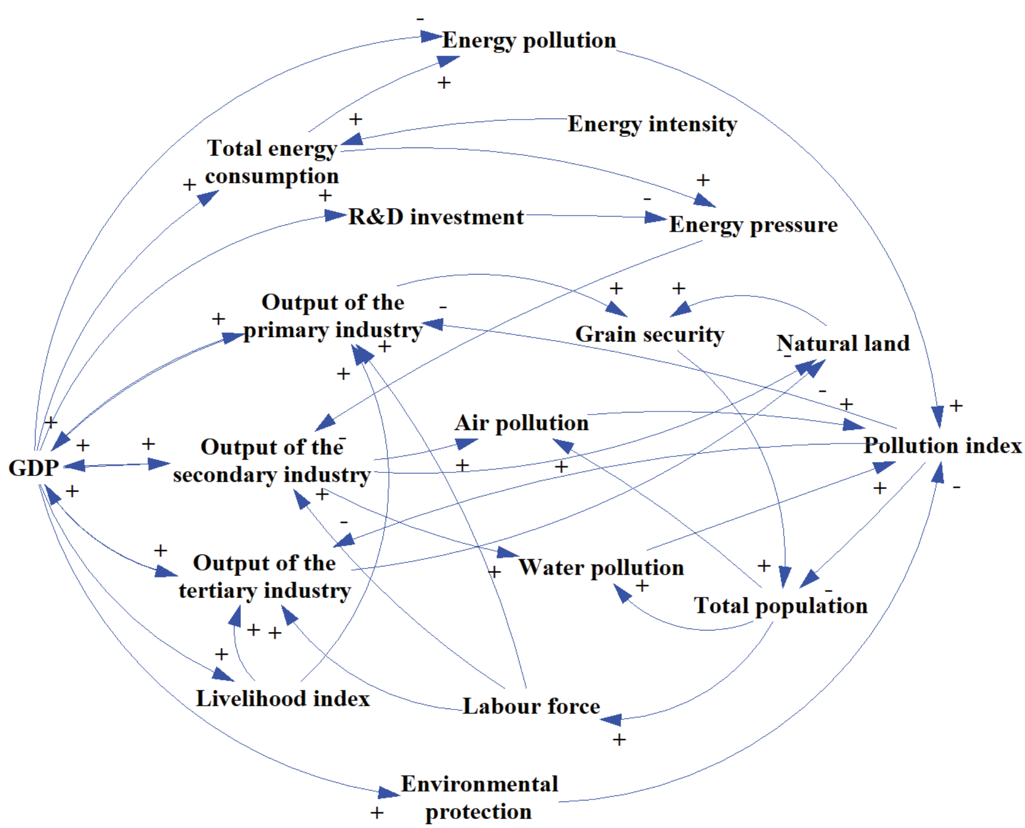

Figure 1. Causal loop diagram of the urban system.

Secondly, this paper hopes to provide a reference for promoting coordination development, considering the subsystems of the socio-economy and the environment. The socio-economy mainly covers the population, livelihood, three industries, and technology investment. The environmental subsystem investigates air and water pollution, energy consumption, and investment in protection.

2.1.2. Model Formulation

Based on the causal loop diagram, this paper further defines the urban system with various elements and interacting formulations (Appendix A). Then, the stock and flow chart of the system model is formulated, as shown in Figure 2. The model builds an urban system and aims to examine how the evolution of grain security (grain yield per capita) will influence the system coordination level. The determination methods of parameters in the interactions are shown in Appendix B.

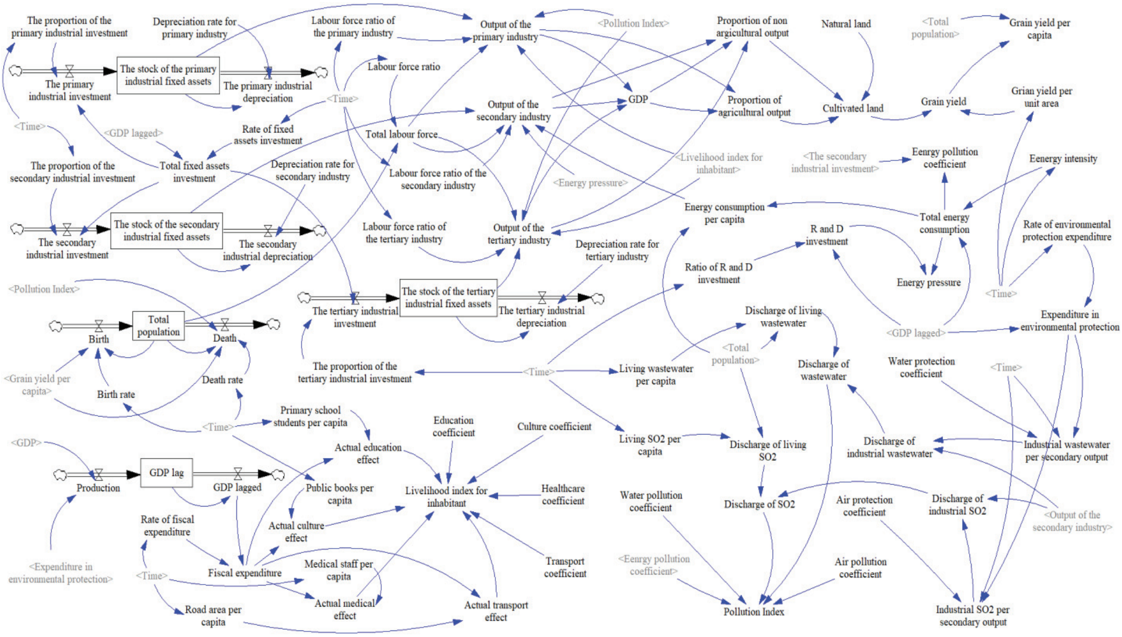

Figure 2. Stock and flow chart of the urban system.

To confirm the model's accuracy, this paper compares the simulated results with the actual data through the following formulas [19].

$$MARE = \frac{1}{N \times T} \sum_{j=1}^{N} \sum_{t=1}^{T} \left| \left(\widehat{Y_{jt}} - Y_{jt} \right) / Y_{jt} \right| \quad (1)$$

MARE represents Mean Absolute Relative Error, and a smaller value inflects a higher matching degree and a better simulation validation. Y_{it} is the actual value of indicator j at time t, and $\widehat{Y_{jt}}$ is the simulated one.

2.1.3. Scenario Settings

After establishing the urban system, the food role of urban agriculture is examined. To this end, three scenarios have been designed, as shown in Table 1. The first is the current scenario, with all variables evolving as the current trend. The second is the scenario of high protection in urban agriculture, with related parameters being adjusted to promote the growth of grain yield at a higher rate than the current value. The third scenario is low protection in urban agriculture, where the grain yield grows at a lower rate or decreases.

Table 1. Parameter setting of three scenarios to examine food role.

Parameters	Scenario 1: Current Trend	Scenario 2: Higher-Rate Grain Yield Growth	Scenario 3: Lower-Rate Grain Yield Growth
LFRP	0.012	0.041	0.006
LFRS	0.2782	0.2492	0.2842
PPII	0.008	0.026	0.002
PSII	0.1308	0.1128	0.1368
GYUA	662	800	602
REPE	0.032	0.037	0.026

Notes: LFRP: labor force ratio of the primary industry; LFRS: labor force ratio of the secondary industry; PPII: proportion of the primary industrial investment; PSII: proportion of the secondary industrial investment; GYUA: grain yield per unit area; REPE: rate of environmental protection expenditure.

2.2. *Coupling Coordination Degree Model*

To evaluate the coordination level between the urban socio-economy and the environment, this paper applies the coupling coordination degree model, a widely use method for complex systems with various interactions [37–39].

2.2.1. Indicator System and Data Source

Firstly, the indicator system of the urban system is established in consideration of data accessibility and previous studies [35,36,40,41], as shown in Table 2. This paper mainly collects data from Shanghai Statistical Yearbooks, and the simulation span is 1995–2030. To ensure the results are reasonable, this paper applies indicators of per capita value and converts the ones related to currency into values with 2000 as the base year.

Table 2. Indicator system of the urban system.

Subsystem	Indicators	Weight	Direction
Socio-economy	X_{11}: GDP per capita (¥10 thousand)	7.77%	+
	X_{12}: The proportion of agriculture in GDP (%)	15.93%	+
	X_{13}: Fixed assets investment per capita (¥10 thousand)	9.84%	+
	X_{14}: Fiscal expenditure per capita (¥10 thousand)	10.43%	+
	X_{15}: R & D expenditure per capita (¥10 thousand)	23.55%	+
	X_{16}: Birth (10 thousand persons)	32.47%	+
Environment	X_{21}: Cultivated land per capita (km^2/10 thousand persons)	11.95%	+
	X_{22}: Grain yield per capita (t/10 thousand persons)	21.32%	+
	X_{23}: Energy consumption per capita (Ton of standard coal)	11.02%	−
	X_{24}: Discharge of wastewater per capita (t)	13.34%	−
	X_{25}: Discharge of SO_2 per capita (t)	23.62%	−
	X_{26}: Expenditure in environmental protection per capita (¥10 thousand)	18.74%	+

2.2.2. Performance Evaluation of Subsystems

Then, the performance of the socio-economy and environment is evaluated in the following three steps.

Step 1: The indicator values are standardized with the two formulas to eliminate the possible impacts of dimensions.

$$\text{Positive indicators}: \ X'_{ij} = \left(X_{ij} - min\{X_j\}\right) / \left(max\{X_j\} - min\{X_j\}\right) \tag{2}$$

$$\text{Negative indicators}: \; X'_{ij} = \left(max\{X_j\} - X_{ij}\right) / \left(max\{X_j\} - min\{X_j\}\right) \tag{3}$$

where X_{ij} and X'_{ij} represent data before and after standardization, and $max\{X_j\}$ and $min\{X_j\}$ represent the maximum and minimum data of indicator *j*.

Step 2: The weights of indicators are obtained with the entropy method.

$$\text{Proportion of indicator } j \text{ in } i\text{th year}: \; P_{ij} = X'_{ij} / \sum_{i=1}^{m} X'_{ij} \tag{4}$$

$$\text{Entropy redundancy of indicator } j: \; d_j = 1 - \left(-\frac{1}{ln\ m} \sum_{i=1}^{m} P_{ij} \cdot ln\ P_{ij}\right) \tag{5}$$

$$\text{Weight of indicator } j: \; w_j = d_j / \sum_{j=1}^{n} d_j \tag{6}$$

Step 3: The performance levels are obtained.

$$S_i = \sum_{j=1}^{n} w_j \cdot X'_{ij} \tag{7}$$

2.2.3. Coordination Evaluation of the Urban System

Finally, the coordination level of the urban system is evaluated with the coupling coordination model.

$$\text{The overall level of the urban system}: \; T = \beta_1 \cdot f(SE) + \beta_2 \cdot g(EN) \tag{8}$$

$$\text{The coupling degree}: \; C = 2 \cdot \left[\frac{f(SE) \cdot g(EN)}{\left(f(SE) + g(EN)\right)^2}\right]^{\frac{1}{2}} \tag{9}$$

$$\text{The coordination level}: \; D = \sqrt{C \cdot T} \tag{10}$$

where $f(SE)$ and $g(EN)$ are the performance level of the socio-economy and the environment, and β_1 and β_2 represent their contributions, respectively. The values of β_1 and β_2 are both 0.5 [37].

Based on previous studies [19,37], the coordination degree can be divided into five levels, i.e., seriously unbalanced ($0 \leq D < 0.25$), slightly unbalanced ($0.25 \leq D < 0.5$), barely balanced ($0.5 \leq D < 0.75$), and superior balanced ($0.75 \leq D \leq 1$).

2.3. Study Area

Shanghai, a cosmopolitan megacity, is located at 120°52′~122°12′ E and 30°40′~31°53′ N. It has absorbed about 25 million people with a total area of 6340.5 km^2. It plays a central role in multi-aspects of national development, such as the economy, technology, finance, etc. Therefore, it is significant for China and the world to study sustainable and coordinated development in Shanghai city. Since 2010, the Shanghai Municipal Government has made many efforts in farmland supplement and reclamation of inefficient construction land. However, there are still problems, such as insufficient reserve resources of agricultural land and contradiction of land use. Thus, agricultural land protection and food security are still severe.

3. Results

3.1. Model Accuracy

This paper compares the simulated results with the actual data to confirm the model's accuracy. The average relative errors of these representative indicators are all within 5%, as shown in Figure 3; these results mean that the simulation values have good agreement with the actual values [34]. Therefore, the model's behavior is reliable for simulating the development of Shanghai.

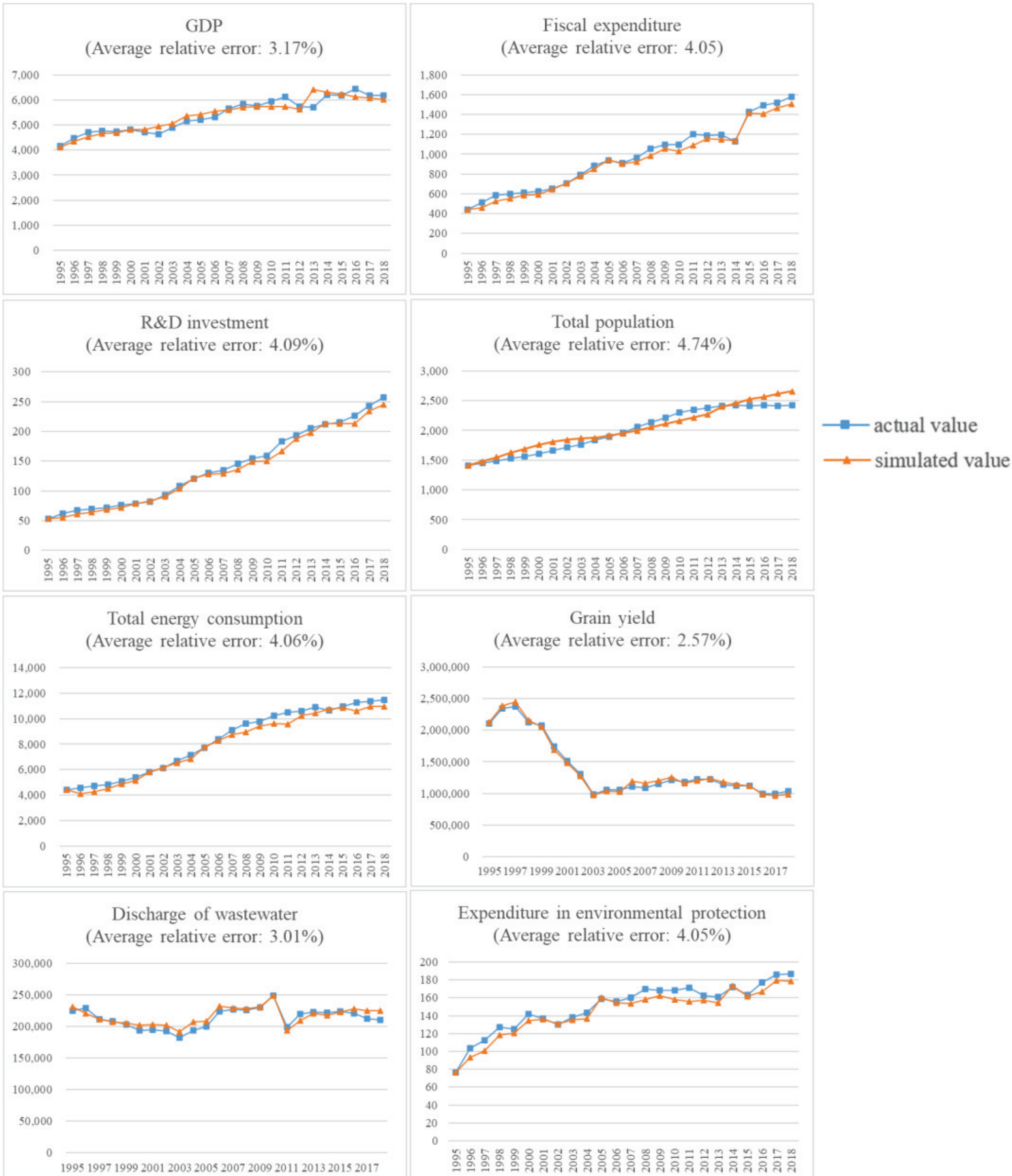

Figure 3. Average relative error of some key indicators in the model.

3.2. Model Results of Three Scenarios

3.2.1. Development of Food in Urban Agriculture

Under different scenarios, cultivated land will perform differently, as shown in Figure 4. If Shanghai follows the current development trend, agricultural land resources will be increasingly severe, and the lower-rate grain yield growth scenario will see a more serious situation. In contrast, the higher-rate grain yield growth scenario can somewhat protect cultivated land and promote resource increase at a gentle rate.

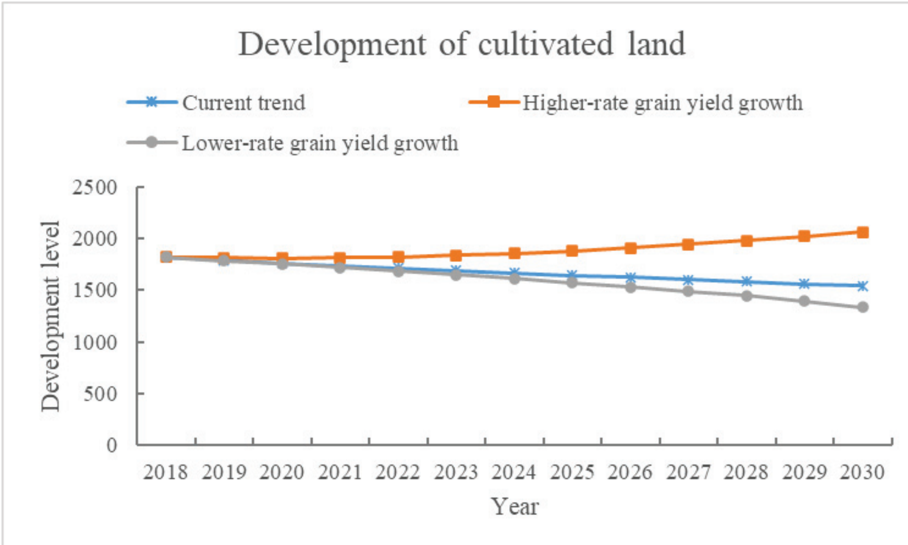

Figure 4. Development of cultivated land under three scenarios.

Similarly, the development of grain yield per capita sees the same development trends, as shown in Figure 5. Therefore, the higher-rate grain yield growth scenario that is set by this paper can protect cultivated land resources and ensure food security.

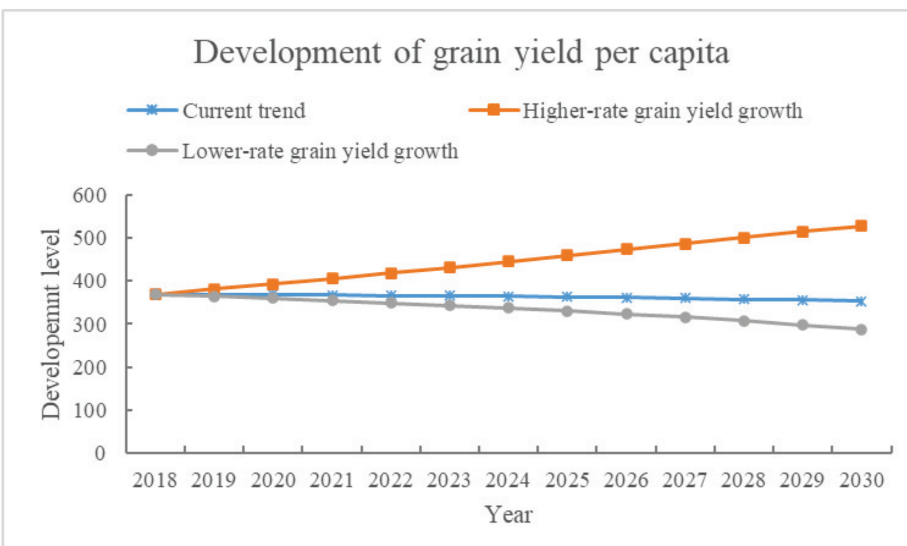

Figure 5. Development of grain yield per capita under three scenarios.

3.2.2. Socioeconomic and Environmental Performance

Under different scenarios, the performance of the socio-economy and the environment in Shanghai differs. As shown in Figure 6, the socio-economy shows an upward trend under all three scenarios during 2018–2030. The lower-rate grain yield growth scenario shows a minimum rise from 0.32 to 0.55. In contrast, the performance under higher-rate grain yield increases significantly from 0.32 to 0.67. The results imply that ensuring food security benefits socioeconomic development, which can be explained through the indicators' weights, as shown in Table 2. The top three important indicators are birth (32.47%), R & D expenditure per capita (23.55%), and the proportion of agriculture in GDP (15.93%), contributing to over 70% of the socioeconomic growth in total. High grain yield brings high growth in agriculture and promotes population growth, resulting in a high socio-economy. Therefore, the socioeconomic performances ranks are shown below: scenario under higher-rate grain yield growth > current scenario > scenario under lower-rate grain yield growth.

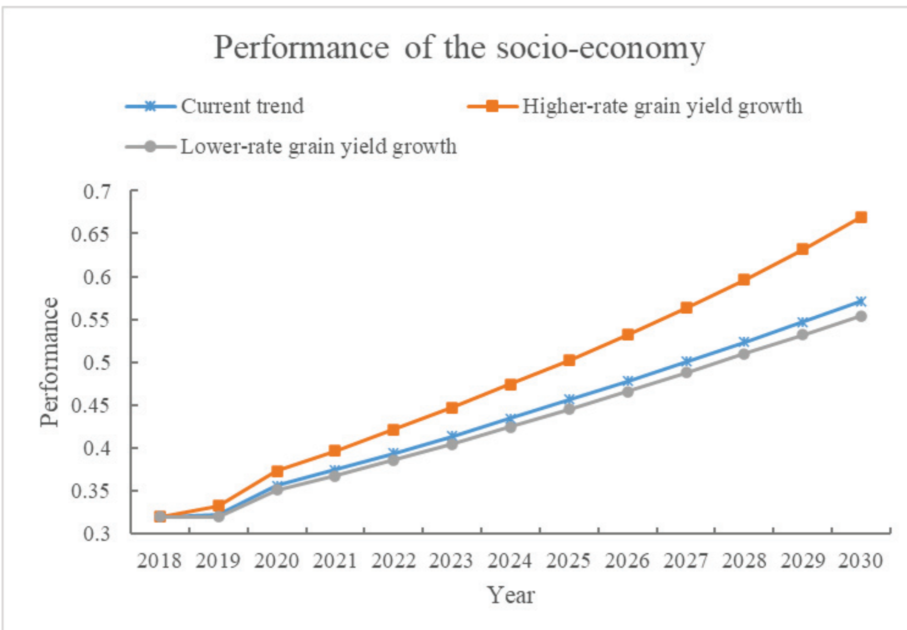

Figure 6. Performance of the socio-economy under three scenarios.

For the environment, the performance shows an opposite trend during 2018–2030, as shown in Figure 7. It will decrease sharply from 0.66 to 0.32 on the current development trend, and the situation under lower-rate grain yield growth will be even more serious. By comparison, the environmental performance can almost maintain the present level under higher-rate grain yield growth. The results imply that ensuring food security can also benefit environmental development, which can be explained through the indicators' weights in Table 2. Grain yield per capita and cultivated land per capita contribute to 23.32% and 11.95% of environmental performance, respectively; this is one-third in total. Therefore, the environmental performance ranks are shown below: scenario under higher-rate grain yield growth > current scenario > scenario under lower-rate grain yield growth.

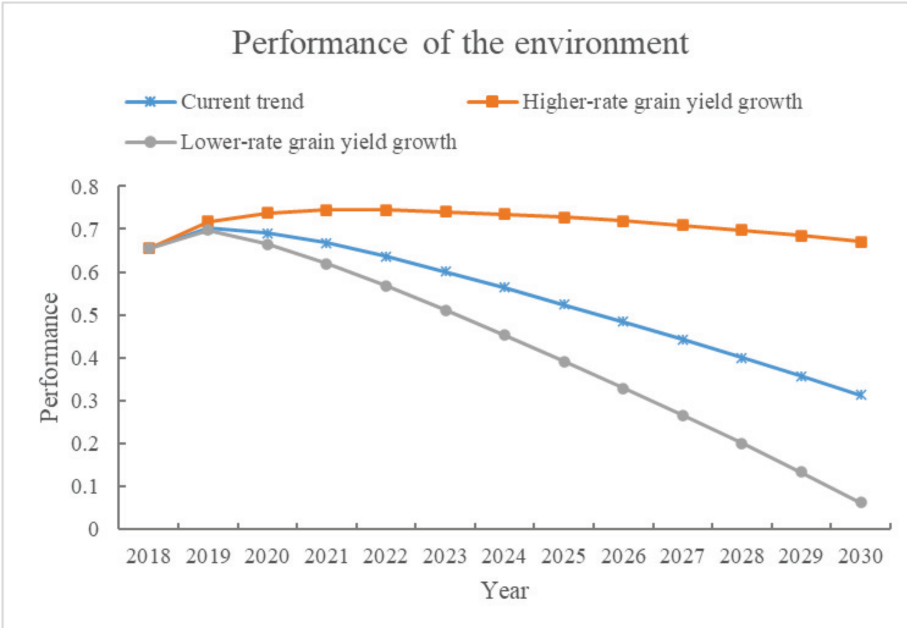

Figure 7. Performance of the environment under three scenarios.

3.2.3. Coupling Coordination Level

The coupling degrees under three scenarios are shown in Figure 8, reflecting the interacting intensity between the socio-economy and the environment. The trends under the current and higher-rate yield growth scenarios are similar, increasing from 0.2 to almost 1. In contrast, the coupling degree under lower-rate grain yield scenario growth sharply declines after 2027 to the original level.

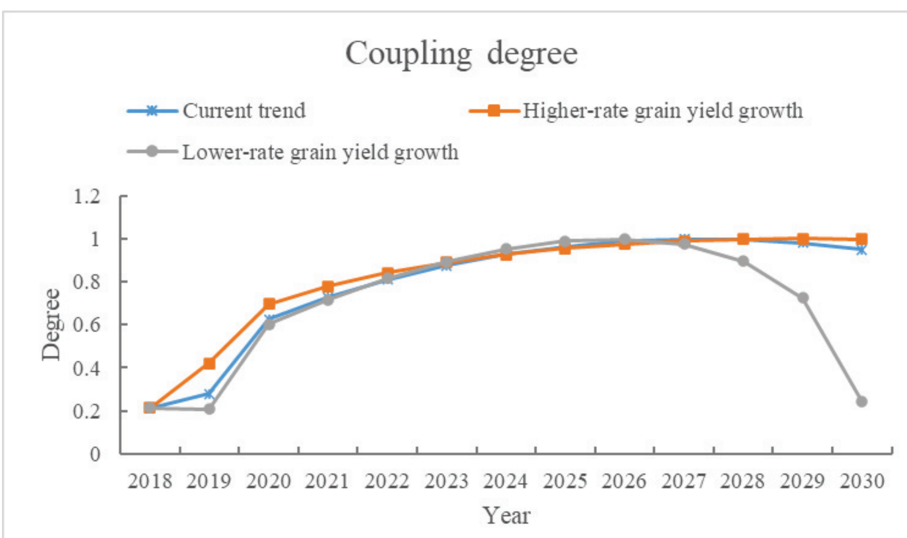

Figure 8. Coupling degree under three scenarios.

The coordination degrees under three scenarios are shown in Figure 9. In general, the coordination levels under current and higher-rate grain yield growth scenarios show an upward trend, while that of the under lower-rate grain yield growth scenario begins to decrease after 2025. Specifically, the coordination level of the current scenario increases gently from 0.3 (slightly unbalanced) to 0.7 (barely balanced). Coordination of higher-rate grain yield growth scenario is the highest and increases significantly to 0.967 (superior balanced). In contrast, that of the lower-rate grain yield growth is the lowest and first increases slowly to slightly unbalanced by 2025, and then, falls back to slightly unbalanced by 2030. These results indicate that neglecting the food role of urban agriculture will lead to uncoordinated development.

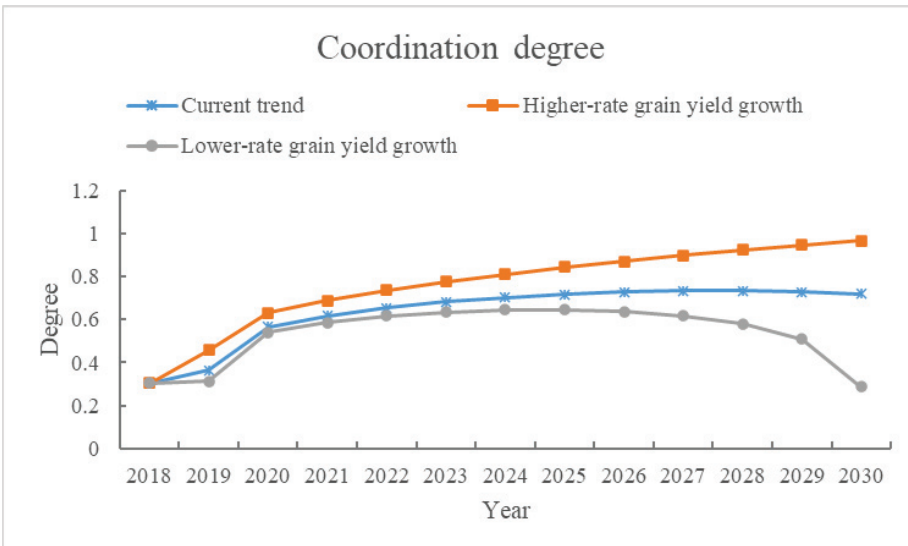

Figure 9. Coordination degree under three scenarios.

4. Discussion

Firstly, we can confirm the food role of urban agriculture in promoting the socio-economy by comparing the prediction results of different scenarios (Figure 6). The high-rate grain yield growth scenario promotes investment in the labor force and assets of the primary industry as well as improves the efficiency of food production. In addition, it alleviates the secondary industry's occupation of cultivated land resources and the negative impact of environmental damage on cultivated productivity. All these adjustments can promote the proportion of agriculture in GDP and have a positive effect on population development, which are essential aspects of the socioeconomic subsystem. These discoveries are in line with previous studies. Strengthening the development of food resources has been proven to be an optimized scenario to improve food security and GDP per capita [34]. Urban agriculture significantly benefits economic stability and physical health [42].

Secondly, we can also confirm the food role of urban agriculture in promoting the environment by comparing the prediction results of different scenarios (Figure 7). The high-rate grain yield growth scenario reduces the investment in the labor force and assets of the secondary industry as well as improves environmental protection, which can reduce pollution emissions and energy consumption. In addition, it protects the cultivated land resources and enhances food security, which has already been recognized as feasible in rich regions [27]. All these adjustments can promote the environmental subsystem. These findings align with other studies that show that more sustainable urban food systems allow energy conservation and emission reduction [42]. The results also provide quantitative evidence for previous views that urban agriculture is essential to deal with environmental deterioration [43]. Agriculture presents the potential for meeting sustainable goals in reducing adverse environmental impacts [44].

Finally, the food role of urban agriculture in promoting coordinated development is confirmed by comparing the prediction results of different scenarios (Figures 8 and 9). The high-rate grain yield growth scenario improves the performance of the socioeconomic subsystem, mitigates the decline in environmental performance, and ensures a high coupling degree, which promotes coordinated development. These discoveries further expand the previous research results, further identifying that improving food security can benefit the development of the socioeconomic and the environmental subsystems and their coordination level.

5. Policy Implications

Based on the simulation results, this paper attaches importance to agriculture and proposes the following suggestions for Shanghai city and other metropolises worldwide with tense cultivated land resources and food security capacity to improve sustainability. Food-focused urban planning has already been recommended in some countries [45].

Firstly, increase the input of the labor force and assets in the primary industry to promote its development and improve food security. In the high-rate grain yield growth scenario, the labor force ratio of the primary industry is set to increase back to the size of 2012, rather than fall to less than half of the current level; and the proportion of the primary industrial investment will grow at twice the rate of the current growth trend. Comprehensive means, including these measures, can significantly improve the performance of socioeconomic and environmental subsystems and promote their coordinated development.

Secondly, improve food production efficiency through technical means or manual training to promote the development of the primary industry and improve food security. In the high-rate grain yield growth scenario, the grain yield per unit area is set to increase back to the capacity of 1997, much faster than the current trend, which has been proven by simulation as an effective way to improve food security.

Thirdly, mitigate the occupation of cultivated land resources by the secondary industry. In the high-rate grain yield growth scenario, the labor force ratio of the secondary industry is set to decrease at a faster rate than the actual trend; the same is true for the proportion of the secondary industrial investment. Comprehensive means, including these measures, can also significantly improve the performance of socioeconomic and environmental subsystems and promote their coordinated development.

Last but not least, strengthen environmental protection and mitigate the negative impact of environmental damage on cultivated land production. In the high-rate grain yield growth scenario, the rate of environmental protection expenditure is set to increase faster than the current trend, which has been proven by simulation as an effective way to improve food security.

6. Conclusions

This paper applies system dynamics to innovatively analyze the quantitative role of food and cultivated land resources in complex urban systems of the socio-economy and the environment. Three scenarios, the current trend scenario, low-rate grain yield growth scenario, and high-rate grain yield growth scenario, are set to adjust food and cultivated land resources to analyze their roles. The coupling coordinated degree model is applied to evaluate the coordination level.

The results confirm the positive role of food and cultivated land resources in promoting the performance of socioeconomic and environmental subsystems in Shanghai city and coordinated development. The results indicate that future urban planning should increase the input of labor force and assets in the primary industry, improve food productivity per unit area through technical means or person training, alleviate the occupation of cultivated land resources by the secondary industry, and mitigate the negative impact of environmental pollution on cultivated land productivity.

It must be admitted that this study also has some limitations. The first limitation comes from data availability. For example, urban agriculture can also produce water pollution and play a role in promoting metabolism. However, due to the unavailability of data, these factors are not considered in the urban system. In addition to improving data quality, future research can continuously improve the representativeness of complex urban systems, such as incorporating the interactions between other elements as well as between different cities into the comprehensive system, making it more reflective of the actual development pattern.

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Data Availability Statement: Not applicable.

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

Appendix A Model Formulations

[1] Air pollution coefficient = 0.81
[2] Air protection coefficient = 0.2553
[3] Birth = Birth rate × Total population × Grain yield per capita^0.3384
[4] Birth rate ([(1995, 0)–(2030, 0.01)], (1995, 0.0055), (1996, 0.0056), (1997, 0.0055), (1998, 0.0052), (1999, 0.0054), (2000, 0.0053), (2001, 0.0043), (2002, 0.0047), (2003, 0.0043), (2004, 0.006), (2005, 0.0061), (2006, 0.006), (2007, 0.0073), (2008, 0.007), (2009, 0.0066), (2010, 0.0071), (2011, 0.0072), (2012, 0.0096), (2013, 0.0076), (2014, 0.0086), (2015, 0.0074), (2016, 0.009), (2017, 0.0081), (2018, 0.0067), (2030, 0.0085))
[5] Cultivated land = Natural land × Proportion of agricultural output^0.2342/Proportion of nonagricultural outputt^8.975
[6] Culture coefficient = 0.3105
[7] Death = Death rate × Total population × (1 + Pollution index × 6.3084)/Grain yield per capita^0.3384
[8] Death rate ([(1995, 0)–(2030, 0.01)], (1995, 0.0075), (1996, 0.007), (1997, 0.0068), (1998, 0.007), (1999, 0.0065), (2000, 0.0072), (2001, 0.0071), (2002, 0.0073), (2003, 0.0075), (2004, 0.0072), (2005, 0.0075), (2006, 0.0072), (2007, 0.0074), (2008, 0.0077), (2009, 0.0076), (2010, 0.0077), (2011, 0.0079), (2012, 0.0054), (2013, 0.0082), (2014, 0.0083), (2015, 0.0086), (2016, 0.0085), (2017, 0.0087), (2018, 0.0086), (2030, 0.0095))
[9] Depreciation rate for primary industry = 0.045
[10] Depreciation rate for secondary industry = 0.0698
[11] Depreciation rate for tertiary industry = 0.045
[12] Discharge of industrial SO_2 = Output of the secondary industry × Industrial SO_2 per secondary output/1000
[13] Discharge of industrial wastewater = Output of the secondary industry × Industrial wastewater per secondary output
[14] Discharge of living SO_2 = Total population × Living SO_2 per capita/1000
[15] Discharge of living wastewater = Total population × Living wastewater per capita
[16] Discharge OF SO_2 = Discharge of industrial SO_2 + Discharge of living SO_2
[17] Discharge of wastewater = Discharge of industrial wastewater + Discharge of living wastewater
[18] Education coefficient = 0.1915
[19] Energy intensity ([(1995, 0.8)–(2030, 2.2)], (1995, 1.0581), (1996, 1.0172), (1997, 0.9991), (1998, 1.0156), (1999, 1.0713), (2000, 1.125), (2001, 1.2388), (2002, 1.3188), (2003, 1.359), (2004, 1.3919), (2005, 1.4852), (2006, 1.5712), (2007, 1.6117), (2008, 1.6427), (2009, 1.6948), (2010, 1.7256), (2011, 1.7102), (2012, 1.8409), (2013, 1.9079), (2014, 1.7114), (2015, 1.7664), (2016, 1.7471), (2017, 1.8431), (2018, 1.855), (2019, 1.7215), (2030, 2.1033))

[20] Energy pollution coefficient = Total energy consumption × 0.63/LN (The secondary industrial investment)
[21] Energy consumption per capita = Total energy consumption/Total population
[22] Energy pressure = Total energy consumption × 0.01/LN (R and D investment)
[23] Expenditure in environmental protection = GDP lagged × Rate of environmental protection expenditure
[24] FINAL TIME = 2030
[25] Fiscal expenditure = GDP lagged × Rate of fiscal expenditure
[26] GDP = Output of the primary industry + Output of the secondary industry + Output of the tertiary industry
[27] GDP lag = INTEG (Production-GDP lagged,4151.4)
[28] GDP lagged = GDP lag
[29] Grain yield = Cultivated land × Grain yield per unit area
[30] Grain yield per capita = Grain yield/Total population
[31] Grain yield per unit area ([(1995, 370)–(2030, 800)], (1995, 725.517), (1996, 781.171), (1997, 798.154), (1998, 723.485), (1999, 715.366), (2000, 608.604), (2001, 539.629), (2002, 482.47), (2003, 383.793), (2004, 432.641), (2005, 443.995), (2006, 535.096), (2007, 530.097), (2008, 564.244), (2009, 601.483), (2010, 589.055), (2011, 610.972), (2012, 615.025), (2013, 607.181), (2014, 597.981), (2015, 590.516), (2016, 519.979), (2017, 520.772), (2018, 539.329), (2030, 762.012))
[32] Healthcare coefficient = 0.129
[33] Industrial SO_2 per secondary output = 53.29 × EXP (−((Time − 1995)/19.46)^5)/(Expenditure in environmental protection^Air protection coefficient)
[34] Industrial wastewater per secondary output = 1411 × EXP(−0.02637 × (Time − 1995))/(Expenditure in environmental protection^Water protection coefficient)
[35] INITIAL TIME = 1995
[36] Labor force ratio([(1995, 0.45)–(2030, 0.6)], (1995, 0.5617), (1996, 0.5838), (1997, 0.5639), (1998, 0.5416), (1999, 0.5113), (2000, 0.5082), (2001, 0.4763), (2002, 0.4886), (2003, 0.4946), (2004, 0.5521), (2005, 0.5333), (2006, 0.5396), (2007, 0.5334), (2008, 0.5328), (2009, 0.5239), (2010, 0.5213), (2011, 0.5126), (2012, 0.4976), (2013, 0.5923), (2014, 0.5709), (2015, 0.5527), (2016, 0.5353), (2017, 0.5217), (2018, 0.5095), (2030, 0.5316))
[37] Labor force ratio of the primary industry ([(1995, 0.01)–(2030, 0.14)], (1995, 0.0985), (1996, 0.1204), (1997, 0.1271), (1998, 0.1244), (1999, 0.1141), (2000, 0.1077), (2001, 0.11), (2002, 0.1015), (2003, 0.0863), (2004, 0.0688), (2005, 0.063), (2006, 0.055), (2007, 0.0524), (2008, 0.0469), (2009, 0.0456), (2010, 0.034), (2011, 0.0338), (2012, 0.041), (2013, 0.037), (2014, 0.0328), (2015, 0.0338), (2016, 0.0333), (2017, 0.0309), (2018, 0.0297), (2030, 0.012))
[38] Labor force ratio of the secondary industry ([(1995, 0.25)–(2030, 0.56)], (1995, 0.5447), (1996, 0.5226), (1997, 0.491), (1998, 0.4603), (1999, 0.4646), (2000, 0.4431), (2001, 0.3987), (2002, 0.3967), (2003, 0.4076), (2004, 0.4535), (2005, 0.4243), (2006, 0.4168), (2007, 0.4125), (2008, 0.4027), (2009, 0.3974), (2010, 0.4068), (2011, 0.403), (2012, 0.3944), (2013, 0.3501), (2014, 0.3492), (2015, 0.3377), (2016, 0.3285), (2017, 0.3136), (2018, 0.3074), (2030, 0.2782))
[39] Labor force ratio of the tertiary industry ([(1995, 0.35)–(2030, 0.75)], (1995, 0.3568), (1996, 0.357), (1997, 0.3819), (1998, 0.4153), (1999, 0.4213), (2000, 0.4492), (2001, 0.4912), (2002, 0.5017), (2003, 0.5061), (2004, 0.4777), (2005, 0.5128), (2006, 0.5282), (2007, 0.5351), (2008, 0.5504), (2009, 0.557), (2010, 0.5592), (2011, 0.5632), (2012, 0.5646), (2013, 0.6129), (2014, 0.618), (2015, 0.6285), (2016, 0.6382), (2017, 0.6554), (2018, 0.663), (2030, 0.7098))
[40] Livelihood index for inhabitant = LN (Fiscal expenditure × (Culture coefficient × Public books per capita + Education coefficient*Primary school students per capita + Healthcare coefficient × Medical staff per capita + Transport coefficient × Road area per capita))
[41] Living SO_2 per capita ([(1994, 0)–(2030, 12)], (1994, 6.402), (1995, 10.792), (1996, 5.307), (1997, 4.856), (1998, 6.417), (1999, 5.888), (2000, 8.585), (2001, 10.348), (2002, 7.105), (2003, 7.627), (2004, 6.736), (2005, 7.28), (2006, 6.808), (2007, 6.463), (2008, 6.917), (2009,

6.317), (2010, 4.121), (2011, 1.272), (2012, 1.46), (2013, 1.778), (2014, 1.351), (2015, 2.733), (2016, 0.283), (2017, 0.241), (2018, 0.033), (2019, 0.041), (2030, 0.131))

[42] Living wastewater per capita ([(1994, 60)–(2030, 95)], (1994, 61.2117), (1995, 76.662), (1996, 78.8422), (1997, 74.6138), (1998, 77.3412), (1999, 75.0479), (2000, 75.345), (2001, 76.124), (2002, 74.257), (2003, 68.5793), (2004, 74.66), (2005, 78.6243), (2006, 89.3075), (2007, 86.7248), (2008, 84.9603), (2009, 85.6561), (2010, 91.8367), (2011, 65.6157), (2012, 72.0773), (2013, 73.5404), (2014, 73.0833), (2015, 73.3747), (2016, 76.1157), (2017, 74.6071), (2018, 74.5462), (2019, 74.1606), (2030, 77.1461))

[43] Medical staff per capita([(1995, 0.005)–(2030, 0.011)], (1995, 0.0078), (1996, 0.0075), (1997, 0.0073), (1998, 0.0071), (1999, 0.0069), (2000, 0.0067), (2001, 0.0063), (2002, 0.0059), (2003, 0.0058), (2004, 0.0055), (2005, 0.0055), (2006, 0.0056), (2007, 0.0059), (2008, 0.006), (2009, 0.0059), (2010, 0.0059), (2011, 0.0059), (2012, 0.0062), (2013, 0.0065), (2014, 0.0068), (2015, 0.007), (2016, 0.0074), (2017, 0.0078), (2018, 0.0085), (2019, 0.0084), (2030, 0.0107))

[44] Natural land = 6341

[45] Output of the primary industry = 0.086/Pollution index^0.8284 × Livelihood index for inhabitant^0.1163 × The stock of the primary industrial fixed assets^0.91 × (Labor force ratio of the primary industry × Total labor force)^0.5272

[46] Output of the secondary industry = 0.3843/Energy pressure^0.4549 × Energy consumption per capita^0.6016 × The stock of the secondary industrial fixed assets^0.8047 × (Total labor force*Labor force ratio of the secondary industry) ^0.3084

[47] Output of the tertiary industry = 23.0808/Pollution index^0.8284 × Livelihood index for inhabitant^0.1163 × The stock of the tertiary industrial fixed assets^0.162 × (Total labor force × Labor force ratio of the tertiary industry) ^0.7136

[48] Pollution index = LN (Energy pollution coefficient × (Air pollution coefficient × Discharge of SO2+Water pollution coefficient × Discharge of wastewater)/(Discharge of SO2+Discharge of wastewater))

[49] Primary school students per capita([(1995, 0.02)–(2030, 0.08)], (1995, 0.0776), (1996, 0.0734), (1997, 0.0688), (1998, 0.063), (1999, 0.0556), (2000, 0.049), (2001, 0.0433), (2002, 0.0393), (2003, 0.0367), (2004, 0.0293), (2005, 0.0283), (2006, 0.0272), (2007, 0.0258), (2008, 0.0276), (2009, 0.0304), (2010, 0.0305), (2011, 0.0312), (2012, 0.032), (2013, 0.0328), (2014, 0.0331), (2015, 0.0331), (2016, 0.0326), (2017, 0.0325), (2018, 0.0342), (2019, 0.034), (2030, 0.0415))

[50] Production = GDP-Expenditure in environmental protection

[51] Proportion of agricultural output = Output of the primary industry/GDP

[52] Proportion of nonagricultural output = (Output of the secondary industry + Output of the tertiary industry)/GDP

[53] Public books per capita([(1995, 1)–(2030, 4)], (1995, 1.1216), (1996, 1.1392), (1997, 3.2102), (1998, 3.1493), (1999, 3.0989), (2000, 3.4191), (2001, 3.3974), (2002, 3.3959), (2003, 3.3378), (2004, 3.1891), (2005, 3.2005), (2006, 3.0866), (2007, 3.03), (2008, 2.9865), (2009, 2.9833), (2010, 2.9566), (2011, 2.9369), (2012, 3.0261), (2013, 2.9975), (2014, 3.035), (2015, 3.1337), (2016, 3.1719), (2017, 3.2146), (2018, 3.2567), (2019, 3.3208), (2030, 3.8485))

[54] R and D investment = GDP lagged × Ratio of R and D investment

[55] Rate of environmental protection expenditure ([(1995, 0)–(2030, 0.1)], (1995, 0.01846), (1996, 0.02309), (1997, 0.02376), (1998, 0.02666), (1999, 0.02642), (2000, 0.02949), (2001, 0.02909), (2002, 0.02802), (2003, 0.02815), (2004, 0.02782), (2005, 0.03057), (2006, 0.02933), (2007, 0.02843), (2008, 0.02906), (2009, 0.02925), (2010, 0.02833), (2011, 0.02788), (2012, 0.02827), (2013, 0.02814), (2014, 0.0277), (2015, 0.02636), (2016, 0.02756), (2017, 0.03015), (2018, 0.03027), (2019, 0.02829), (2030, 0.035))

[56] Rate of fiscal expenditure ([(1995, 0.1)–(2030, 0.35)], (1995, 0.1064), (1996, 0.115), (1997, 0.1238), (1998, 0.1255), (1999, 0.1294), (2000, 0.1294), (2001, 0.1382), (2002, 0.1515), (2003, 0.1621), (2004, 0.1723), (2005, 0.1805), (2006, 0.1711), (2007, 0.1709), (2008, 0.1801), (2009, 0.1899), (2010, 0.1844), (2011, 0.1956), (2012, 0.2073), (2013, 0.2096), (2014, 0.1815), (2015, 0.2303), (2016, 0.2315), (2017, 0.2464), (2018, 0.2556), (2030, 0.3096))

[57] Rate of fixed assets investment ([(1995, 0.1)–(2030, 0.7)], (1995, 0.6361), (1996, 0.6549), (1997, 0.5707), (1998, 0.5129), (1999, 0.4397), (2000, 0.3885), (2001, 0.3794), (2002, 0.3774), (2003, 0.3604), (2004, 0.3807), (2005, 0.3852), (2006, 0.3703), (2007, 0.3462), (2008, 0.3322), (2009, 0.335), (2010, 0.2968), (2011, 0.2532), (2012, 0.2604), (2013, 0.2614), (2014, 0.2381), (2015, 0.2363), (2016, 0.226), (2017, 0.2366), (2018, 0.2334), (2030, 0.1108))
[58] Ratio of R and D investment ([(1995, 0.01)–(2030, 0.06)], (1995, 0.0129), (1996, 0.0137), (1997, 0.0144), (1998, 0.0145), (1999, 0.0151), (2000, 0.0159), (2001, 0.0168), (2002, 0.0177), (2003, 0.0189), (2004, 0.021), (2005, 0.0232), (2006, 0.0244), (2007, 0.0239), (2008, 0.0249), (2009, 0.0269), (2010, 0.0269), (2011, 0.0299), (2012, 0.0337), (2013, 0.036), (2014, 0.0341), (2015, 0.0348), (2016, 0.0351), (2017, 0.0393), (2018, 0.0416), (2030, 0.054))
[59] Road area per capita ([(1995, 4)–(2030, 18)], (1995, 4.01), (1996, 4.46), (1997, 4.91), (1998, 6.04), (1999, 8.52), (2000, 8.68), (2001, 13.6), (2002, 11.6), (2003, 12.46), (2004, 15.36), (2005, 11.78), (2006, 11.84), (2007, 15.4), (2008, 15.7), (2009, 17.54), (2010, 11.12), (2011, 11.18), (2012, 11.24), (2013, 11.3), (2014, 11.51), (2015, 11.83), (2016, 12.09), (2017, 12.34), (2018, 12.49), (2019, 12.7), (2030, 14.63))
[60] SAVEPER = TIME STEP
[61] The primary industrial depreciation = The stock of the primary industrial fixed assets × Depreciation rate for primary industry
[62] The primary industrial investment = Total fixed assets investment × The proportion of the primary industrial investment
[63] The proportion of the primary industrial investment ([(1995, 0)–(2030, 0.012)], (1995, 0.0061), (1996, 0.0107), (1997, 0.004), (1998, 0.0033), (1999, 0.0044), (2000, 0.0044), (2001, 0.0035), (2002, 0.0025), (2003, 0.0018), (2004, 0.0018), (2005, 0.0017), (2006, 0.0037), (2007, 0.002), (2008, 0.0018), (2009, 0.0022), (2010, 0.0032), (2011, 0.0038), (2012, 0.0023), (2013, 0.0034), (2014, 0.0021), (2015, 0.0007), (2016, 0.0006), (2017, 0.0003), (2018, 0.0007), (2030, 0.0003))
[64] The proportion of the secondary industrial investment ([(1995, 0)–(2030, 0.4)], (1995, 0.3226), (1996, 0.3314), (1997, 0.3354), (1998, 0.3333), (1999, 0.3323), (2000, 0.3294), (2001, 0.3427), (2002, 0.332), (2003, 0.3291), (2004, 0.3275), (2005, 0.3055), (2006, 0.309), (2007, 0.3135), (2008, 0.2942), (2009, 0.2707), (2010, 0.2699), (2011, 0.2557), (2012, 0.2463), (2013, 0.2199), (2014, 0.1924), (2015, 0.1509), (2016, 0.1455), (2017, 0.1426), (2018, 0.1588), (2030, 0.075))
[65] The proportion of the tertiary industrial investment ([(1995, 0.6)–(2030, 1)], (1995, 0.6713), (1996, 0.6582), (1997, 0.6611), (1998, 0.6636), (1999, 0.6635), (2000, 0.6664), (2001, 0.654), (2002, 0.6656), (2003, 0.6692), (2004, 0.6708), (2005, 0.693), (2006, 0.6874), (2007, 0.6847), (2008, 0.7041), (2009, 0.7271), (2010, 0.727), (2011, 0.7406), (2012, 0.7516), (2013, 0.7768), (2014, 0.8057), (2015, 0.8484), (2016, 0.8539), (2017, 0.8572), (2018, 0.8405), (2030, 0.922))
[66] The secondary industrial depreciation = The stock of the secondary industrial fixed assets × Depreciation rate for secondary industry
[67] The secondary industrial investment = Total fixed assets investment × The proportion of the secondary industrial investment
[68] The stock of the primary industrial fixed assets = INTEG (The primary industrial investment-The primary industrial depreciation,464.362)
[69] The stock of the secondary industrial fixed assets = INTEG (The secondary industrial investment-The secondary industrial depreciation,8072)
[70] The stock of the tertiary industrial fixed assets = INTEG (The tertiary industrial investment-The tertiary industrial depreciation,5501.27)
[71] The tertiary industrial depreciation = The stock of the tertiary industrial fixed assets*Depreciation rate for tertiary industry
[72] The tertiary industrial investment = Total fixed assets investment × The proportion of the tertiary industrial investment
[73] TIME STEP = 1
[74] Total energy consumption = Energy intensity × GDP lagged

[75] Total fixed assets investment = GDP lagged × Rate of fixed assets investment
[76] Total labor force =Total population × Labor force ratio
[77] Total population = INTEG (Birth-Death,1414)
[78] Transport coefficient = 0.2399
[79] Water pollution coefficient = 0.35
[80] Water protection coefficient = 0.7555

Appendix B

Table A1. The Determination Methods of Parameters.

No.	Parameters	Values	Methods
1	Air pollution coefficient	Appendix A	[19]
2	Air protection coefficient	Appendix A	Regression analysis
3	Elastic coefficient of Grain yield per capita for Birth	0.3384	Regression analysis
4	Birth rate	Appendix A	Table function
5	Elastic coefficient of Proportion of agricultural output for Cultivated land	0.2342	Regression analysis
6	Elastic coefficient of Proportion of nonagricultural output for Cultivated land	8.975	Regression analysis
7	Culture coefficient	Appendix A	Regression analysis
8	Elastic coefficient of Pollution index for Death	6.3084	Regression analysis
9	Elastic coefficient of Gain yield per capita for Birth	0.3384	Regression analysis
10	Death rate	Appendix A	Table function
11	Depreciation rate for primary industry	Appendix A	[19]
12	Depreciation rate for secondary industry	Appendix A	Regression analysis
13	Depreciation rate for tertiary industry	Appendix A	[19]
14	Education coefficient	Appendix A	Regression analysis
15	Energy intensity	Appendix A	Table function
16	Elastic coefficient of Total energy consumption for energy pollution coefficient	0.63	Regression analysis
17	Elastic coefficient of Total energy consumption for Energy pressure	0.01	Regression analysis
18	Grain yield per unit area	Appendix A	Table function
19	Healthcare coefficient	Appendix A	Regression analysis
20	Industrial wastewater per secondary output	Appendix A	Regression analysis
21	Labor force ratio	Appendix A	Table function
22	Labor force ratio of the primary industry	Appendix A	Table function
23	Labor force ratio of the secondary industry	Appendix A	Table function
24	Labor force ratio of the tertiary industry	Appendix A	Table function
25	Living SO_2 per capita	Appendix A	Table function
26	Living wastewater per capita	Appendix A	Table function
27	Medical staff per capita	Appendix A	Table function
28	Natural land	Appendix A	Constant
29	Output of the primary industry	Appendix A	Regression analysis
30	Elastic coefficient of Pollution index for Output of the primary industry	0.8284	Regression analysis
31	Elastic coefficient of Livelihood index for inhabitant for Output of the primary industry	0.1163	Regression analysis
32	Elastic coefficient of the stock of the primary industrial fixed assets for Output of the primary industry	0.91	Regression analysis
33	Elastic coefficient of the labor force for Output of the primary industry	0.5272	Regression analysis
34	Output of the secondary industry	Appendix A	Regression analysis

Table A1. *Cont.*

No.	Parameters	Values	Methods
35	Elastic coefficient of Energy pressure for Output of secondary industry	0.4549	Regression analysis
36	Elastic coefficient of Energy consumption per capita for Output of secondary industry	0.6061	Regression analysis
37	Elastic coefficient of the stock of the secondary industrial fixed assets for Output of the secondary industry	0.8047	Regression analysis
38	Elastic coefficient of the labor force for Output of the secondary industry	0.3084	Regression analysis
39	Output of the tertiary industry	Appendix A	Regression analysis
40	Elastic coefficient of Pollution index for Output of the tertiary industry	0.8284	Regression analysis
41	Elastic coefficient of Livelihood index for inhabitant for Output of the secondary industry	0.1163	Regression analysis
42	Elastic coefficient of the stock of the tertiary industrial fixed assets for Output of the tertiary industry	0.162	Regression analysis
43	Elastic coefficient of the labor force for Output of the tertiary industry	0.7136	Regression analysis
44	Primary school students per capita	Appendix A	Table function
45	Public books per capita	Appendix A	Table function
46	Rate of environmental protection expenditure	Appendix A	Table function
47	Rate of fiscal expenditure	Appendix A	Table function
48	Rate of fixed assets investment	Appendix A	Table function
49	Ratio of R and D investment	Appendix A	Table function
50	Road area per capita	Appendix A	Table function
51	The proportion of the primary industrial investment	Appendix A	Table function
52	The proportion of the secondary industrial investment	Appendix A	Table function
53	The proportion of the tertiary industrial investment	Appendix A	Table function
54	Transport coefficient	Appendix A	Regression analysis
55	Water pollution coefficient	Appendix A	(Xing et al., 2019)
56	Water protection coefficient	Appendix A	Regression analysis

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Evaluation of the Contribution of Farmland Attributes to the Total Benefit from Its Contamination Remediation: Evidence from Taiwan

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Abstract: This study fills the gap in the existing literature by developing a two-stage quantile spatial Durbin model to evaluate the benefit from the cancellation of controlled contaminated farmlands. The results of monetary benefit are to identify the contribution of farmland attributed to the change in the total benefit resulting from the cancellation of contaminated farmlands. The results show that the significant impacts are the attributes resulting from the size of the transacted farmland, the distance between the transacted farmland and the main traffic artery, and the price of the construction site where the transacted farmlands are located. The results indicate that for every 1000 square meter increase in farmland size, the farmland price increases by about 45–105% in the non-agricultural planning zone, the Taoyuan Aerotropolis life circle, and decreases by about 81–131% in the agricultural planning zones. Moreover, for the price quantiles of 50% and above, the total benefit from the announcement of contamination cancellation to the ensuing transaction is reflected by an increase in the transaction price of 1.67–12.98% of the total benefit for non-agricultural Taoyuan Aerotropolis life circle zoning. By contrast, the total benefit from the same action taken for the other three agricultural development life circles is reflected by a reduction in the transaction price of 1.89–134.89%. These results indicate that the cancellation of highly priced contaminated farmlands is not anticipated if they are planned for agricultural purposes.

Keywords: endogeneity; geographic information system; not-in-my-backyard; remediation of contaminated farmland; two-stage quantile regression; spatial Durbin model; spatial land planning

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1. Introduction

Agricultural production relies to a high degree upon natural conditions, with climate being the most important, and soil and water resources being essential factors for the cultivation of agricultural products. The quality of water and soil has a significant impact on the quantity of agricultural production and the related output values. This is usually not easy to detect and thus tends to result in the soil being contaminated by different types of heavy metal pollutants. Similarly, various kinds of pollutants lead to the contamination of groundwater. The groundwater is an important water source for irrigation in agricultural production. The soil and groundwater contamination mainly comes from the improper application of nitrogen [1]. In Egypt, water is a scarce resource and thus it is preserved underground for recyclable use. If the groundwater is contaminated, the impact is not only felt in the specific region, sector, or industry, but throughout the whole country [2]. In addition, the method of cultivation and the types and application frequencies of chemical fertilizers and pesticides also have a key role to play in the heavy metal contamination of farmlands [3]. It can thus be concluded that soil and groundwater contamination impacts not only the amount and value of agricultural products, but also farmland transactions, food security, human health, and ecosystem services [4–7].

To eliminate the hazards that might arise from contaminated farmland sites, the U.S. Environmental Protection Agency passed the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), also referred to as the Superfund, in 1980. About 70% of sites with soil or related contamination are the responsibility of industries, and there are no definite responsible targets for the remaining 30% of sites [8]. Cleaning these contaminated sites poses a huge financial burden for the U.S. government. The Environmental Protection Administration in Taiwan (Taiwan EPA) started to implement the Soil and Groundwater Pollution Remediation Act (Remediation Act hereafter) in 2000. Along with the progress in pollution investigation, the polluted sites increase year by year. The most recent amendment to the Remediation Act classifies all soil-contaminated sites as "controlled sites", "remediated sites", "cancellation of controlled sites", or "cancellation of remediated sites" [9].

There are six municipalities in Taiwan, and their major cities account for 71.53% of the total population in Taiwan [10]. Among these, Taoyuan city has the smallest population and has the largest number of soil-contaminated farmland controlled sites. It, however, has the highest value of crops, with its share of the whole country being 5.83% [11]. These crops have a high probability of being grown on contaminated farmlands. Under the proposal of *Taiwan's Comprehensive National Spatial Land Planning Act* (*Spatial Planning Act* hereafter) legislated in 2016, each city and county has its own planning for industrial, agricultural, residential, and natural conservation zoning development [12].

In order to have a proper arrangement of different zoning developments, determining the characteristic benefits of rectifying the contaminated sites is essential. The benefits are commonly explored with the hedonic price method (HPM) by connecting the farmland price and all types of characteristics of farmlands. In terms of research topics in this regard, some studies have focused on the zone classification in Ontario, Canada, and New York state, US [13,14]; other studies explored the factors that have major impacts on farmland prices in Argentina, the Netherlands, Aragón, Illinois in the US, and New South Wales [15–19]; and yet a few other studies concentrated on the specification of functional forms with the analysis of five corn belt states in the US [20]. In terms of where research is conducted, in large countries such as the United States, studies have been conducted to find the farmland price relationship in a setting with agricultural zones or agricultural productivity of Illinois and Ohio farmlands in the US [18,21], and similar studies have also been conducted in Canada [13]. Impact studies on factors influencing farmland prices were conducted by [19] in Australia. Factors influencing farmland prices were also explored in the Netherlands by [16], and in Argentina by [15].

As for Taiwan, a study conducted by [22] sought to find the factors influencing farmland prices using a simple regression without accounting for the spatial differentiation. Moreover, this study mainly focused on the factors influencing farmland prices in rural areas without the concern of adding or deleting any new or existing element on or around farmland. There have been many related studies since 1 August 2012, when the actual details of real estate transactions were compiled and made known to the public by Taiwan's Ministry of the Interior [23]. Ref. [24] explored the impact of solar panel installation on the prices of farmland. Ref. [25] evaluated the not-in-my-back-yard (NIMBY) and yes-in-my-back-yard (YIMBY) effects from cropland open spaces while accounting for spatial differentiation among farmlands.

It can be concluded that studies using the HPM in different parts of the world to explore the issues in relation to farmland remediation and their prices are mainly affected by the characteristics of farmland per se, such as the types of crops grown on the farmland, the production conditions for the farmland, the size of the farmland, and the surrounding characteristics of the farmland. However, most of the studies stated above do not account for the spatial issues related to the farmlands. If farmlands exhibit spatial dependence, then spatial HPM has to be considered. Spatial types of HPM have become accessible since the obstacles due to software operations have been reduced. The application of spatial HPM to farmland prices is discussed in [26–28].

Other types of studies consider the impact of a change in a specific farmland attribute on farmland prices. Examples are found in [29] regarding Czech farmland buyers. Different types of buyers place different emphases on different farmland characteristics. This, in turn, will have different impacts on farmland prices. Similarly, examples can be found in the study conducted by [30] of Germany's farmland prices due to the impact of government intervention, and that by [31] of farmland prices in the US from farm program payments. A study by [32] explored the prices of Belgian farmland with cadmium contamination, and another study by [33] considered the impact of natural amenities on farmland prices. The results from all these studies indicate that the changes in human-made policies or natural characteristics of farmland have different impacts on farmland prices. Thus, a quantile regression is much more appropriate than ordinary least squares regression when the relationship between farmland prices and all the potential explanatory characteristics is established [34].

It can thus be reasonably assumed that when looking into the factors that influence farmland prices, one should not only account for the spatial differentiation of farmland, but should also consider the divergent impacts of all types of farmland characteristics on farmland prices. As a result, the HPM has to combine both spatial differences and the dissimilar impacts on farmland prices through quantile regression. When spatialization occurs both in relation to the farmland prices and all types of attributes of farmland, the spatial Durbin model (SDM) should be employed [35–37]. It can be clearly seen that accounting for the spatial problem in relation to the dependent variable, namely, the farmland price, and/or the explanatory variables of farmland attributes involves considering the factors that have essential impacts on the farmland price when endogeneity might exist among the explanatory variables with adjustments in the spatial farmland price. Under such circumstances, the adoption of ordinary quantile SDM is not sufficient. When combining a two-stage quantile regression proposed by [38] with SDM by developing a new two-stage quantile, SDM is an appropriate method that can be used to resolve the variation in the spatial impact on the dependent variable of the farmland price and endogeneity among the spatial explanatory factors.

The benefits from the remediation of farmlands in different cities or counties are essential information for the land planning of a specific city or county and for the country as a whole. To the best of our knowledge, there is no study evaluating the monetary benefit via a change in the transacted farmland price due to farmland attributes that have a potential impact on the remediation of contaminated sites. The benefit generated by each farmland attribute is the foundation for prioritizing the cancellation order for all types of contaminated farmlands. Moreover, the results of the evaluated benefits can be used as a compensation guideline when zones are classified for agricultural purposes, and this is deemed to be a beneficial and a fair action for agricultural development [39,40].

As a result, the purpose of this study is to evaluate the monetary benefits of cancelling contaminated farmlands using a two-stage quantile SDM, newly developed in this study. The results identify the contribution of each farmland attribute or group of attributes to the change in the total benefit due to the cancellation of contaminated farmlands. The results can be used by related agencies to command the potential benefits of farmlands located in different cities or counties to determine the priority of cancelling contaminated farmlands.

The remaining sections of this paper are arranged as follows. Section 2 explains the conceptual framework of benefit evaluation for contaminated farmland remediation. Section 3 presents the evaluation methods for the two-stage quantile SDM. Section 4 discusses the data sources and selection of characteristics and their treatment. Section 5 provides a specification of the empirical model and an analysis of the results. The final section is the conclusion of this study.

2. Method and Models

2.1. A Panoramic View of Contaminated Farmlands and Spatial Planning of the Study Area

The major crops grown in Taoyuan city are rice and various kinds of vegetables. These contaminated farmlands have a high possibility of having a negative impact on the production of all types of agricultural products. This, in turn, has a further negative impact on the revenues from such production. Agricultural development is without a doubt ruined by contaminated farmlands. According to the records compiled by the Soil and Groundwater Remediation Fund Management Board of the Taiwan EPA [9], it is known that the latest available data from 31 December 2020, when this study started, show that 38.71% of the farmland in Taoyuan city consists of controlled contaminated farmland sites, and 29.75% of the area and each percentage is ranked the highest among all six municipalities in Taiwan. The contaminated farmland hot spots in the six municipalities of Taiwan are shown in Figure 1.

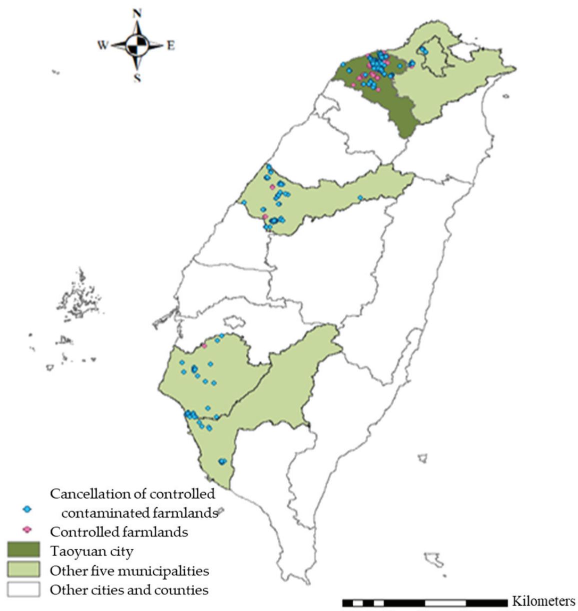

Figure 1. The contaminated farmland hot spots in the six municipalities of Taiwan.

The newest land zoning plan in Taiwan under the *Spatial Planning Act* has been proposed to maintain the agricultural development zone and non-agricultural zones to ensure food security and protect the infrastructure for the production areas. Thus, the planned farmlands should not be fragmented under the *Spatial Planning Act*. It is a comprehensive, policy-oriented, and objective guideline for zoning in each city and county. In order to achieve the appropriate zoning, data collection for existing administrative areas, data investigation, comprehensive analyses of the land spatial planning, and related arrangements are necessary tasks for each city or county.

Although the contaminated farmland sites and areas for Taoyuan city are not ranked the highest in Taiwan, the share of production in terms of total crop quantities in Taoyuan city is 12.29% among the six municipalities [11]. The food security and safety of these crops in relation to Taoyuan city and the nearby cities, namely, the capital of Taiwan, Taipei, and the city with the largest population in Taiwan, New Taipei city, have become a major focus of attention. Thus, it is essential to command the remediation benefit of planned farmlands from the existing agricultural development zone and non-agricultural development zones in Taoyuan city. The benefits are not only to be used to prioritize the remediation of all contaminated sites, but also for the compensation of areas zoned as farmland, which is deemed to have a lower price. Past research considered the farmer's personal situation, such as age or cultivated area, for compensation [41]. The results of the evaluation can be used to determine the amount of compensation due to the possible reduction in the farmland price from zoning for agricultural purposes.

2.2. Evaluation Methods

In order to achieve the purpose of this study, an appropriate estimation model is required. The hedonic price model is the link between the farmland prices and all types of characteristics that have different influences on the farmland price. Assume that a piece of farmland h has various characteristics $L = L_h(\boldsymbol{S}, \boldsymbol{O}, \boldsymbol{C})$, where $\boldsymbol{S}$ is the characteristics matrix of the farmland per se, such as the size of the transacted farmland, and $\boldsymbol{O}$ is the matrix of the surrounding attributes of the farmland, such as the distance between the transacted farmland and the main traffic artery, the nearby construction price, and other NIMBY and/or YIMBY objects. The issue of most concern in this study is the matrix related to the contamination of the farmland, $\boldsymbol{C}$. The price of farmland is PL_h. The differentiation of the farmland price is reflected by the characteristics of the farmland. The marginal implicit price of a specific characteristic can then be derived from the linkage of the farmland price and all the characteristics [42]. The hedonic price function is written as Equation (1) below:

$$PL_h = PL_h(S_1, \ldots, S_i, O_1, \ldots, O_j, C_1 \ldots, C_k) \tag{1}$$

In Equation (1), i is the number of variables related to the attributes of the transacted farmland per se, j is the number of surrounding characteristics of the transacted farmland, and k is the number of related contaminated attributes of the transacted farmland.

Since for each piece of farmland located in different places there might exist spatial correlation, without accounting for the spatial relationship, the evaluation results will be biased and inefficient. Furthermore, the fluctuation in farmland prices could be high, and this is especially significant in a country such as Taiwan with a high population density. Thus, the impact of a particular farmland attribute on the farmland price is expected to be different. Quantile regression involving the estimation of different percentiles can reflect such a phenomenon. The HPM should combine both the spatial and quantile attributes in the hedonic price function estimation. Taiwan's EPA classifies the status of contaminated farmlands as "controlled sites", "remediated sites", "cancellation of controlled sites", and "cancellation of remediated sites". The change in a specific characteristic is expected to have a different impact on farmland prices due to their different statuses.

The hedonic spatial quantile model accounts for the spatial dependence of explanatory variables and independent farmland prices. The change in a specific characteristic, however, also has different impacts on the farmland prices. The impact on the farmland price of a change in a specific characteristic for a particular piece of farmland announced as a "controlled site" or as a "remediated site" is expected to be different, since for some potential contaminated farmlands, more time is needed to evaluate their impacts on farmland prices. Furthermore, Taoyuan city is close to the Taipei metropolitan life circle. This results a wide gap among farmland prices in Taoyuan city. Quantile regression is a method used to catch the impact of each farmland characteristic on a specific level of farmland price [34]. Most importantly, by using quantile regression, we can observe the impact of extreme farmland prices. Such drastically high and extremely low farmland prices normally give rise to controversies in zone planning for agricultural development.

2.3. Hedonic Quantile SDM

In addition to accounting for the different farmland price impacts from a specific change in farmland attributes, it is frequently observed that both the explanatory variables and dependent variables related to farmland prices give rise to the problem of spatial dependence. The spatial adjustment both for the explanatory variables and dependent variable is achieved by using the SDM [35,36]. The application of SDM is very limited, and most studies in this regard have been conducted in recent years [43–45]. By accounting for the farmland price differentiation, the combination of the SDM and quantile model has resulted in the quantile SDM [36,37,45–47].

This model can be expressed as (2) below:

$$PL_h = \rho_\theta \mathbf{W} PL_h + \alpha_{0\theta} + \boldsymbol{\alpha}_{I\theta}\boldsymbol{S} + \boldsymbol{\alpha}_{J\theta}\boldsymbol{O} + \boldsymbol{\alpha}_{K\theta}\boldsymbol{C} + \beta_\theta \mathbf{W}\mathbf{Z} + \nu_\theta \qquad \nu \overset{i.i.d}{\sim} N(0,\sigma^2) \tag{2}$$

The left-hand side of Equation (2) is the farmland price, the right-hand side **W** is the spatial weight matrix, and θ is the designed percentile and ranges between 0 and 1. Moreover, ρ is the coefficient with the modification of the spatial matrix. $\boldsymbol{S}$ is the matrix of farmland attributes per se; $\boldsymbol{C}$ is the matrix of contamination-related variables for transacted farmland; $\boldsymbol{O}$ is the matrix of other explanatory variables, such as the surrounding characteristics of the transacted farmland; $\boldsymbol{\alpha}_{I\theta}$, $\boldsymbol{\alpha}_{J\theta}$, and $\boldsymbol{\alpha}_{K\theta}$ are the coefficient matrices for variables $\boldsymbol{S}$, $\boldsymbol{O}$, and $\boldsymbol{C}$, respectively; α_0 is the intercept term; and $\boldsymbol{\nu}_\theta$ is the error term. β_θ is the coefficient matrix for those explanatory variables of $\boldsymbol{S}$, $\boldsymbol{O}$, and/or $\boldsymbol{C}$ with spatial dependence.

2.4. Two-Stage Hedonic Quantile SDM

2.4.1. The First-Stage Hedonic Quantile SDM

The hedonic quantile SDM adjusts the spatial dependence of the dependent variable by adding the weighted farmland price variable **W**PL. Since this might result in endogeneity with all other explanatory variables, i.e., $\boldsymbol{S}$, $\boldsymbol{O}$, and $\boldsymbol{C}$, there are two methods proposed to deal with the endogeneity problem in spatially related models. One of these was developed by [38], and was extended to become a two-stage hedonic quantile SDM. The other was proposed by [48] and involves instrumental quantile regression. Similarly, their model has been extended to deal with the endogeneity when the spatially related variables are added to adjust for the spatial issues.

The method proposed by [48] to adjust the endogeneity is less likely to work in practice because it is difficult to transform their theoretical concept into an empirical operation. On the contrary, when the endogeneity originates from the spatially adjusted farmland price variable and the differences in farmland prices are accounted for, the method proposed by [38] is much more feasible. In order to apply the quantile SDM, θ is classified as various farmland price levels [34]. The model proposed by [38] to circumvent the endogeneity problem involves the operation of a two-stage estimation quantile SDM. The first stage of the estimation involves combining the SDM in (2), and the quantile regression turns out to be as follows:

$$\min_{\boldsymbol{\alpha},\, \boldsymbol{\beta}_\theta} \left[\sum_{PL_h \geq (\boldsymbol{\alpha}_\theta \mathbf{X} + \boldsymbol{\beta}_\theta \mathbf{Z})} \theta |PL_h - \boldsymbol{\alpha}_\theta \mathbf{X} - \boldsymbol{\beta}_\theta \mathbf{Z}| \sum_{PL_h < (\boldsymbol{\alpha}_\theta \mathbf{X} + \boldsymbol{\beta}_\theta \mathbf{Z})} (1-\theta)|PL_h - \boldsymbol{\alpha}_\theta \mathbf{X} - \boldsymbol{\beta}_\theta \mathbf{Z}| \right] \tag{3}$$

where the θ s are the divisions of the percentiles for the first-stage quantile SDM estimation. The same notations that appear in previous equations have similar definitions. **X** is designated as the non-spatial characteristics matrix of $\boldsymbol{S}$, $\boldsymbol{O}$, and $\boldsymbol{C}$ stated above, and $\boldsymbol{Z}$ refers to the corresponding characteristics' explanatory variables with spatial dependence. $\boldsymbol{\alpha}_\theta$ and $\boldsymbol{\beta}_\theta$ are the matrices of the corresponding estimated coefficients for the non-spatial explanatory attributes and spatial explanatory characteristics stated above. The predicted farmland price matrices $\widehat{PL_h}$ are then obtained from Equation (3).

2.4.2. The Second-Stage Hedonic Quantile SDM

The results predicted for $\widehat{PL_h}$ from (3) account for the spatial correlation both for several of the explanatory variables and the dependent variable, as well as the price differences in the dependent variable for farmland prices. These predicted values of $\widehat{PL_h}$

are one of the explanatory variables in the second-stage quantile regression [38]. The second-stage hedonic quantile SDM is estimated in Equation (4) as follows:

$$\min_{\widehat{\alpha_\theta}}\left[\sum_{PL_h \geq \widehat{PL_h}} \theta\left|PL_h - \widehat{PL_h}\right| \sum_{PL_h < \widehat{PL_h}} (1-\theta)\left|PL_h - \widehat{PL_h}\right|\right] \tag{4}$$

From the estimation results, the marginal effect (price) for every unit of contaminated farmland that is remediated can be computed. Thus, the total remediation benefit for a certain size of contaminated farmland accompanied by a set of characteristics is consequently obtained.

Under the estimation of a two-stage quantile SDM, the marginal benefit for a specific characteristic g with spatial dependence is the marginal implicit price referred to as the marginal willingness-to-pay (MWTP) can thus be computed as (5):

$$\mathrm{MWTP}_g = \frac{\alpha_{g\theta} + \beta_{g\theta}}{(1-\rho_\theta)} \tag{5}$$

The total benefit for the corresponding characteristic g is then computed as in (6) below:

$$\mathrm{TB}_g = \int \mathrm{MWTP}_g dg \tag{6}$$

Equation (6) is the benefit contributed by a certain characteristic g to the total benefit of the contaminated farmland cancellation for different zonal divisions under the *Spatial Planning Act*.

3. Data Sources and Selection of Characteristics and Their Treatments

All transacted farmland-related data from 1 August 2012 to 31 December 2020 were collected from the Web Service of Actual Real Transactions of Real Estate [23]. There were 26,695 pieces of farmland with completed transactions. A total of 3 pieces of farmland were then eliminated, with 0 transacted prices and 599 transacted prices including parking lots and buildings, and 3767 pieces of farmland transacted for special transactions between relatives or employees or urgent selling and urgent buying, etc. A further 446 pieces of farmland with the highest and the lowest 1% of prices were also excluded to avoid possible outliers. As a result, there were 21,880 pieces of farmland transacted. Among these transacted farmlands, 1141 pieces of transacted farmlands were cancelled contaminated controlled sites. All these farmland prices were deflated by the consumer price index of 2020 to remain on the same base for further analysis [49].

3.1. Planning for the Development of a New Life Circle under the Spatial Planning Act

Taoyuan city is not a major agricultural production base in Taiwan. Since it belongs to the metropolitan life circle of Taipei, the production of agricultural products makes it one of the local suppliers of ingredients to more than 10 million people in the Taipei metropolitan area. As such, the quality of these products is essential for about half of the population in Taiwan. Taoyuan city has verified the conditions of environmental resources, current land use, population, distribution of the ethnic groups, and the industrial structural development under "*The Draft of the Spatial Planning Act of Taoyuan City*" (*Spatial Planning Act of Taoyuan City* hereafter) to replan the city. Accordingly, the city is being planned to be divided into six life circles including the Zhongli metropolitan life circle, ecological leisure life circle, Taoyuan Aerotropolis life circle, Taoyuan metropolitan urban life circle, rural development life circle, and new town life circle [50]. Each life circle currently covers two to four administrative districts of the city. Since these are planned life circles, a shape file and overlay map under ArcGIS were employed for further analysis.

3.2. Selection and Price Treatment for Farmlands with Contamination of Controlled Sites

The detection of farmland pollution began in 2002 before data collection by the Ministry of Interior through the Web Service of Actual Real Transactions of Real Estate on 1 August 2012. The function Generate near the table for ArcGIS was used to identify whether the transacted farmland had been controlled, contaminated, and cancelled. The plots of transactions for all farmlands, the announced controlled farmlands, and the cancellation of contaminated controlled farmlands are shown in Figure 2.

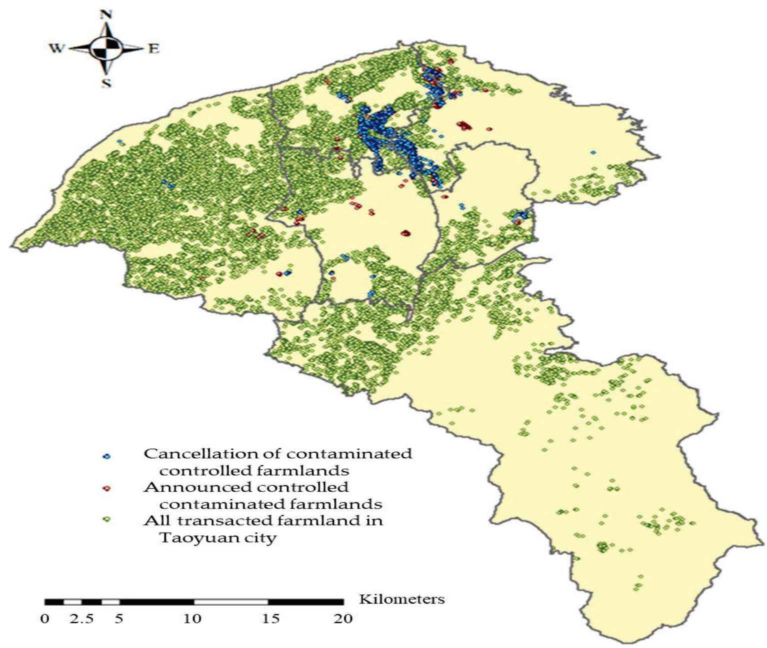

Figure 2. The plots of all cancelled contaminated controlled farmlands, announced controlled farmlands, and all transacted farmlands in Taoyuan city from 1 January 2002 to 31 December 2020.

3.3. Selection of Farmland Characteristics Based on the Price for the Cancellation of Contaminated Farmlands

The characteristics that impact farmland prices are less complex than those impacting housing prices. From the past literature, it is known that the size of the farmland, the characteristics of the farmland per se, and the surrounding characteristics of the farmland have impacts on farmland prices [14–18,20,24]. Three types of characteristics were selected to reflect their potential impacts on farmland prices. The first type refers to the characteristics directly related to the transacted farmland itself. The second type refers to the contamination of controlled sites surrounding the transacted farmland. The third type refers to the surrounding characteristics of the transacted farmland. The specific factors for each type of characteristic and the collection of the data are discussed in the subsections listed below.

3.3.1. Characteristics of Transacted Contaminated Controlled Farmlands

The first type of characteristics that influence farmland prices is the farmland itself. It includes the size of the farmland (AreaT) and the attributes in regard to the transacted farmland and the process of cancelling its contamination. It can be observed in two stages. How long does it take from the announcement that a piece of farmland is a "controlled site" to the "cancellation of the controlled site"? (DmT). Furthermore, how long does it take to transact a "cancellation of controlled farmland"? (SmT). The longer it takes for the DmT indicates that the farmland is seriously polluted. A longer period of time is required to confirm and detect if the pollution is eliminated based on a regular schedule. The severity of the degree of contamination of the farmland is represented by the length of time in months.

The reason for using months as the time length representation is a reasonable and differential measurement based on the data from the Web Service of Actual Real Transactions of Real Estate. The overall number of months for 1141 cancellations of controlled farmland to their transactions is 28.63 months, as shown in Table 1. It took 57.51 months for all these farmlands to be announced as "controlled sites". It takes a longer period of time to announce a particular piece of farmland as a "controlled site" than to transact it once the controlled contamination is cancelled. Since the controlled sites are not allowed to trade for the duration between the cancellation of the site and the transaction, this might indirectly imply how zealous a farmland owner is to remedy the contaminated farmland.

Table 1. The definitions, notations, mean values, and standard deviations of all variables in the estimation.

Notation of Variable	Variable Definition	Mean Value *	Standard Deviation
	Dependent Variable		
PL	Average price of 1141 transacted cancellations of controlled farmland until 31 December 2020 (USD)	956,526.86	803,719.82
	Characteristics of transacted cancellations of contaminated controlled farmlands per se		
AreaT	Average size of all cancellations of controlled farmlands (1000 m^2)	1.24	1.00
Area2T	The average of the square size of all transacted farmlands (1000 m^2)	2.55	3.92
TT1	Dummy variable of 1 if transacted farmland is in the Taoyuan Aerotropolis life circle; 0 otherwise	0.82	0.38
TT2	Dummy variable of 1 if transacted farmland is in the Zhongli metropolitan, ecological leisure, Taoyuan metropolitan urban, new town, or rural development life circle; 0 otherwise	0.18	0.38
DmT	Average months of transacted farmlands from being announced a controlled site to the cancellation of control	57.51	29.90
SmT	Average months of transacted farmlands from the cancellation of control to the transaction (months)	28.63	28.83
	Characteristics of contamination of controlled sites surrounding the transacted farmland		
NdmT	The average duration of the nearest announced controlled site prior to the date of a specific piece of transacted farmland (months)	84.82	31.38
NsmT	The average duration of the nearest announced cancelled controlled site prior to the date of a specific piece of transacted farmland (months)	28.22	28.55
TFd11	The distance between a transacted cancellation site of farmland and its nearest controlled farmland (meters)	58.54	34.13
TFd21	The distance between a transacted cancelled site of farmland and the nearest cancellation of another piece of controlled farmland (meters)	67.05	37.18
	Surrounding characteristics of the transacted farmland		
HighT	Distance between transacted farmland and its nearest main traffic artery (1000 m)	1.26	0.69
High2T	Square for the distance between transacted farmland and its nearest main traffic artery (1000 m)	2.05	2.25
TC	The price of the construction site for the life circle where the transacted farmland is located (USD/m^2)	1424.65	76.48

Note: * The exchange rate for USD to NTD in 2012–2020 is 29.609, 29.770, 30.382, 31.927, 32.301, 30.421, 30.189, 30.924, and 29.567. This results in an average exchange rate in 2012–2020 of 30.566.

All the transactions fall within four life circles, and the number of transactions in each life circle is shown in Table 2. It is observed that among these transactions, about 60% of the total contaminated farmlands were transacted within 2.5 years of the cancellation of control. It is also found that among the 1141 pieces of transacted farmland, 82% of the contaminated controlled sites cancelled are located in the Taoyuan Aerotropolis life circle. Such a dramatic difference in the number of pieces of transacted farmland implies that the expectation that farmland will be switched to other uses is high in the Taoyuan Aerotropolis life circle. The Taoyuan Aerotropolis life circle is planned for industrial and residential use, and is a hub for all types of communication and transportation. Thus, this life circle is less likely to involve the development of agriculture. In order to differentiate the farmland price in different life circles, a dummy variable is used to represent the transactions in the Taoyuan Aerotropolis life circle, TT1 = 1 from the transactions in all the other five life circles, TT2 = 1.

Table 2. The months taken between the cancellation of controlled farmlands and the transaction in different life circles in 2012–2020 [a].

Months between the Cancellation of a Controlled Site and Its Transaction	Life Circle [b]				Total Transacted Farmlands
	Zhongli Metropolitan Life Circle	Taoyuan Aerotropolis Life Circle	Taoyuan Metropolitan Urban Life Circle	Rural Development Life Circle	
<10 months	7	422	7	3	439
10~19 months	36	147	8	1	192
20~29 months	4	15	27	2	48
30~39 months	5	24	17	0	46
40~49 months	1	60	12	0	73
50~59 months	3	189	13	0	205
60~69 months	1	60	2	0	63
70~79 months	0	22	8	1	31
>80 months	1	1	42	0	44
Total farmlands	58	940	136	7	1141
Average months from cancelled controlled site until transaction	18.34	24.90	59.21	20.86	28.63

Notes: [a]: Since the *Web Service of Actual Real Transactions of Real Estate* from [23] started collecting data on 1 August 2012, data for the year 2012 cover only 1 August to 31 December. All other years include a full year of transactions. [b]: There is no transaction for the ecological leisure life circle and new town life circle among the six life circles in Taoyuan for the period covered in this study.

3.3.2. Characteristics of the Contamination of Controlled Sites Surrounding the Transacted Farmland

The characteristics of the contamination of controlled sites surrounding the transacted farmland might also have a potential impact on the price of the designated transacted cancellation of contaminated farmland. This includes the date on which the nearest contaminated controlled site is announced prior to the date of the transaction involving the contaminated cancelled farmland. For reasons similar to those stated earlier, the time difference is measured in months and is shown as NdmT. From this attribute, it can be observed how the price of transacted cancelled contaminated controlled farmland changes when its nearest contaminated controlled site is announced much earlier than the transaction. The outcome indicates whether a piece of transacted farmland is damaged by its noxious site, i.e., a NIMBY facility, or benefited by an innocuous nearby site, i.e., a YIMBY facility.

Similarly, one can also observe whether the price of transacted cancelled contaminated controlled farmland might change when its nearest contaminated controlled farmland is cancelled much earlier than when it is transacted. The difference in months is designated as NsmT. Moreover, the distance between these transactions and other announced controlled sites and the cancellation of other contaminated controlled farmlands is accounted for by the dummy variables TFD11 and TFD21. These represent the different statuses of the surrounding farmlands with different potential impacts on the price of the transacted farmlands. The details of all variables stated above are listed in Table 1.

3.3.3. Surrounding Characteristics of Transacted Cancelled Contaminated Controlled Farmlands

The farmland price is expected to be higher if there is a main traffic artery surrounding the farmland for the convenient transportation of agricultural products. The data on the entrance and exit in relation to surrounding interchanges and traffic data were accessed from the web shape files compiled by the Ministry of the Interior, Taiwan [51]. The Generate near table in ArcGIS test was conducted to obtain the distance between each piece of farmland and the entrance of the exit for its closest interchange. It was found that there are seven main traffic interchanges surrounding Taoyuan city. The average distance between the 1141 pieces of transacted cancelled contaminated controlled farmland and their nearest interchange (HighT) is 1260 m. As Taoyuan city is a metropolitan satellite city of Taipei, the capital of Taiwan, many pieces of farmland are mainly located in the urban–rural border areas. The impacts on the farmland price are not only based on the distance between a particular piece of farmland and the main traffic arteries, but also the prices of the surrounding real estate, such as the price of housing or construction sites. The high price of such real estate normally drives a high degree of speculation for farmland conversion [24,27,52].

Farmland located in different life circles planned under the *Spatial Planning Act of Taoyuan City* indicates its potential for being switched to non-farming use. The higher the construction price surrounding the transacted cancelled controlled contaminated farmland (TC), the higher the price of the farmland will be once its control is cancelled. The average price of these construction sites in the period from 1 August 2012 to 31 December 2020 was computed for each life circle to stand for the level of the speculation related to switching the farmland for other purposes.

4. Specification of Empirical Model and Estimation Results

4.1. Specification for the Transacted Cancelled Contaminated Controlled Farmland Price

Before the estimation was conducted, Moran's I value was employed in ArcGIS to test the existence of spatial dependence for the farmland price and each explanatory variable. The test of Moran's I is used to determine if the spatial issue exists in the dependent and/or independent variable, and its value ranges between −1 and 1. Any non-zero value implies the variable concerned will have a spatial problem. The value of Moran's I for the dependent variable of farmland is 0.588. The value of Moran's I for any explanatory variable greater than 0.5 will then need a corresponding spatial adjustment. All the explanatory variables with Moran's I value exceed this threshold except for the squared term for the size of the transacted farmland in the Taoyuan Aerotropolis life circle, Area2T × TT1. Thus, the specification for each explanatory variable has an additional variable to adjust its spatial problem. The estimation was then conducted to find the factors that have different impacts on the prices of all transacted farmlands. The specification of the first-stage quantile SDM is shown in (7) below:

$$\begin{aligned}
\mathrm{PL_j} = {} & \rho_\theta \mathrm{W} \times \mathrm{PL_j} + \alpha_{\theta 0} + \alpha_{\theta 1}\mathrm{AreaT_j} \times \mathrm{TT1_j} + \beta_{\theta 2}\mathrm{W} \times \mathrm{AreaT_j} \times \mathrm{TT1_j} + \alpha_{\theta 3}\mathrm{Area2T_j} \times \mathrm{TT1_j} \\
& + \alpha_{\theta 4}\mathrm{AreaT_j} \times \mathrm{TT2_j} + \beta_{\theta 5}\mathrm{W} \times \mathrm{AreaT_j} \times \mathrm{TT2_j} + \alpha_{\theta 6}\mathrm{Area2T_j} \times \mathrm{TT2_j} + \beta_{\theta 7}\mathrm{W} \times \mathrm{Area2T_j} \times \mathrm{TT2_j} \\
& + \alpha_{\theta 8}\mathrm{DmT_j} \times \mathrm{TT1_j} + \beta_{\theta 9}\mathrm{W} \times \mathrm{DmT_j} \times \mathrm{TT1_j} + \alpha_{\theta 10}\mathrm{DmT_j} \times \mathrm{TT2_j} + \beta_{\theta 11}\mathrm{W} \times \mathrm{DmT_j} \times \mathrm{TT2_j} \\
& + \alpha_{\theta 12}\mathrm{SmT_j} \times \mathrm{TT1_j} + \beta_{\theta 13}\mathrm{W} \times \mathrm{SmT_j} \times \mathrm{TT1_j} + \alpha_{\theta 14}\mathrm{SmT_j} \times \mathrm{TT2_j} + \beta_{\theta 15}\mathrm{W} \times \mathrm{SmT_j} \times \mathrm{TT2_j} \\
& + \alpha_{\theta 16}\mathrm{NdmT_j} + \beta_{\theta 17}\mathrm{W} \times \mathrm{NdmT_j} + \alpha_{\theta 18}\mathrm{NsmT_j} + \beta_{\theta 19}\mathrm{W} \times \mathrm{NsmT_j} + \alpha_{\theta 20}\mathrm{TFd11_j} + \beta_{\theta 21}\mathrm{W} \times \mathrm{TFd11_j} \\
& + \alpha_{\theta 22}\mathrm{TFd21_j} + \beta_{\theta 23}\mathrm{W} \times \mathrm{TFd21_j} + \alpha_{\theta 24}\mathrm{TC_j} \times \mathrm{TT1_j} + \beta_{\theta 25}\mathrm{W} \times \mathrm{TC_j} \times \mathrm{TT1_j} + \alpha_{\theta 26}\mathrm{TC_j} \times \mathrm{TT2_j} \\
& + \beta_{\theta 27}\mathrm{W} \times \mathrm{TC_j} \times \mathrm{TT2_j} + \alpha_{\theta 28}\mathrm{HighT_j} \times \mathrm{TT1_j} + \beta_{\theta 29}\mathrm{W} \times \mathrm{HighT_j} \times \mathrm{TT1_j} + \alpha_{\theta 30}\mathrm{High2T_j} \times \mathrm{TT1_j} \\
& + \beta_{\theta 31}\mathrm{W} \times \mathrm{High2T_j} \times \mathrm{TT1_j} + \alpha_{\theta 32}\mathrm{HighT_j} \times \mathrm{TT2_j} + \beta_{\theta 33}\mathrm{W} \times \mathrm{HighT_j} \times \mathrm{TT2_j} + \alpha_{\theta 34}\mathrm{High2T_j} \times \mathrm{TT2_j} \\
& + \beta_{\theta 35}\mathrm{W} \times \mathrm{High2T_j} \times \mathrm{TT2_j} + \upsilon_j, \quad j = 1, \ldots, 1141\,, \quad \theta = 10, 25, 50, 75, 90
\end{aligned} \tag{7}$$

All the α_θs and ρ_θ in (7) are coefficients to be estimated. The 10%, 25%, 50%, 75%, and 90% price levels were selected to observe the impact differences for all types of characteristics. The estimation from (7) has already adjusted the potential spatial and price differentiation issues. The estimation results of (7) are shown in Table 3. The prices predicted, $\widehat{\mathrm{PL}}$, from (7) for each quantile can further adjust the possible endogeneity problem for the explanatory variables and spatial dependent price variable. Thus, a second-stage quantile SDM estimation, shown in (8), was required:

$$
\begin{aligned}
\widehat{\mathrm{PL_i}} = {} & \rho'_\theta \mathrm{W} \times \widehat{\mathrm{PL_i}} + \alpha'_{\theta 0} + \alpha'_{\theta 1}\mathrm{AreaT_j} \times \mathrm{TT1_j} + \beta'_{\theta 2}\mathrm{W} \times \mathrm{AreaT_j} \times \mathrm{TT1_j} + \alpha'_{\theta 3}\mathrm{Area2T_j} \times \mathrm{TT1_j} \\
& + \alpha'_{\theta 4}\mathrm{AreaT_j} \times \mathrm{TT2_j} + \beta'_{\theta 5}\mathrm{W} \times \mathrm{AreaT_j} \times \mathrm{TT2_j} + \alpha'_{\theta 6}\mathrm{Area2T_j} \times \mathrm{TT2_j} + \beta'_{\theta 7}\mathrm{W} \times \mathrm{Area2T_j} \times \mathrm{TT2_j} \\
& + \alpha'_{\theta 8}\mathrm{DmT_j} \times \mathrm{TT1_j} + \beta'_{\theta 9}\mathrm{W} \times \mathrm{DmT_j} \times \mathrm{TT1_j} + \alpha'_{\theta 10}\mathrm{DmT_j} \times \mathrm{TT2_j} + \beta'_{\theta 11}\mathrm{W} \times \mathrm{DmT_j} \times \mathrm{TT2_j} \\
& + \alpha'_{\theta 12}\mathrm{SmT_j} \times \mathrm{TT1_j} + \beta'_{\theta 13}\mathrm{W} \times \mathrm{SmT_j} \times \mathrm{TT1_j} + \alpha'_{\theta 14}\mathrm{SmT_j} \times \mathrm{TT2_j} + \beta'_{\theta 15}\mathrm{W} \times \mathrm{SmT_j} \times \mathrm{TT2_j} \\
& + \alpha'_{\theta 16}\mathrm{NdmT_j} + \beta'_{\theta 17}\mathrm{W} \times \mathrm{NdmT_j} + \alpha'_{\theta 18}\mathrm{NsmT_j} + \beta'_{\theta 19}\mathrm{W} \times \mathrm{NsmT_j} + \alpha'_{\theta 20}\mathrm{TFd11_j} \\
& + \beta'_{\theta 21}\mathrm{W} \times \mathrm{TFd11_j} + \alpha'_{\theta 22}\mathrm{TFd21_j} + \beta'_{\theta 23}\mathrm{W} \times \mathrm{TFd21_j} + \alpha'_{\theta 24}\mathrm{TC_j} \times \mathrm{TT1_j} \\
& + \beta'_{\theta 25}\mathrm{W} \times \mathrm{TC_j} \times \mathrm{TT1_j} + \alpha'_{\theta 26}\mathrm{TC_j} \times \mathrm{TT2_j} + \beta'_{\theta 27}\mathrm{W} \times \mathrm{TC_j} \times \mathrm{TT2_j} \\
& + \alpha'_{\theta 28}\mathrm{HighT_j} \times \mathrm{TT1_j} + \beta'_{\theta 29}\mathrm{W} \times \mathrm{HighT_j} \times \mathrm{TT1_j} + \alpha'_{\theta 30}\mathrm{High2T_j} \times \mathrm{TT1_j} \\
& + \beta'_{\theta 31}\mathrm{W} \times \mathrm{High2T_j} \times \mathrm{TT1_j} + \alpha'_{\theta 32}\mathrm{HighT_j} \times \mathrm{TT2_j} + \beta'_{\theta 33}\mathrm{W} \times \mathrm{HighT_j} \times \mathrm{TT2_j} \\
& + \alpha'_{\theta 34}\mathrm{High2T_j} \times \mathrm{TT2}_i + \beta'_{\theta 35}\mathrm{W} \times \mathrm{High2T_j} \times \mathrm{TT2_j} + \mu'_i, \quad \mathrm{j} = 1, \ldots, 1141, \quad \theta = 10, 25, 50, 75, 90
\end{aligned}
\tag{8}
$$

All the α'_θs and ρ'_θ in (8) are also coefficients to be estimated. Similar to the first-stage estimation, five quantiles for the second-stage SDM were employed for the final results. The estimation results are listed in Table 4, and all the analyses were taken from the two-stage quantile SDM estimation.

4.2. Analyses of the Estimations

The second-stage estimation results clearly show that there are more significant explanatory variables in the estimation than those in the first stage, as the second-stage estimation adjusts for not only the spatial and price differentiation but also the endogeneity problem. All the explanatory variables have a dimension of spatial one and non-spatial one, except for the squared term of the size of the transacted farmland. The specification was set for some explanatory variables in quadratic form, such as the distance between two objects and the size of the farmland. The signs of the different quantiles in the second-stage quantile SDM estimation for these variables do not necessarily have to be the same. What matters is the total impact from the spatial and non-spatial influence of a specific explanatory variable on the transacted farmland price.

As with the transaction of cancelled contaminated controlled farmlands in the Taoyuan Aerotropolis life circle, the results show that the sign of the linear term for farmland size is positive and its quadratic term is negative for all quantiles. This indicates that the larger the size of the transacted farmland is, the higher the farmland price will be. The transacted farmland price decreases after the adjustment of the spatial problem for farmland size. The results for the other three life circles do not have a consistent impact on the farmland price for all quantiles. This is because there are only 200 pieces of transacted farmland for the other three life circles. The locations of these farmlands are very dispersed. Thus, it is hard to observe impacts on farmland prices that are consistent with the farmland size with or without spatial considerations.

In addition to the size of the transacted farmland, the impact of all other variables on the farmland price is a combination of a specific explanatory variable with its adjustment for the spatial problem. That is, the marginal effect through (5) for each explanatory variable was computed for this purpose.

Table 3. The first-stage quantile SDM estimation results for the transacted cancellation of contaminated controlled farmlands.

Variable	$\theta = 10$		$\theta = 25$		$\theta = 50$		$\theta = 75$		$\theta = 90$	
	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
W × PL	0.27969 ***	0.062	0.32699 ***	0.062	0.32802 ***	0.063	0.23591 ***	0.062	0.29139 ***	0.099
AreaT × TT1	2144.53929 ***	76.979	2219.49001 ***	76.340	2643.95958 ***	77.302	3026.44436 ***	76.795	3333.88032 ***	122.651
W × AreaT × TT1	−753.77099 ***	156.566	−824.73965 ***	155.268	−821.79514 ***	157.223	−656.46156 ***	156.192	−721.75108 ***	249.458
Area2T × TT1	−57.08680 ***	19.305	−23.89028	19.145	−73.86038 ***	19.386	−89.83783 ***	19.259	−116.28741 ***	30.760
AreaT × TT2	1122.74642 ***	187.844	1146.16862 ***	186.287	1453.87683 ***	188.632	1921.91428 ***	187.395	2009.06092 ***	299.294
W × AreaT × TT2	−610.68094 *	315.341	−463.06473	312.726	−360.50165	316.663	−255.33356	314.587	−371.36050	502.435
Area2T × TT2	4.32667	40.569	40.55915	40.232	53.90735	40.739	−35.18512	40.472	112.94204 *	64.638
W × Area2T × TT2	38.88052	73.192	−6.63868	72.585	−34.02774	73.499	−36.27863	73.017	−32.05499	116.617
DmT × TT1	0.93664	2.522	4.19233 *	2.501	5.03103 **	2.532	3.02552	2.516	6.40637	4.018
W × DmT × TT1	−2.12633	5.555	−5.24183	5.509	0.17818	5.578	−3.01206	5.541	8.75418	8.850
DmT × TT2	−3.80623	2.973	−3.02136	2.949	−2.65582	2.986	−2.12289	2.966	−0.67860	4.738
W × DmT × TT2	−1.94780	5.694	−0.67135	5.647	3.16638	5.718	1.64758	5.680	18.60552 **	9.072
SmT × TT1	7.17177	5.945	8.67244	5.896	8.36727	5.970	11.03534 *	5.931	9.53037	9.472
W × SmT × TT1	−0.04704	13.148	−8.83640	13.039	−6.24354	13.203	−6.44615	13.116	15.64050	20.949
SmT × TT2	−1.54079	5.945	−2.48724	5.896	−2.46295	5.970	2.81570	5.931	3.25217	9.472
W × SmT × TT2	7.01458	13.008	3.72989	12.900	2.89319	13.063	0.89679	12.977	20.51948	20.726
NdmT	4.20647 **	2.123	2.91134	2.105	1.72694	2.132	0.85875	2.118	0.44864	3.383
W × NdmT	−1.92237	4.919	0.46857	4.878	−3.76235	4.939	−0.43874	4.907	−17.53501 **	7.837
NsmT	−5.55217	5.344	−2.32690	5.300	−0.74934	5.367	−5.71724	5.331	−4.03591	8.515
W × NsmT	−3.79705	11.777	−0.74078	11.679	2.61899	11.826	1.36889	11.749	−2.22539	18.764
TFd11	2.08126	1.492	2.86060 *	1.479	1.56983	1.498	1.44959	1.488	0.34875	2.377
W × TFd11	2.05125	2.678	−0.76596	2.656	−1.10499	2.690	0.11969	2.672	−0.26821	4.268
TFd21	−1.83134	1.285	−1.24215	1.275	−0.05067	1.291	−0.85056	1.282	0.19335	2.048
W × TFd21	−2.21531	2.446	−1.17893	2.426	−0.36057	2.456	−1.28722	2.440	−0.56339	3.897
TC × TT1	−0.02809	0.027	−0.01109	0.027	−0.01850	0.027	−0.01797	0.027	−0.03854	0.043
W × TC × TT1	0.10212 ***	0.038	0.06967 *	0.038	0.02398	0.038	0.01901	0.038	0.04302	0.060
TC × TT2	0.00086	0.026	0.03418	0.026	0.02859	0.026	0.01848	0.026	0.00613	0.041
W × TC × TT2	0.06677 *	0.036	0.02044	0.036	−0.01399	0.036	−0.01635	0.036	−0.00577	0.058
HighT × TT1	491.05389	541.201	−386.34171	536.713	−693.98820	543.471	−350.11166	539.907	176.81742	862.300
W × HighT × TT1	−595.45319	570.049	265.08674	565.322	593.92725	572.440	169.84652	568.686	−428.78431	908.265
HighT × TT2	−247.74887	941.149	−2084.82326 **	933.344	−2122.27123 **	945.096	−1594.14662 *	938.898	−870.07419	1499.541
W × HighT × TT2	1660.38584	1143.653	2538.03692 **	1134.170	1928.43550 *	1148.450	1432.68647	1140.919	591.58764	1822.194
High2T × TT1	−193.40553	121.897	60.20723	120.886	104.38330	122.408	49.61242	121.606	−4.10463	194.220
W × High2T × TT1	225.07601 *	132.474	−17.43810	131.376	−68.70747	133.030	−2.35215	132.158	68.53098	211.073
High2T × TT2	165.64340	319.076	752.11291 **	316.430	703.67106 **	320.414	507.26719	318.313	280.59356	508.386
W × High2T × TT2	−728.00787 *	398.782	−932.30394 **	395.475	−643.83970	400.454	−473.59254	397.828	−188.31585	635.382
Constant	−3266.65921 ***	998.009	−2629.95589 ***	989.733	−472.56818	1002.194	131.21710	995.622	105.70152	1590.136
R^2	0.6480		0.7087		0.7437		0.7671		0.7769	
$n = 1141$										

Note: Numbers with *, **, and *** indicate that the estimated coefficients are significantly different from zero at 10%, 5%, and 1% significance levels, respectively.

Table 4. The second-stage quantile SDM estimation results for the transacted cancellation of contaminated controlled farmlands.

Variable	θ = 10		θ = 25		θ = 50		θ = 75		θ = 90	
	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
W × $\widehat{PL}$	0.69963 ***	0.034	0.82800 ***	0.029	0.76764 ***	0.031	0.60845 ***	0.038	0.59382 ***	0.039
AreaT × TT1	2132.17230 ***	11.530	2204.44804 ***	9.768	2607.53071 ***	10.580	3018.47241 ***	10.840	3310.46467 ***	14.488
W × AreaT × TT1	−1471.40834 ***	64.346	−1822.32887 ***	61.173	−1870.66198 ***	72.379	−1698.75253 ***	100.406	−1726.26050 ***	112.483
Area2 × TT1	−52.65457 ***	2.902	−21.30718 ***	2.456	−64.03781 ***	2.659	−86.60906 ***	2.732	−110.42939 ***	3.635
AreaT × TT2	1128.73282 ***	28.088	1120.25737 ***	23.769	1425.40262 ***	25.693	1916.85119 ***	26.381	2021.76451 ***	35.062
W × AreaT × TT2	−959.35733 ***	57.819	−995.08767 ***	52.782	−1062.60650 ***	64.050	−1102.61202 ***	87.217	−1067.52242 ***	97.149
Area2T × TT2	1.21243	6.065	44.20168 ***	5.133	59.45443 ***	5.549	−31.09312 ***	5.699	112.26524 ***	7.573
W × Area2T × TT2	39.43325 ***	10.937	−18.63587 **	9.266	−51.15672 ***	10.028	6.94172	10.540	−92.83453 ***	14.149
DmT × TT1	1.77761 ***	0.377	4.78522 ***	0.320	5.26758 ***	0.345	3.45832 ***	0.354	5.86725 ***	0.473
W × DmT × TT1	−1.52087 *	0.830	−5.23210 ***	0.704	−1.70639 **	0.774	−2.45510 ***	0.782	5.15025 ***	1.089
DmT × TT2	−3.15926 ***	0.445	−2.49186 ***	0.376	−2.67401 ***	0.406	−1.58211 ***	0.417	−1.45869 ***	0.564
W × DmT × TT2	−0.17341	0.864	0.64507	0.724	3.09811 ***	0.779	1.48060 *	0.799	13.19676 ***	1.097
SmT × TT1	9.17411 ***	0.888	9.92087 ***	0.753	9.71141 ***	0.813	11.36121 ***	0.835	8.71693 ***	1.111
W × SmT × TT1	−4.01732 **	1.973	−11.15248 ***	1.668	−8.32943 ***	1.807	−7.93912 ***	1.874	11.01435 ***	2.523
SmT × TT2	−0.49368	0.889	−2.02028 ***	0.752	−1.18903	0.812	3.18498 ***	0.834	2.16210 *	1.112
W × SmT × TT2	4.15303 **	1.945	1.37751	1.646	1.07958	1.779	−0.78934	1.835	15.53052 ***	2.461
NdmT	4.08806 ***	0.317	2.42449 ***	0.268	1.51230 ***	0.290	0.26471	0.298	1.57965 ***	0.409
W × NdmT	−3.06441 ***	0.742	−1.29147 **	0.628	−3.37794 ***	0.672	−0.71588	0.691	−13.87550 ***	0.954
NsmT	−6.69853 ***	0.799	−2.82151 ***	0.676	−1.88626 ***	0.731	−5.63121 ***	0.750	−4.28454 ***	0.997
W × NsmT	1.08292	1.773	2.53721 *	1.493	3.41758 **	1.611	3.10276 *	1.668	−2.03879	2.202
TFd11	1.98192 ***	0.223	3.01874 ***	0.189	1.50736 ***	0.204	1.55436 ***	0.209	0.14291	0.278
W × TFd11	0.82869 **	0.420	−2.15791 ***	0.350	−1.17792 ***	0.370	−0.90475 **	0.386	−0.06465	0.503
TFd21	−1.61056 ***	0.193	−1.23379 ***	0.163	0.05565	0.176	−0.87115 ***	0.181	0.42089 *	0.240
W × TFd21	−1.39639 ***	0.388	−0.04232	0.320	−0.73106 **	0.336	−0.21179	0.355	−0.67298	0.460
TC × TT1	−0.02745 ***	0.004	−0.01393 ***	0.003	−0.01924 ***	0.004	−0.01564 ***	0.004	−0.03414 ***	0.005
W*TC × TT1	0.08446 ***	0.006	0.05201 ***	0.005	0.02322 ***	0.005	0.01600 ***	0.005	0.03178 ***	0.007
TC × TT2	0.00488	0.004	0.03380 ***	0.003	0.02992 ***	0.004	0.02047 ***	0.004	0.00978 **	0.005
W*TC × TT2	0.04854 ***	0.005	−0.00143	0.005	−0.02320 ***	0.005	−0.01816 ***	0.005	−0.01160 *	0.007
HighT × TT1	659.04644 ***	80.780	−431.05289 ***	68.403	−675.84204 ***	73.977	−327.30231 ***	75.906	262.68773 ***	100.950
W*HighT*TT1	−735.30497 ***	85.018	405.53827 ***	72.300	624.24798 ***	78.312	245.68931 ***	80.541	−414.47119 ***	106.455
HighT × TT2	−360.01226 **	140.645	−2233.61067 ***	119.095	−2116.94733 ***	128.667	−1475.33421 ***	132.103	−653.07420 ***	175.611
W × HighT × TT2	1478.06867 ***	174.189	2877.20797 ***	144.778	2380.19809 ***	156.233	1563.92686 ***	160.403	613.85302 ***	213.316
High2T × TT1	−212.17173 ***	18.220	78.41233 ***	15.419	109.28209 ***	16.670	51.38790 ***	17.112	−14.21774	22.750
W × High2T × TT1	244.04416 ***	19.769	−67.56086 ***	16.864	−86.71288 ***	18.233	−28.59628	18.736	52.39476 **	24.837
High2T × TT2	251.28484 ***	47.702	816.08639 ***	40.383	707.57398 ***	43.632	487.55109 ***	44.800	251.26357 ***	59.555
W × High2T × TT2	−707.13719 ***	60.786	−1059.47273 ***	50.456	−802.98503 ***	54.402	−538.00267 ***	55.888	−261.10911 ***	74.319
Constant	−2572.53058 ***	166.772	−1665.01516 ***	144.739	−304.98999 **	138.993	16.29999	138.967	263.19113	183.934
R^2	0.9480		0.9537		0.9630		0.9765		0.9750	
n = 1141										

Note: Numbers with *, **, and *** indicate that the estimated coefficients are significantly different from zero at 10%, 5%, and 1% significance levels, respectively.

5. Discussion for the Monetary Benefit of Characteristics

5.1. Attribute with the Largest Contribution to the Total Benefit for Contaminated Farmlands

The marginal effect for each factor is shown in Table 5. The total benefit of contamination remediation of controlled farmlands contributed by each factor was computed and is presented in Table 6. The results show that for every 1000 square meter increase in farmland size, the farmland price in the Taoyuan Aerotropolis life circle increases for every quantile of the farmland price. On the other hand, the transactions of farmland of the same size increasing in all three other life circles results in the farmland price decreasing for all levels of farmland price. The marginal effect of the transacted farmland size results in the highest share of the contribution to the total benefit, either positive or negative, for the transactions involving cancelled contaminated controlled farmlands. The marginal effect and the total benefit for the attribute of transacted farmland size are shown in Figure 3. A comparison is made between two different life circles and different quantiles for farmland prices. The total farmland price increases by about 45–105% for an average 1000 m^2 increase in the farmland size for non-agricultural use in the Taoyuan Aerotropolis life circle and decreases by about 81–131% for the same size of increase in the other three agricultural-development-purpose life circles. The transacted farmland increases by the scale of its average size, while the total benefit declines for those transactions occurring in the other three life circles. This is because these life circles cover most of the cultivated lands in Taoyuan city. Thus, the farmland price via the change in total benefit will not increase instantly after the farmland's contamination is cancelled. The total benefit of the farmland price in the Taoyuan Aerotropolis life circle increases for all price levels once the contaminated controlled site is cancelled. Although the cancellation of the control releases more farmland for cultivation, the rise in the farmland price is inevitable due to a high degree of expectation that the farmland will be converted for another purpose. Thus, the cancellation of contaminated farmlands in the Taoyuan Aerotropolis life circle may not benefit the development of agriculture.

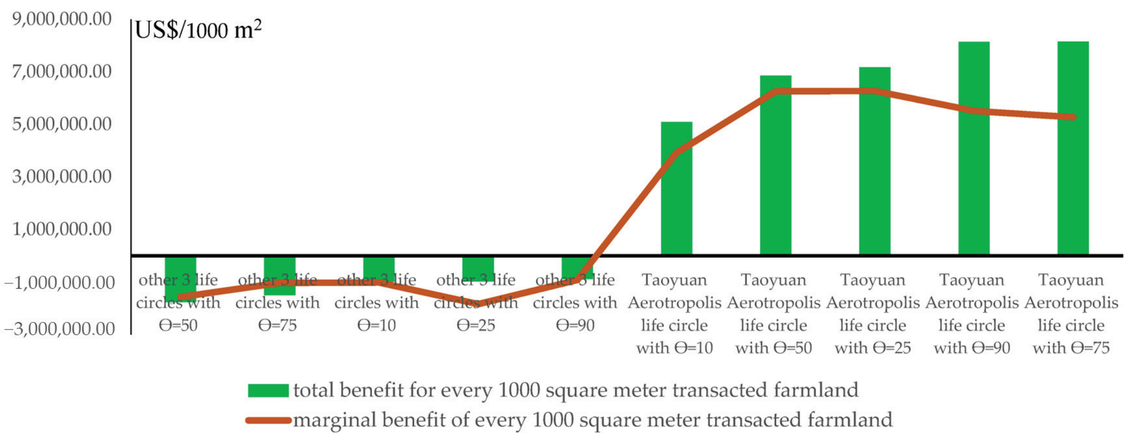

Figure 3. The relationship between the marginal benefit and total benefit of every 1000 square meter change in the transacted farmland size for different life circles with different price quantiles.

5.2. Monetary Benefit of Other Characteristics of Contaminated Farmland per Se and Its Surroundings

Table 6 indicates that the number of months from announcing a controlled contaminated farmland to its cancellation in the Taoyuan Aerotropolis life circle is lower than that for the other three life circles. Similarly, the length of time for a cancelled piece of farmland to complete its transaction in the Taoyuan Aerotropolis life circle is also much shorter than that in the other three life circles once the control has been cancelled. The total benefit for a contaminated controlled farmland from the announcement to its cancellation and from its cancellation to the transaction are shown in Table 6 for each quantile of farmland price, respectively. A comparison of each part of the marginal benefit and the total benefit is displayed in Figure 4. It is observed that the total benefit contributed positively by these two attributes is higher for farmlands in the Taoyuan Aerotropolis life circle than the counterpart price quantile in the other three life circles.

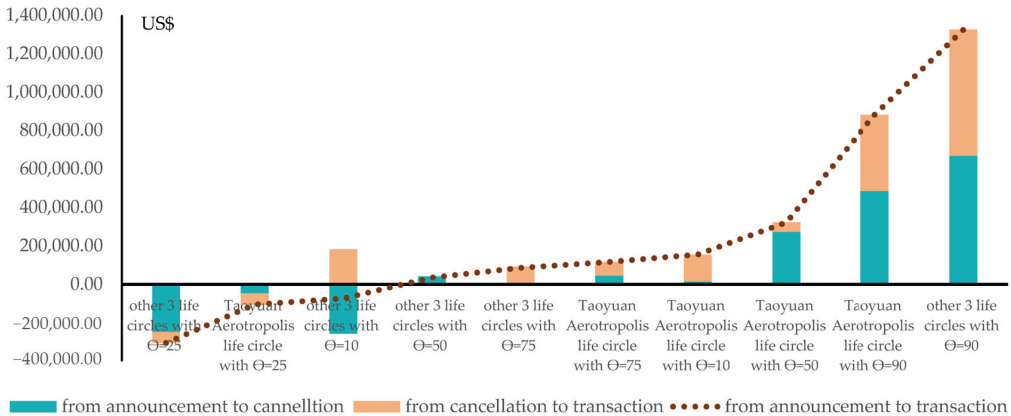

Figure 4. Total benefit for a piece of transacted farmland from announcing its cancellation to the transaction.

Table 5. Marginal benefit for the transaction of cancelled contaminated controlled farmland.

Factor on Farmland Price	Quantile				
	$\theta = 10$	$\theta = 25$	$\theta = 50$	$\theta = 75$	$\theta = 90$
Size of transacted farmland in Taoyuan Aerotropolis life circle (USD/1000 m^2)	3,920,751.43	6,274,969.18	6,263,082.59	5,272,919.47	5,516,051.80
Size of transacted farmland in the other 3 life circles (USD/1000 m^2)	−1,017,560.41	−1,840,228.23	−1,563,949.08	−1,032,273.13	−918,841.98
Average months of transacted farmland in Taoyuan Aerotropolis life circle from announcing a controlled site to the cancellation of the site (USD/month)	279.64	−850.01	5014.12	838.25	8874.13
Average months of transacted farmland in other 3 life circles from announcing a controlled site to the cancellation of the site (USD/month)	−3629.92	−3512.78	597.13	−84.82	9454.52
Average months of transacted farmland in Taoyuan Aerotropolis life circle from the cancellation of a site to the transaction (USD/month)	5616.74	−2342.64	1945.82	2859.34	15,892.71
Average months of transacted farmland in the other 3 life circles from the cancellation of a site to the transaction (USD/month)	3985.74	−1222.61	−154.11	2001.68	14,250.66
The average duration of the nearest announced controlled site prior to the date of a specific piece of transacted farmland (USD/month)	1114.95	2155.12	−2626.80	−376.98	−9903.79
The average duration of the nearest cancelled controlled site prior to the date of a specific piece of transacted farmland (USD/month)	−6116.48	−540.77	2156.09	−2112.65	−5093.18
The distance between the transacted farmland and the nearest controlled farmland (USD/meter)	3061.30	1637.38	463.85	542.78	63.03
The distance between the transacted farmland and the nearest cancelled contaminated controlled farmland (USD/meter)	−3275.15	−2427.29	−950.97	−904.86	−203.05
The price of a construction site in Taoyuan Aerotropolis life circle (USD/meter)	62.10	72.43	5.60	0.30	−1.90
The price of a construction site in the other 3 life circles (USD/meter)	58.19	61.57	9.46	1.93	−1.47
The distance between transacted farmland in Taoyuan Aerotropolis life circle and its nearest main traffic artery (USD/1000 m)	2,854,043.26	2,904,022.75	821,320.68	110,342.66	−198,448.04
The distance between transacted farmland in the other 3 life circles and its nearest main traffic artery (USD/1000 m)	−1,452,537.24	−1,366,066.75	−370,619.40	−107,227.67	6995.91

Table 6. Total benefit contributed by each factor for the cancellation of contaminated farmland transaction price.

Impact Factor of Total Benefit [a]	Quantile [b]				
	θ = 10	**θ = 25**	**θ = 50**	**θ = 75**	**θ = 90**
Benefit of the average size of transacted farmland in the Taoyuan Aerotropolis life circle (1300 m^2)	5,096,977.03 (45.03%)	8,157,459.27 (55.02%)	8,142,007.46 (85.58%)	6,854,796.18 (97.80%)	7,170,866.32 (105.20%)
Benefit of the average size of transacted farmland in the other 3 life circles (970 m^2)	−976,856.64 (104.31%)	−1,766,619.77 (131.24%)	−1,501,390.43 (80.67%)	−990,983.45 (85.93%)	−882,087.94 (89.81%)
Benefit of the average months of transacted farmland in Taoyuan from announcing a controlled site to the cancellation of the site (54.68 months)	15,291.50 (0.14%)	−46,479.75 (−0.31%)	274,170.65 (2.88%)	45,835.24 (0.65%)	485,238.50 (7.12%)
Benefit of the average months of transacted farmland in the other 3 life circles from announcing a controlled site to the cancellation of the site (70.75 months)	−256,818.03 (27.42%)	−248,527.78 (18.46%)	42,246.29 (−2.27%)	−6000.13 (0.52%)	668,906.63 (−68.10%)
Benefit of the average months of transacted farmland in the Taoyuan Aerotropolis life circle from the cancellation of a site to the transaction (24.92 months)	139,969.25 (1.24%)	−58,378.59 (−0.39%)	48,488.52 (0.51%)	71,255.64 (1.02%)	396,047.90 (5.81%)
Benefit of the average months of transacted farmland in the other 3 life circles from the cancellation of a site to the transaction (46.03 month)	183,462.02 (−19.59%)	−56,278.22 (4.18%)	−7,092.85 (0.38%)	92,138.32 (−7.99%)	655,957.60 (−66.79%)
Benefit of the average duration of the nearest announced controlled site prior to the date of a specific transacted farmland in the Taoyuan Aerotropolis life circle (78.54 months)	87,567.89 (0.77%)	169,263.23 (1.14%)	−206,307.66 (−2.17%)	−29,608.06 (−0.42%)	−777,844.66 (−11.41%)
Benefit of the average duration of the nearest announced controlled site prior to the date of a specific transacted farmland in the other 3 life circles (114.19 months)	127,314.66 (−13.59%)	246,093.70 (−18.28%)	−299,954.20 (16.12%)	−43,047.83 (3.73%)	−1,130,913.43 (115.14%)
Benefit of the average duration of the nearest cancelled contaminated controlled site prior to the date of a specific transacted farmland in the Taoyuan Aerotropolis life circle (24.55 months)	−150,160.31 (−1.33%)	−13,276.19 (−0.09%)	52,931.36 (0.56%)	−51,864.82 (−0.74%)	−125,037.62 (−1.83%)
Benefit of the average duration of the nearest cancelled contaminated controlled site prior to the date of a specific transacted farmland in the other 3 life circles (45.37 months)	−277,504.42 (29.63%)	−24,533.80 (1.82%)	97,821.11 (−5.26%)	−95,851.60 (8.31%)	−231,077.01 (23.53%)
Benefit of the distance between a transacted farmland in the Taoyuan Aerotropolis life circle and its nearest controlled site (56.30 m)	172,351.63 (1.52%)	92,184.13 (0.62%)	26,113.98 (0.27%)	30,560.10 (0.44%)	3549.70 (0.05%)
Benefit of the distance between a transacted farmland in the other 3 life circles and its nearest controlled site (69.00 m)	211,228.16 (−22.56%)	112,978.47 (−8.39%)	32,006.15 (−1.72%)	37,453.38 (−3.25%)	4347.97 (−0.44%)
Benefit of the distance between a transacted farmland in the Taoyuan Aerotropolis life circle and its nearest cancelled contaminated controlled site (65.14 m)	−213,341.62 (−1.88%)	−158,113.59 (−1.07%)	−61,947.92 (−0.65%)	−58,941.31 (−0.84%)	−13,227.12 (−0.19%)
Benefit of the distance between a transacted farmland in the other 3 life circles and its nearest cancelled contaminated controlled site (75.61 m)	−247,634.63 (26.44%)	−183,527.45 (13.63%)	−71,903.42 (3.86%)	−68,415.89 (5.93%)	−15,353.66 (1.56%)
Benefit of the price of a construction site in the Taoyuan Aerotropolis life circle (US$1431.22)	2,716,452.92 (24.00%)	3,168,716.87 (21.37%)	245,167.83 (2.58%)	13,168.23 (0.19%)	−83,154.49 (−1.22%)
Benefit of the price of a construction site in the other 3 life circles (US$1393.94)	2,479,117.32 (−264.72%)	2,623,388.73 (−194.88%)	403,127.66 (−21.66%)	82,241.71 (−7.13%)	−62,448.47 (6.36%)
Benefit of the distance between a transacted farmland in the Taoyuan Aerotropolis life circle and its nearest main traffic artery (1210 m)	3,453,392.66 (30.51%)	3,513,868.35 (23.70%)	993,797.03 (10.45%)	133,514.36 (1.90%)	−240,123.01 (−3.52%)
Benefit of the distance between a transacted farmland in the other 3 life circles and its nearest main traffic artery (1500 m)	−2,178,806.52 (232.65%)	−2,049,100.31 (152.22%)	−555,928.16 (29.87%)	−160,842.11 (13.95%)	10,495.32 (−1.07%)
Total benefit of the Taoyuan Aerotropolis life circle (total %)	11,318,500.95 (100.00%)	14,825,243.73 (100.00%)	9,514,421.25 (100.00%)	7,008,715.56 (100.00%)	6,816,315.52 (100.00%)
Total benefit of the other 3 life circles (total %)	−936,498.08 (100.00%)	−1,346,126.43 (100.00%)	−1,861,067.85 (100.00%)	−1,153,307.60 (100.00%)	−982,172.99 (100.00%)

Notes: [a]: The magnitudes in parentheses under the column of the impact factor are the average of each factor in the related transaction life circle. [b]: The numbers in the parentheses under each quantile are the percentages of each factor provided to the total benefit of different life circles.

For the 50% price quantile and above, the total benefit from the announcement of the contamination cancellation to its transaction results in an increase in the transaction price of 1.67–12.98% of the total benefit for non-agricultural Taoyuan Aerotropolis life circle zoning. The total benefit from the same action taken for the other three agricultural development life circles leads to a reduction in the transaction price by 1.89–134.89%. This result indicates that the cancellation of the high price level for contaminated farmlands is not anticipated if they are planned for agricultural purposes. Under the specific marginal benefit, the positive total benefit indicates that there is a longer period of time either from the announcement to the cancellation or from the cancellation to the transaction, so the transacted farmland price increases because it tends to gain enough time to earn the trust of people regarding the non-toxicity and cleanliness of the farmland for all purposes.

Furthermore, there are various factors that can either be characterized by the NIMBY or YIMBY attribute, such as a piece of transacted farmland surrounded by a controlled site which has existed there longer than the specific transacted farmland. Likewise, a transacted piece of farmland surrounded by other cancelled contaminated controlled sites has a similar impact on the price of a piece of transacted farmland. Although the contaminated site has been cancelled, its existence around the transacted farmland might have a stigma attached to it. The impact on the price of the transacted farmland arises not only from the existence of the surrounding potential NIMBY or YIMBY sites, but also from the distance between the designated transacted farmland and these sites. As with the distance between the surrounding sites and the designated transacted farmland, there is a minor impact on the price of the farmland.

When both the distances between the sites and the transacted farmland are shorter, the total transacted farmland price for the Taoyuan Aerotropolis life circle is higher, resulting in an increase in the price of the transacted farmland of 0.14–0.45%. It is obvious that the distance attributes of other controlled sites or cancelled contaminated sites are deemed as YIMBY in the Taoyuan Aerotropolis life circle. This indicates that once the cancellation of contaminated farmland is not mainly for agricultural purposes, it does not matter if the transacted farmland is close to the surrounding controlled or cancelled contaminated sites. These distance attributes, however, reduce the price of transacted farmlands by 1.12–5.24% for different price levels in the other three life circles. This means that if the contaminated transacted farmland is cancelled for agricultural purposes, the farther the transacted farmland is from its nearby surrounding controlled sites and cancelled contaminated site, the higher the transacted farmland price is.

The impact of the existence of the nearby controlled sites and cancelled contaminated sites on the transacted farmland price is much higher than the distance between these sites and the transacted farmland. For the transacted farmlands located in the Taoyuan Aerotropolis life circles, the existence of these two types of sites depletes all levels of farmland by 0.56–12.97%, except for the price level of the 25% quantile. On the other hand, the existence of these sites increases all levels of farmland by 10.86–138.64%, except for the price level of the 25% quantile. The total effect of the existence of the controlled site and the cancelled contaminated site surrounding the designated transacted farmland and the distance of these sites from the transacted farmlands is shown in Figure 5. The figure shows that there is a highly negative impact on the highest farmland price for both life circles, i.e., the Taoyuan Aerotropolis life circle planned for non-agricultural purposes and the other three life circles zoned for agricultural purposes under the *Spatial Planning Act of Taoyuan City*.

As there are various factors with different impacts on the price of all transacted farmlands, it is worth computing and comparing the percentage of each factor that contributes to the total benefit measured by the price change in the transacted farmlands. According to the total benefit computed, as shown in Table 6 above, all factors are classified into nine types. A comparison is made for the total benefit of all transacted farmlands in the Taoyuan Aerotropolis life circle zoned for non-agricultural purposes under the *Spatial Planning Act of Taoyuan City* and for the Zhongli metropolitan, Taoyuan metropolitan urban, and rural development life circles planned for agricultural development, respectively.

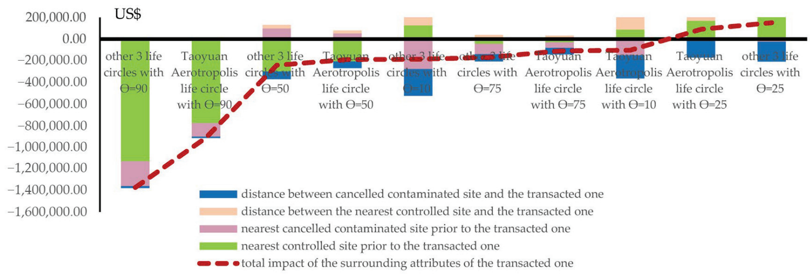

Figure 5. The impact of surrounding contaminated sites with different attributes on the price of transacted farmland.

The specific benefit share of each factor to the total benefit, either positive or negative, is presented in Table 6. Figures 6 and 7 are the composition and share of the total benefit through the change in the transacted farmland price for each factor. Both types of life circles have similar factors that contribute a larger share to the total benefit. These factors are the size of the transacted farmland, the distance between the main traffic artery and the transacted farmland, and the price of construction sites in both life circles for all price levels. The rankings of the benefit share for each quantile price level or for both life circles have slight differences. Moreover, it is not necessary for the higher quantile of the farmland price to contribute to the total benefit. The total benefit can be computed either in monetary terms or as a share of different combinations of benefit contributed by the attributes of the related contaminated farmlands.

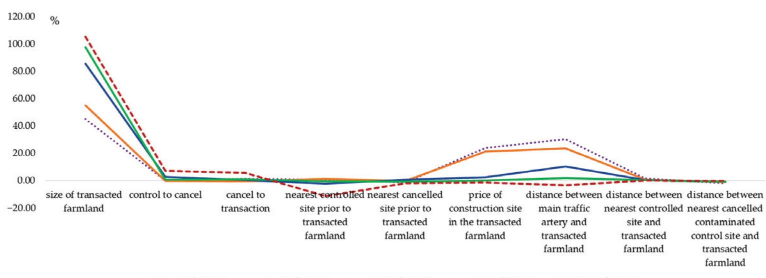

Figure 6. The share of the impact for each factor on the change in the total benefit for the Taoyuan Aerotropolis life circle.

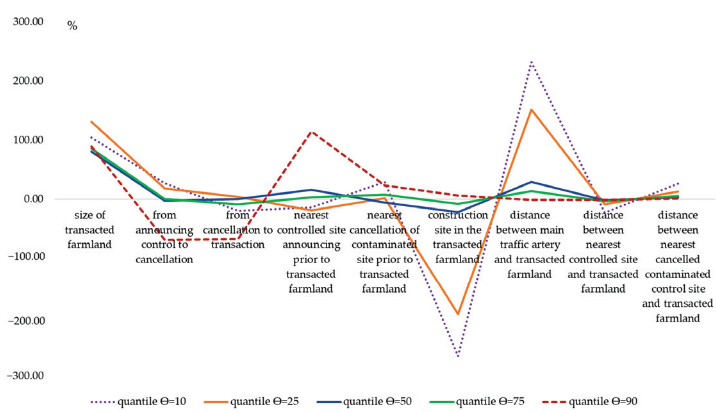

Figure 7. The share of the impact for each factor on the change in the total benefit for all life circles other than the Taoyuan Aerotropolis life circle.

6. Conclusions

This study developed a two-stage quantile spatial Durbin model to evaluate one of the municipalities in Taiwan with the most cancelled contaminated controlled farmlands, namely, Taoyuan city. The changes in the characteristics with significant impacts on the changes in the transacted farmland price were determined. Their corresponding benefits via the changes in the farmland price were computed accordingly. The benefit contributed by the length of time from the cancellation of the contaminated land to the transaction involving the farmland per se and the most related surrounding attributes such as the duration of the nearest announced controlled site and/or the cancelled controlled site prior to the specific transacted farmland does not have the impact anticipated by the remediation mission. The significant attributes for the price impacts are the size of the transacted farmland, the distance between the transacted farmland and the main traffic artery, and the price of the construction site. These attributes indicate that the cancellation of contaminated controlled farmlands apparently leads to the supply of more un-polluted lands for non-agricultural purposes based on the planning act drawn up by the city.

The impact of each attribute on the total benefit of farmland remediation was evaluated in this study. The magnitude of the evaluated benefit of each factor can be used in accordance with the *Spatial Planning Act of Taoyuan City* for the zone planning of different life circles. As the life circle is zoned to be mainly used for agricultural production purposes, the farmland transaction price may not increase once the contaminated land is cancelled. However, retaining a certain amount of good-quality space for agricultural production is essential not only for the city, but also for the whole country. Thus, the benefit evaluated in this study can contribute a guideline to selecting the appropriate attribute that is mainly related to the contamination remediation of the transacted site per se and/or similar attributes surrounding the transacted site. Whether the compensation is implemented depends not only on the evaluated benefit of each attribute accomplished here but also relies highly on understanding and interpreting the evaluated benefits by decision makers. From the farmland owners' viewpoint, once the contamination of farmland is remediated but causes a decline in the price of the farmland, compensation is an unavoidable and fair action to encourage farmland owners to continue to cultivate farmland. Compensation for farmers remaining in agricultural production is contradictory to the viewpoint of the land speculator.

This study develops a comprehensive spatial and quantile model to evaluate the monetary-term benefit via the change in the transacted farmland price for each attribute that potentially has an impact on the remediation of contaminated farmland sites. The accomplishment of such a mission largely relies upon the accuracy of the investigation, detection, elimination, and cancellation of the contaminated sites. However, uncertainty in any process stated above might occur. This causes the elimination of the contaminated sites to lose momentum. On the contrary, the investigation or detection process might be too stringent. This leads to too many controlled sites. This study does not account for any type of uncertainty arising from the confirmation of farmland contamination. Thus, future work can go beyond the study accomplished here and account for either type of uncertainty in determining the contaminated farmlands. Moreover, the study accomplished here can be applied to other cities, counties, or areas where the spatial zoning of land is planned. Further analyses can also be conducted by classifying the planned zones and spaces by ranking the importance of farmlands for different agricultural purposes.

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Article

Sustainable Management of Land Resources: The Case of China's Forestry Carbon Sink Mechanism

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Abstract: Compared to more developed countries, the use of land resources is less efficient in China. China's vast forest land area gives it a rich and underutilized carbon sink. This is an important way for China to achieve the goals of "carbon peaking" and "carbon neutrality", which is of great significance to China's sustainable development. In the past 20 years, China has designed a series of policies to serve the development of forestry carbon sinks, namely the forestry carbon sink mechanism (FCSM). However, the questions of which policy is the most important, and what is the socio-economic value it generates, have not been fully investigated. Accordingly, this paper studied 30 provincial-level regions in China from 2005 to 2020 using the difference-in-differences (DID) model. The conclusions show that: (1) the FCSM does increase the socio-economic value of land resources, thus improving the sustainability of land resources; (2) the FCSM helps to increase forest coverage, forest stock volume and the forest coverage rate, which increases the social value of land resources from the greening path; (3) the FCSM helps to increase the gross forestry product, which increases the economic value of land resources through the path of increasing production value.

Keywords: difference-in-differences model; forestry carbon sink mechanism; governance and policy of land resources; socio-economic value of land resource management

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1. Introduction

The *World Conservation Strategy* of 1980 called on humankind to recognize the need to consider the resource and ecological needs of future generations in the pursuit of economic development and the enjoyment of natural wealth. The *Rio Declaration* of 1992 emphasized that ecological protection is central to achieving sustainable development and called on countries around the world to take action according to their own circumstances. In 2015, 17 Sustainable Development Goals (SDGs) were presented in *Transforming our World: The 2030 Agenda for Sustainable Development*, which included the three dimensions of sustainable development: social, economic and environmental, as well as important aspects related to peace, justice and effective institutions [1]. The SDG15 emphasized the sustainable management of forests [1]. Today, sustainable development has become an important goal in the common quest for humanity. Researchers have been carrying out rich work on sustainable development from many perspectives, such as environmental protection [2–4], economic development [5–7] and human quality of life [8,9]. Greenhouse gas emissions are an issue that must be taken into account in the process of sustainable development. As shown in Figure 1, annual global CO2 emissions are increasing year by year and will be almost seven times higher in 2020 than in 1920. According to the IPCC, 1.5 °C of global warming above pre-industrial levels is due to greenhouse gases [10]. In addition, it has been shown that the increase in GHG emissions is associated with infectious and non-infectious diseases, negative effects on nutrition, water insecurity and other social disruptions [11]. Therefore, controlling greenhouse gases, especially carbon dioxide emissions, has become an important issue for humanity as it seeks to achieve sustainable development. China's total CO_2 emissions have been among the highest in the world for more than a decade [12]. Undoubtedly, China's practices and exploration of low-carbon development has important social value for the world's carbon reduction and environmental protection, as well as being an important inspiration for other developing countries to plan their own carbon reduction path.

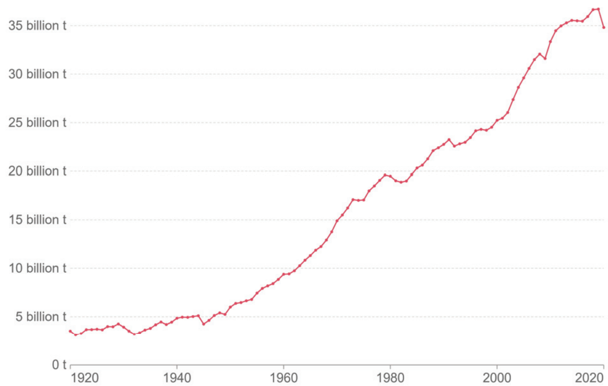

Figure 1. Annual global CO_2 emissions over the last 100 years. Source: Global Carbon Project [12].

On the other hand, after decades of rapid development, China's insufficient efficiency in the use of land resources has become increasingly evident [13]. Along with land degradation and increased urban pollution, the past extensive mode of growth can no longer meet China's demand for high-quality economic development. China urgently needs to improve the way it uses its land resources. A better way is to implement land control policies, such as what was described in the World Bank's "Land Reform Policy Paper" in 1975 [14], China's "Requisition-Compensation Balance of Arable Land" [15], etc. Although land management policies may also have negative effects, such as economic conflicts, social injustice and government corruption [16], overall, they have more or less increased the economic output of land resources.

In order to achieve low carbon development, the Chinese government has enacted a number of environmental regulatory policies in the last decade or so. One of the most promising and effective approaches is the emissions trading scheme (ETS) [17,18]. The ETS allows companies to purchase carbon sinks to partially offset emissions in excess of their allowances, creating the basis for the forestry carbon sink mechanism (FCSM). China has a potential market of nearly USD 31.35 billion in Chinese Certified Emission Reduction [19] as well as abundant forestry resources [20]. Therefore, against the background of record-high world carbon sink prices [21], the study of forestry carbon sinks in China is of practical value. The FCSM therefore not only contributes to environmental protection, but also generates economic value and thus improves the use of land resources.

Through reviewing the literature, this study found that the studies on forestry carbon sinks can be divided into the following categories.

The first category involves research on carbon sink forest construction technology. Technical barriers are one of the challenges in building carbon sink forests [22]. Examples include the depth of the oxic peat layer [23], landscape type [24,25], ground-level ozone concentration [26], atmospheric CO_2 concentration [27], tree age [28], blockchain technology [29], etc. This type of research is usually in the scientific and technical field and requires certain technical tools and analytical instruments to complete the research work. A few scholars have also conducted research from a management perspective, such as reasonable deforestation patterns [30] and the investment models applicable to forestry carbon sink projects [31].

In the second category, the main focus is on the measurement of the productivity of forestry carbon sinks and carbon storage. The common measures are the Slacks-Based Measure (SBM) method [32], the DEA model [33], and the Malmquist–Luenberger index [34]. In addition, many researchers have furthered the analysis and discussion based on the measurement results. Chen et al. pointed out the contribution of forestry carbon sinks in reducing greenhouse gases and achieving carbon neutrality [35]. Shi et al. pointed out that there are deficiencies in the carbon trading market and imperfect accounting of forestry carbon sinks in China [36]. Wei and Shen analyzed the factors (urbanization rate, forestry financial allocation, etc.) affecting forestry carbon sinks in China [37]. Montagnini and Porras pointed out the shortcomings of the FCSM in China from the perspective of economic, social and environmental considerations [38].

The third category, which focuses on the role and drivers of forestry carbon sinks, is also a literature that is of interest in this study. As an investment project, forestry carbon sinks are not a sure thing [39,40]. In the field of economics, researchers typically use econometric models to examine the role and drivers of the FCSM. In terms of its role, the FCSM helps to upgrade the industrial structure at the county level and has a pro-poor effect [41]; the FCSM improves the environment [42]. In terms of drivers, factors such as climate change have a huge impact on the forestry carbon sink [43,44]. Meanwhile, human intervention is also an important factor that cannot be ignored, such as government subsidies [45], investment of fixed assets and FCSM projects [46].

It can be found that economists' studies in the field of forestry carbon sinks are focused on two effects: economic and social effects. The social effects are mainly in the promotion of greening and the reduction of greenhouse gases. However, from an economic standpoint, these studies are relatively crude in the use of econometric models, failing to better overcome the endogeneity problem. Therefore, this paper aims to improve the existing literature by using the DID model. On the one hand, several FCSM policies have been published in China since 2011, but no study has yet answered the question of which policy is most important for the development of the forest carbon sink. On the other hand, DID models have been used to identify causal relationships between variables. This helps to avoid the problem of model endogeneity, and thus can better identify whether the FCSM is delivering social and economic value. Figure 2 shows the process of proving the above questions.

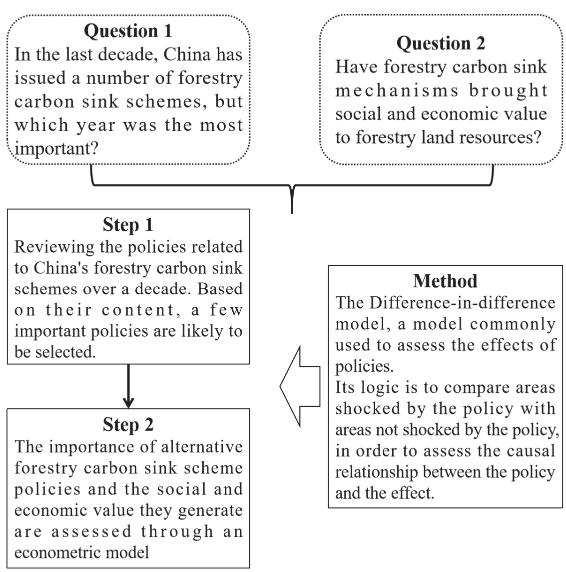

Figure 2. Guidance on research idea.

The remainder of this paper is structured as follows: Section 2 describes the materials needed for the study, including the details of the FCSM, the strategy for selecting the object of study (treatment group area), the basis for selecting variables, and the sources. Section 2 also shows the construction process of the research method (DID model). Section 3 reports the results of the study and the corresponding analysis, mainly including an analysis of the regression results of the DID model, an analysis of the social and economic value generated by the FCSM, and an extended discussion. Section 4 summarizes the previous findings and proposes policy recommendations.

2. Materials and Methods

2.1. Materials

2.1.1. Introduction to the Forestry Carbon Sink Mechanism

The forestry carbon sink is an important element in the process of "carbon peaking" and "carbon neutrality". The forestry carbon sink refers to the market-based means to participate in forestry resources trading, thus generating additional economic value (carbon sink). It can be divided into carbon sink afforestation, bamboo afforestation, forest management, bamboo forest management and grassland carbon sink, according to the type of subject matter. Carbon sink forests are forests created and managed according to certain methodologies and technical standards, and common methods include: the Climate-Community-Biodiversity Standard (CCB standard), the Verified Carbon Standard (VCS), the Kyoto Protocol Clean Development Mechanism (CDM), etc. Therefore, carbon sink forests are different from ordinary plantation forests in that they ensure that the project brings real, measurable and long-term carbon sequestration and environmental optimization effects for climate change mitigation [47].

The 1992 United Nations Framework Convention on Climate Change (UNFCCC) is a basic framework for international cooperation to address global climate change and the cornerstone of forestry carbon sink implementation. The 1997 Kyoto Protocol further established three cooperative mechanisms for reducing greenhouse gas emissions: International Emissions Trading (IET), the Joint Implementation Mechanism (JI) and the Clean Development Mechanism (CDM). This was the prototype of the international carbon trading market, and also laid the foundation for the circulation of forestry carbon sinks. In China, the year 2011 is generally taken as the initial point for the rapid development of forestry carbon sinks. During the period from 2011 to 2021, many policies related to forestry carbon sinks were issued by relevant parts of China (see Table 1).

The above analysis shows that the FCSM is dependent on the ETS for its realization. In other words, the Chinese carbon emission trading market is the key to the implementation of the FCSM. Therefore, policies that contribute to the integration of the FCSM into the carbon emission trading markets are potentially important. From Table 1, there are two policies that have a turning point: the *Interim Measures for the Management of Voluntary Greenhouse Gas Emission Reduction Trading*[1] in 2012 (FCSM2012), and the *Guidance of the State Forestry Administration on Promoting Forestry Carbon Sink Trading*[2] in 2014 (FCSM2014).

FCSM2012 aims to promote ecological civilization, facilitate innovation in institutional mechanisms and give full play to the decisive role of the market in the allocation of resources for greenhouse gas emissions. FCSM2012 emphasizes that Chinese Certified Emission Reduction (CCER) projects can participate in carbon trading after application and certification. In terms of allowance management, free allocation will be the main focus initially, with paid allocation introduced in due course and the proportion of paid allocation gradually increased. For emission units that fail to fulfil their obligations to clear their allowances on time, the carbon trading authorities of the relevant regions will impose administrative penalties in accordance with the law. As a result, enterprises with excessive emission allowances will purchase forestry carbon sink transactions for offsetting.

Table 1. Policies related to the forestry carbon sink scheme in China.

Date	Policy Name	Release Department	Key Content
2011-10	Notice on the Pilot Project of Carbon Emission Trading	National Development and Reform Commission	Agreed to launch carbon emissions trading pilot in 6 regions.
2012-06	Interim Measures for the Management of Voluntary Greenhouse Gas Emission Reduction Trading	National Development and Reform Commission	Recorded and certified CCER projects can participate in carbon trading.
2014-04	Guidance of the State Forestry Administration on Promoting Forestry Carbon Sink Trading	State Forestry Administration	Improved and promoted CCER forestry carbon sink projects.
2018-01	Opinions on the Implementation of Rural Revitalization Strategy	State Council	Promoted exploring market-based compensation systems such as forest carbon sinks.
2018-05	Opinions on further liberalization of collective management rights	State Forestry and Grassland Administration	Promoted actively developing forest carbon sinks and further exploring market-based compensation systems such as forest carbon sinks.
2018-12	Action Plan for Establishing Market-oriented and Diversified Ecological Protection Compensation Mechanism	National Development and Reform Commission and other nine departments	Sound carbon offset mechanism were based on CCER; encouraged the development of forestry carbon sinks through carbon-neutral, carbon-inclusive and other forms of support.
2020-12	Interim Measures for the Management of Carbon Emissions Trading (for Trial Implementation)	Ministry of Ecology and Environment	Provisions on the proportion of carbon emissions that could be offset by forestry carbon sinks.
2021-03	Interim Regulations on the Management of Carbon Emission Trading (Draft Revision) (Draft for Comments)	Ministry of Ecology and Environment	Encouraged enterprises and institutions to carry out forestry carbon sink projects.
2021-04	Opinions on Establishing a Sound Mechanism for Realizing the Value of Ecological Products	State Council	Sound carbon emission trading mechanism.

FCSM2014 aims to accelerate the construction of ecological forestry and forestry for people's livelihoods, strives to increase forestry carbon sinks, and actively promotes forestry carbon sink trading. In terms of basic principles, FCSM2014 emphasizes the need to adhere to and improve the trading of forestry carbon sink projects for CDM. In terms of a carbon trading market, China's National Development and Reform Commission has identified Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen as the national pilot regions for carbon emissions trading, requiring the pilot regions to study and consider relevant measures, including forestry, in light of the actual local situation. The FCSM2014 encourages research on forestry carbon sink laws and regulations, implementation schemes, trading models and regulatory systems. Overall, FCSM2014 brings forestry carbon sinks to the forefront on its own, and is a guiding policy to promote the development of forestry carbon sinks.

These two policies play a key role in the construction of the forestry carbon sink market. Therefore, this study adopts these two years (2012 and 2014) as the FCSM impact times of the DID model, respectively.

2.1.2. Treatment Group

Since the DID model was used to conduct this study, it was necessary to distinguish treatment and control areas. Here, treatment areas refer to areas where the FCSM has been effectively implemented; the remaining areas are control areas. Forestry carbon sink projects exist in most provinces in China. Taking CCER as an example, by 2021 there will be more than 23 provinces in China with CCER carbon sink projects. Further taking CCER as an example, the incomplete 2021 statistics show that 23 provinces in China had implemented CCER carbon sink projects. However, the scale of forestry carbon sinks in most provinces is small and cannot be considered as an effective impact due to their own forestry location factors (growing environment, plantable forest area, etc.). It is therefore necessary to select representative areas from these regions as treatment group areas.

In this study, the larger the number of treatment group areas, the more difficult it is to accurately capture the social and economic value generated by the FCSM; however, the smaller the number of treatment group areas, the more it affects the accuracy of the DID model from a statistical perspective. In this case, it is common practice to select areas that are more affected by the FCSM as treatment group areas, according to the actual situation. Because forest carbon sink projects can be implemented in any area in China, the project sponsor will prioritize the benefits as well as the feasibility of the project. Therefore, factors such as a more suitable environment for carbon sink forestry and a larger area of forested land were the primary considerations for project sponsors. Given the actual conditions in China, this study decided to select eight typical areas as treatment group areas, including Heilongjiang, Jilin, Hubei, Zhejiang, Jiangxi, Fujian, Guangdong and Guangxi. The remaining 22 provincial areas (excluding Hong Kong, Macau, Taiwan and Tibet) were taken as the control group. Figure 3 shows the distribution of the treatment group areas. Table 2 shows the basic information on the treatment group areas, i.e., the reasons for their selection.

Figure 3. The distribution of treatment areas.

Table 2. Basic information on treatment group areas.

Province	Total Area	Landscape Features	Climate Environment	Forestry Resources
Heilongjiang	473,000 km^2	Characterized by "five mountains, one water, one grass and three fields".	(1) Continental monsoon climate; (2) Precipitation: 400–650 mm, concentrated in summer.	(1) One of the largest forestry provinces in China; (2) Forested land: 232,451 km^2.
Jilin	187,400 km^2	The eastern mountains and the central and western plains.	(1) Temperate continental monsoon climate; (2) Precipitation: 400–600 mm, with 80% concentrated in summer.	(1) Asia's largest planted forest: Jingyuetan National Forest Park; (2) Forested land: 87,690 km^2.
Hubei	185,900 km^2	56% mountains, 24% hills, 20% plains and lakes.	(1) Subtropical monsoonal humid climate; (2) Precipitation: 860–2100 mm.	(1) Forestry land: 92,801 km^2.
Zhejiang	105,500 km^2	High in the southwest and low in the northeast, dominated by mountains.	(1) Monsoonal humid climate; (2) Precipitation: 1600 mm.	(1) Known as the "southeast plant treasure house"; (2) Forest land: 66,797 km^2.
Jiangxi	166,900 km^2	Mainly hilly and mountainous.	(1) Subtropical warm and humid monsoon climate; (2) Precipitation: 1341–1943 mm.	(1) With 139.66 million acres of red soil, suitable for plant growth. (2) Forest land: 106,667 km^2.
Fujian	124,000 km^2	90% mountainous and hilly areas.	(1) Subtropical maritime monsoon climate; (2) Precipitation: 1400–2000 mm.	(1) Highest forest cover in China; (2) Forest land: 76,667 km^2.
Guangdong	179,725 km^2	Mountains (33.7%), hills (24.9%), tablelands (14.2%), plains (21.7%).	(1) Central subtropical, southern subtropical and tropical climate; (2) Precipitation: 1300–2500 mm.	(1) Forestry land: 100,342 km^2; (2) Fertile soil.
Guangxi	237,600 km^2	Mainly mountainous, hilly, terrace and plain types of landforms.	(1) Subtropical monsoon climate zone and tropical monsoon climate; (2) Precipitation: 1653 mm.	(1) Forest land: 148,667 km^2, and the mountains account for 69.7%; (2) High-quality plant growing environment.

Source: information from provincial government websites, summarized by the authors.

2.1.3. Variables Design

The explained variables aim to reflect the social and economic value of the output from the use of forestry resources. Therefore, this study designed the explained variables based on two dimensions, social value and economic value, respectively.

As mentioned above, the social value of the FCSM is mainly in the form of greening, which, if implemented effectively, will contribute to the construction of carbon sink forests, thereby increasing the area of green vegetation in a sustainable and long-term manner. The increase in green vegetation will help to reduce carbon dioxide in the atmosphere and release oxygen. At the same time, the increase in green vegetation helps to restore ecosystems, stop desertification and mitigate soil erosion. This study uses forest coverage (100 km^2), forest cover (%), forest stock volume (10,000 m^3) and area of nature reserve (100 km^2), respectively, to reflect the increase in green vegetation, indirectly showing its social value.

1. Forest coverage (FC) includes the area of coniferous forests of natural origin and artificial origin, the area of broad-leaved forests, the area of mixed coniferous forests

and the area of bamboo forests, excluding the area of shrub woodlands and the area of open woodlands. In addition, this indicator also does not include the area of green land for residents and the area of road and bank protection woodland of railroads, roads, rivers and ditches in the statistics. Since this indicator covers the subject of most forestry carbon sink projects, it can better reflect growth in the area of green vegetation.

2. The forest coverage rate (FCR) is the ratio of forest area to total land area, and is an important indicator of the actual level of forest resources and forest land occupation in a country (or region). Since its denominator is the total land area, the indicator will show significant changes only when the forest resources increase significantly.
3. Forest stock volume (FSV), also known as wood storage, is the total volume of standing timber in a forest. It is a measure of the abundance of forest resources in a country or region. General forestry production can be harvested from mature forests. Although most carbon sink forests cannot be harvested, China still classifies carbon sink forests as forest stock for statistical purposes.
4. Area of nature reserve (NR) is the area of a typical territory designated for the purpose of protecting various important ecosystems and their environments, saving endangered species, and preserving natural historical heritage. Nature reserves have a high-quality ecological environment and are very suitable for carbon sink projects. Although natural forests in nature reserves do not include forestry carbon sinks, their superior geographical locations and ecological environments are suitable for forestry carbon sink projects. However, at present, China does not allow forestry carbon sink projects in nature reserves. It is worth mentioning that the construction of nature reserves and the establishment of forestry carbon sink projects may develop synergistically. Therefore, the aim of this study is to investigate whether the FCSM promotes the construction of nature reserves.

According to the previous section, land management policies such as the FCSM can increase the economic output of forest land resources. The FCSM converts the amount of CO_2 absorbed by forests into a share of the carbon sink, which is traded and profitable via the carbon sink market. Although the economic output of forest land is reflected in the primary, secondary and tertiary industries, the base of these three is too large to reflect the increase in output due to the FCSM. Therefore, this paper only uses the gross forestry product indicator (RMB million) to reflect the development of forestry from an economic perspective.

In the literature that uses the DID model, the explanatory variable is an interaction term between a time dummy variable and an individual dummy variable. This explanatory variable captures whether a region is shocked by an event (policy) in a specific period. In this study, it is expressed as whether region i has implemented an FCSM policy in year t'. This study sets this dummy variable to $D_{it'}$. Details of the construction of $D_{it'}$ are shown in Section 2.2. In addition, as the study needs to compare the regression results of different explained variables, they are required to have common control variables. However, this requirement is clearly difficult to meet. At the same time, the spatial fixed effects variable (μ_i) used in this paper also functions as a control variable, controlling for the effects from provincial characteristics. Therefore, the inclusion of other control variables is not considered in this study.

2.1.4. Data Sources

The raw data of this paper are mainly from the *China Statistical Yearbook* (https://data.cnki.net/, accessed on 15 October 2022.) and the *China Research Database Service Platform* (https://www.ceads.net/, accessed on 15 October 2022.). Table 3 shows the results of descriptive statistics for these raw data. Due to significant order-of-magnitude differences between the data, their logarithmic form was used for the regression analysis.

Table 3. Descriptive statistics of raw data.

Variable	Units	Mean	Std. Dev.	Min	Max	Obs.
Forest coverage (FC)	100 km^2	685.4464	597.9148	1.89	2614.85	480
Forest coverage rate (FCR)	%	32.30269	18.3175	2.94	66.8	480
Forest stock volume (FSV)	10,000 m^3	40,185.84	49,560.69	33.24	197,265.8	480
Area of nature reserve (NR)	100 km^2	355.4916	558.4313	9	2183.49	453
Gross forestry product (GFP)	RMB million	14,600,000	18,100,000	16,987.5	96,800,000	419
$D_{i,2012}$	-	0.1500	0.3574	0	1	480
$D_{i,2014}$	-	0.4375	0.4966	0	1	480

2.2. Method: Difference-in-Difference Model

The difference-in-differences (DID) model is one of the more popular econometric models, and is often used in economics to assess whether there is a causal link between a shock generated by an event and an outcome. Furthermore, DID naturally alleviates the endogeneity problem of econometric models. The purpose of this paper is to examine the social and economic value of China's FCSM. Since FCSM implementations are event shocks, they meet the basic requirements of the DID model. The basic construction of the DID model used in this study is shown in Equation (1).

$$Y_{i,t} = \alpha + \beta * D_{it'} + \mu_i + \varepsilon_{i,t} \tag{1}$$

where, i denotes the serial number of a province ($1 \leq i \leq 30$), and t denotes the serial number of a year ($2005 \leq i \leq 2020$), t' is the time point of the event impact (2012 or 2014, Section 2.1.1 for detail). $Y_{i,t}$ are the set of explained variables. $D_{it'}$ is the key explanatory variable, whose coefficient β is our interest value. μ_i is a spatial fixed effects variable, also known as provincial fixed effects in this study. Because the 30 provincial areas each have their unique characteristics, it is necessary to use the variable μ_i to control for possible interference from these characteristics. $\varepsilon_{i,t}$ is the error term.

Assume that $D_{it'} = Treat_i \times Post_{t'}$. The $Treat_i$ term is the treatment group dummy variable. If i region belongs to the treatment group, then i = 1; otherwise, i = 0. The $Post_{t'}$ term is the time dummy variable. If t' is in and after the policy shock year, then $Post_{t'} = 1$; otherwise, $Post_{t'} = 0$. For $Post_{t'} = 1$ in this study, there are two situations, i.e., $t' \geq 2012$ and $t' \geq 2014$.

3. Results and Discussion

3.1. Results and Analysis of Baseline Regression

Introduction to the Forestry Carbon Sink Mechanism

Table 4 shows the regression results based on Equation (1). Among them, the $D_{i,2012}$ term is the result of using 2012 as the initial year of FCSM shock, whereas the $D_{i,2014}$ term is the result of using 2014 as the initial year of FCSM shock.

Table 4. Results of FCSM identifying forestry land use variables.

Explained Variables	ln (FC)	FCR	ln (FSV)	ln (NR)	ln (GFP)
$D_{i,2012}$	0.1142 *** (3.67)	4.2681 *** (6.60)	0.3202 *** (6.08)	−0.0361 (−1.00)	1.3507 *** (13.44)
$D_{i,2014}$	0.2096 *** (7.19)	4.7496 *** (8.44)	0.3961 *** (8.10)	−0.0360 (−0.55)	1.2529 *** (17.56)
Provincial fixed effect	YES	YES	YES	YES	YES
R^2 ($D_{i,2012}$)	0.2382	0.3995	0.2527	0.1055	0.3245
R^2 ($D_{i,2014}$)	0.3367	0.3803	0.4425	0.1055	0.5848

Note: t-value in parentheses; *** $p < 0.01$.

It can be found that the regression results with FC, FCR, FSV and GFP as the explained variables all passed the 99% confidence test, and the corresponding coefficients are positive. The regression results for the explained variable of area of nature reserve did not pass the 90% confidence level test. The above results indicate that the implementation of the FCSM significantly increased the forest area in treatment group areas, increased their forest cover and forest resource, and increased their forestry income. Meanwhile, comparing different FCSM shock years, it shows that the regression results with 2014 as the FCSM shock year were better than those of 2012, overall. The possible explanations are as follows: (I) there is a time lag due to the development of forestry carbon sink projects and the construction of carbon sink forests, which may be 1–3 years, according to the basic regulations of CCER projects; (II) the FCSM policies of 2012 and 2014 complement each other and their policy effects are superimposed. The proof towards these possibilities will need to be developed in further research in the future.

When the explained variable is FC, the coefficient of the $D_{i,2012}$ term is 0.1142 and the *t*-value is 3.67; the coefficient of the $D_{i,2014}$ term is 0.2096 and the *t*-value is 7.19. Obviously, the effect of FCSM2014 on the corresponding regional forest coverage is much more improved than that of FCSM2012. In other words, the eight treatment group areas had an overall enhancement of about 20.96% in forest coverage after the implementation of FCSM2014 compared to the control group areas.

When the explained variable is FCR, the coefficient of the $D_{i,2012}$ term is 4.2681 with a *t*-value of 6.60, and the coefficient of the $D_{i,2014}$ term is 4.7496 with a *t*-value of 8.44. Similarly to above, the stronger policy effect was generated by FCSM2014. This indicator is similar to the indicator for FC, but it is a relative indicator, as it takes into account the effect of the area of the region's own land area on the growth of the forest area. The results show that the forest coverage rate in treatment group areas increased by 4.7496 percentage points overall compared to control group areas after the implementation of FCSM2014, which also indicates that the FCSM has a greater impact on forest areas and has been able to significantly increase the level of forest coverage rate.

When the explained variable is FSV, the coefficient of the $D_{i,2012}$ term is 0.3202 and the t-value is 6.08; the coefficient of the $D_{i,2014}$ term is 0.3961 and the *t*-value is 8.10. It can be found that when 2014 was the impact year of the FCSM, the forest stock volume is elevated more than that of 2012, but the difference was limited. Of course, compared with the increase of the FCSM on forest coverage, its contribution to forest stock volume was greater, i.e., the treatment group areas had a greater increase of 39.61% in forest stock volume than the other areas, as a whole.

When the explained variable is GFP, the coefficient of the $D_{i,2012}$ term is 1.3507 with a *t*-value of 13.44, and the coefficient of the $D_{i,2014}$ term is 1.2529 with a *t*-value of 17.56. Unlike the previous variables, the enhancement of the gross forestry product by FCSM2014 was smaller than that of that of 2012, but the difference is not significant. It shows an overall increase of 135.07% in gross forestry output values in the treatment group areas compared to other areas after the implementation of FCSM2012. One possible reason is that the capital inflow of forestry carbon sink investment after the FCSM2012 led to an increase in gross forestry product, but the growth of carbon sink forests and further output gains take a certain amount of time, thus leading to a relatively smaller corresponding coefficient in 2014.

3.2. Analysis of the Social and Economic Value Generated by the FCSM

The results of Section 3.1 argue for the social and economic value of the FCSM, i.e., increasing the area of green vegetation and improving the economic output of forestry land resources. This subsection will combine the mapped data to show the impact effect of the FCSM more visually. The specific strategies are as follows.

After the implementation of the FCSM, it generated social and economic value. Therefore, with the policy shock as the node, there should be significant differences in forestry land use in the two sample intervals before and after. This study used maps to show these changes and agglomeration characteristics.

3.2.1. Social Value Generated by the FCSM

The social value generated by the FCSM is reflected in the construction of the greening, i.e., the increase in forestry coverage (FC), forestry coverage rate (FCR) and forest stock volume (FSV). Figure 4 shows the changes in FC and FCR between 2014 and 2020, respectively. The "Top ten", "Middle ten" and "Last ten" represent the range of positive change from high to low.

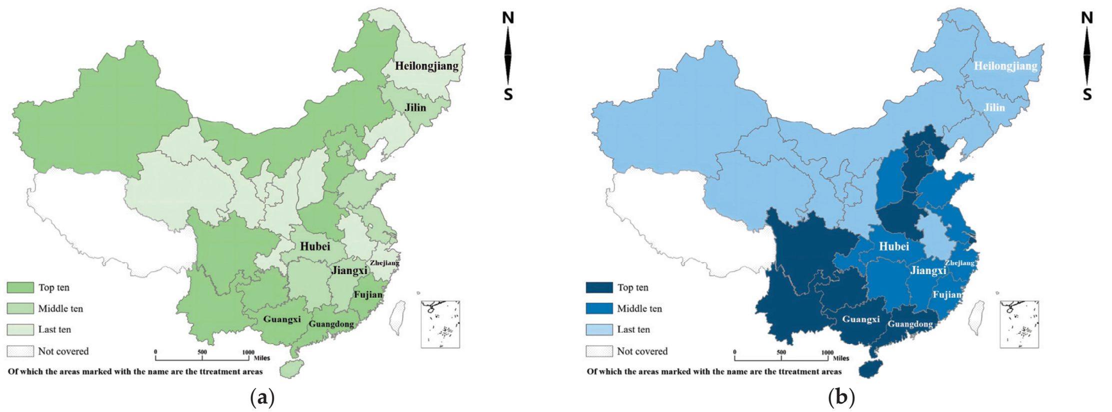

Figure 4. Distribution of forestry land use indicators. (**a**) Change of forestry coverage (FC); (**b**) Change of forestry coverage rate (FCR).

From Figure 4a, the "Top ten" regions are mainly located in southern and northwestern China, indicating that the FC in these regions has increased more after 2014. One important reason for the high growth of FC in southern China is the suitable climate and environment for plant growth; the large variation of FC in northwest China is related to its vast land area and abundant land resources, in addition to the climatic and environmental factors. However, among the eight treatment areas set in this paper, only Guangxi, Guangdong and Fujian are in the "Top ten". This indicates that the impact of FCSM policy on FC goes beyond the treatment group areas set in this paper, which is consistent with the previous section. Of course, this does not affect the conclusions of the econometric model, because the growth of FC in the remaining five areas is also above the average.

From Figure 4b, the "Top ten" regions are mainly located in southern China, indicating that the FCR in these regions has been increased to a higher extent after 2014. At the same time, Figure 4a,b show that the "Top ten" areas overlap to a greater extent, mainly in southern China. Combined with the analysis in the previous paragraph, it can be found that the increase of FC and FCR in southern China was higher after 2014, which indirectly reflects that the FCSM had a higher promotion effect on forest area in southern China than in northwestern China. An important reason for this is that northwestern China has a large volume of land and forest land, which provides the basis for a substantial increase in its forest area. This explanation also applies to Fujian, which has a larger increase in forest area, but has the highest forest cover in the country. Therefore, the increase in FCR in Fujian is limited and it is not a "Top ten" region in FCR.

Overall, the FC and FCR of 8 treatment areas improved more under the impact of the FCSM, while some of the 22 control areas also gained significant positive improvement. This is mainly concentrated in the southwestern part of China. This indicates that, on the one hand, these areas are rich in forestry resources and suitable ecological environments; on the other hand, there may be a spillover effect of the FCSM, which triggers the learning imitation behavior of neighboring regions. Finally, both Figure 4a and b show spatial clustering characteristics, which indicates that the impact of the FCSM is closely related to the locational characteristics of regions.

From Figure 5, the "Top ten" areas are mainly located in southern and northeastern China, indicating that the improvement of forest stock volume (FSV) in these areas is high after 2014. The reasons for the concentration in southern China are similar to the previous section. However, an important reason for the concentration in northeastern China is that the FCSM does not yet involve nature reserves, while northeastern China has many nature reserves with extremely rich forest stock volume. Among the "Top ten" areas, six of them are treatment group areas, namely, Guangxi, Guangdong, Fujian, Jiangxi, Jilin and Heilongjiang, which indicate that the FCSM is more prominent in improving FSV. Combined with the findings in Figure 5, it can be concluded that the FCSM has a significant policy impact on the southern region of China. Of course, due to data limitations, this study only analyzes and discusses the effect of the FCSM on forestry land use in the greening dimension based on four aspects: forest coverage, forest coverage rate, forest stock volume and area of nature reserve. It is believed that when more abundant data are available, more detailed and richer studies can be conducted using the methods of this study.

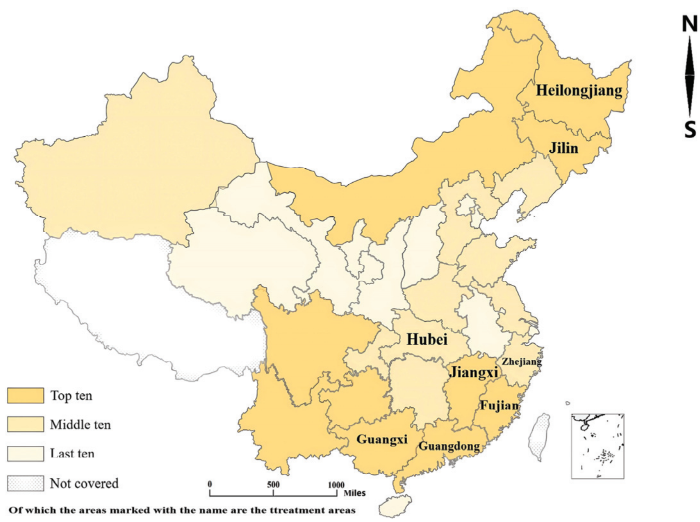

Figure 5. Change of forest stock volume (FSV).

3.2.2. Economic Value Generated by the FCSM

The economic value generated by the FCSM is reflected in the gross forestry production (GFP). Figure 6 shows the overall change in GFP between 2014 and 2020. The "Top ten", "Middle ten" and "Last ten" represent the range of positive change from high to low.

As shown in Figure 6, the "Top ten" regions are clearly clustered in southern China, indicating that the GFP growth in these regions was significant after 2014.

The possible reasons for the high change in GFP in the southern provinces are as follows: (1) since the currently opened carbon emission trading markets (Guangdong, Shenzhen, Fujian, Shanghai, Hube, and Chongqing) are mainly located in the south of China, it is easier for the neighboring provinces to learn about carbon emission trading and start related project activities; (2) many southern provinces have favorable ecological environments and richer land resources, and the plant growth cycle is significantly shorter than that in the north, which facilitates the successful implementation of forestry carbon sink projects; (3) the FCSM policy may have spillover effects. When treatment areas carry out forestry carbon sink activities and obtain objective benefits from them, their neighboring areas can be informed of the relevant information faster than other areas, so that they can imitate and learn from them.

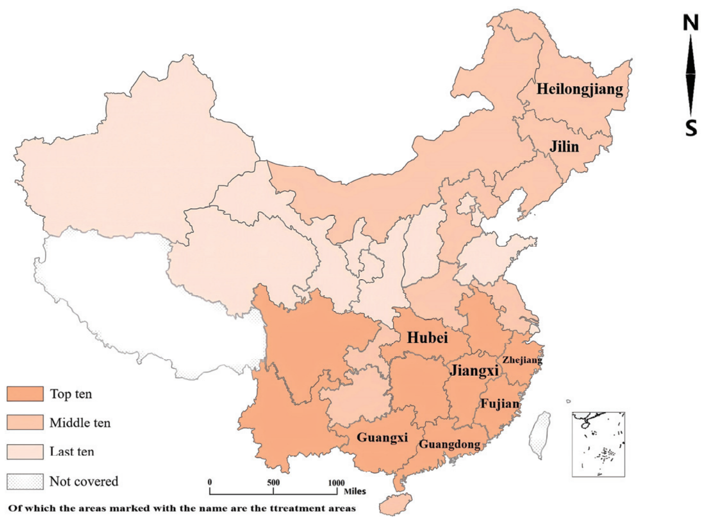

Figure 6. Change of gross forestry production (GFP).

Among the eight treatment areas in this paper, only Heilongjiang and Jilin in northeastern China are not among the "Top ten" areas, suggesting that FCSM policy has a significant policy impact on the southern region of China from the economic development dimension. Combined with the findings in Figure 4, it can be concluded that the FCSM has had a significant policy impact on the southern region of China. Of course, due to data limitations, this paper only uses a comprehensive variable, GFP, as a measure. It is believed that more interesting conclusions will be obtained in future studies using more microscopic data and richer indicators.

3.3. Discussion

The social and economic value of the FCSM as a land resource management tool has been discussed in this study. This subsection discusses the argumentation ideas and methods for the effectiveness of the FCSM, respectively. This section also analyses the shortcomings of the study and looks forward to future work.

3.3.1. Discussion on the Argumentation Ideas for the Effectiveness of the FCSM

The argument for the effectiveness of the FCSM is made by examining and comparing the social and economic value it generates. Kooten and Sohngen start from a cost–benefit perspective and show that not all forestry carbon sink projects are worthwhile. They find that the costs of sequestering carbon are some USD 3–280 per tCO_2, with variations from country to country. For example, in Canada and the USA, carbon sequestration costs range from a low of about USD 2 to nearly 80 per tCO_2 [39]. Bjørnstad and Skonhoft compare the carbon reduction effects of forests as a substitute for fossil fuels and as a carbon sequestration tool, based on the substitutability of commodities. The former reduces fossil fuel consumption and indirectly reduces carbon emissions, whereas the latter directly absorbs CO_2 from the atmosphere and thereby reduces carbon emissions. In comparison, the emission reduction effect of forests as a carbon sequestration tool is superior [40]. This view is supported by Ma et al., who found that replacing fossil energy with forest bioenergy was effective in reducing emissions in mature commercial forests where it already existed [42]. The above studies demonstrate the effectiveness of the FCSM in terms of cost–benefit ratio and commodity substitution. This paper argues for the effectiveness of FCSM policies from the perspective of factual evidence. This study used provincial panel data from 2005 to 2020 to verify the social and economic value of the FCSM using a DID model. As initiating a forestry carbon sink project is a commercial activity, if the project did not bring positive benefits to the project initiator, then such a project is not said to have had a large-scale impact, i.e., the social and economic benefits mentioned in this paper. Therefore, if the FCSM had a significant impact, then forestry carbon sink projects under the influence of the FCSM policy are worthwhile overall. In addition, Song and Peng point out that government subsidies, especially indirect subsidies to insurance companies, are beneficial to the development of forestry carbon sink projects [45]. With the support of the FCSM policy, China's forestry carbon sink projects have received support from local governments, which has also led to a reduction in their costs. Similarly, government support has also helped to strengthen investment in forestry fixed assets, which is important for developing forestry carbon sinks and increasing forestry GDP [46,48].

3.3.2. Discussion on the Argumentation Methods for the Effectiveness of the FCSM

The methods of examining the effectiveness of the FCSM are diverse. Lin and Ge used the SBM-DEA model to assess the role of carbon sink forests in mitigating the greenhouse effect and increasing regional production [34]; Sun et al. used the differential game model to derive the ecological utility (abatement mechanism) of forestry carbon sink projects [29]; Tian et al. used structural dynamic methods to predict the role of carbon sink forests in mitigating the greenhouse effect in the USA over the next century [49]; similarly, Kaipainen et al. studied the issue using the CO_2FIX model [50]. In contrast to these studies, this study is characterized by the use of an econometric model (DID model). This approach alleviates the problem of pseudo-causality. For example, when assessing the impact of the FCSM using methods such as the DEA model, the biggest struggle is the inability to identify a range of impacts as originating from FCSM policies. Similarly, Shi et al. used the difference-in-differences with variation in treatment timing (VTT-DID) model for their study. They examined the pro-poor role and ecological value of the FCSM from an industrial structure provincial perspective, using county-level data from Sichuan Province as an example [41]. However, their study took the implementation of forestry carbon sink projects as the node of DID, and there are significant differences between different forestry carbon sink projects. Therefore, its method has some degree of shortcomings. This study was better able to avoid this problem by taking the implementation of policy as the nodal point. It also avoided the problem that the findings of this study may only be applicable to one region by using 30 provincial regions in China as the target population.

3.3.3. Research Shortcomings and Future Work

The shortcomings of this study are as follows: (1) This paper lists nine major FCSM policies in China for the period 2011–2021. However, due to data length constraints (model requirements), the other seven FCSM policies are not examined in this paper. This, of course, does not affect the conclusions drawn in this paper. (2) In Section 2.1.2, the screening strategy for treatment group areas is not data dependent.

Accordingly, future work could be extended in two ways: (1) To use the methodology of this paper to compare the impact of FCSM policies across countries. (2) To investigate various other FCSM policies in China, especially those that are not yet supported by sufficient data.

4. Conclusions and Recommendations

In attempting to explore the economic and social value generated by sustainable management for land resources, this paper uses the example of the FCSM in China. Using panel data for 30 provincial regions in China from 2005 to 2020, and with the help of a DID model, the paper addresses two questions: (1) in which year the most effective FCSM policies were implemented; (2) whether the FCSM generates economic and social value. The main marginal contributions of this paper are that (1) it enriches the study of FCSM policies by drawing on the methodology of economics; (2) it designs a strategy that can effectively identify the social and economic value generated by the FCSM, compared to existing studies, by drawing on the DID model.

The conclusions show that:

1. The FCSM policies for 2012 and 2014 are all in effect. However, overall, FCSM2014 has had a stronger effect than FCSM2012.
2. In terms of social value, the implementation of the FCSM has significantly increased forest coverage (FC), the forest coverage rate (FCR) and the forest stock volume (FSV) in the eight treatment group provinces. Among them, the largest increase in forest stock volume was observed. However, the implementation of the FCSM has not contributed to the construction of nature reserves (NR). On the one hand, this is due to the fact that natural forests in nature reserves are not the target of FCSM; on the other hand, it may be due to the fact that there are no relevant incentive policies and regulations, so that investors do not include nature reserves in their investment visits. These promotion effects are characterized by spatial agglomeration. The spatial agglomeration characteristics of FC, FCR and FSV differed when the FCSM generated policy shocks, but all of them had the characteristics of "southern agglomeration".
3. In terms of economic value, the implementation of the FCSM has significantly increased the gross forestry product of the eight treatment group provinces. This promotion effect has spatial agglomeration characteristics. When the FCSM produced a policy shock, the increase in gross forestry production (GFP) was higher in southern China than in other regions.

Based on the above, it can be concluded that the FCSM contributes to social and economic value. Therefore, this paper makes the following recommendations on how to optimize the effectiveness of the FCSM.

1. The FCSM makes forestry land resources sustainable in terms of social and economic value. However, the development of the forestry carbon sink business in China is lagging behind. This paper finds that the 2014 FCSM policy is the most efficient forestry carbon sink policy, which verifies this point. Therefore, the current scale of forestry carbon sinks in China is relatively small and the system is still not perfect. In this regard, this paper puts forward recommendations to expand the scale of forestry carbon sinks and improve the related systems in order to give full play to the effectiveness of the FCSM policy. (1) Increase the proportion of forestry carbon sinks to offset corporate carbon emissions. According to Section 2.1.1, the value of China's forestry carbon sinks is that they can offset the carbon emission amount of polluting industries, but this percentage is 5% or 10%, which cannot meet the demand of many enterprises to offset carbon emissions. Therefore, the initial number as well as the allocation ratio of allowances issued in national and local carbon markets can be improved to increase the proportion of forestry carbon sinks offsetting carbon allowances. This pathway can directly increase market demand for carbon sinks, thereby stimulating the establishment of forestry carbon sink projects. (2) Simplify the management process of forestry carbon sink projects. Forestry carbon sink projects are characterized by large areas, multiple elements, and complex measurement and monitoring methods, which constrain the efficiency of their development and implementation. In order for enter-

prises to actively participate in promoting forestry carbon sink projects, it is necessary to simplify the relevant processes and clear the project obstacles for participating entities, for example, through the use of innovative accounting methods, such as using remote sensing, big data and other means. This pathway is an important element in improving the forestry carbon sink system, which can speed up and smooth out forestry carbon sink projects and lower the entry threshold. (3) Developing regionally differentiated FCSM policies. The FCSM has the most obvious positive impact on the southern regions of China, but there is variability in the impact on northern China (northeast and northwest). This is related to the locational factors in the northern region. Therefore, policymakers can better leverage and incentivize the impact of the FCSM on different regions by developing policies with regional differentiation.

2. The FCSM is unable to act on the expansion of nature reserves. At present, FCSM policies are not allowed to be carried out in nature reserves, public welfare forests and other forest stands. However, it cannot be denied that the areas around nature reserves have rich carbon sink potential. In the future, we can study new development strategies, state-sponsored development and other means to release the carbon sink potential of related areas.

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[2] Original information from: http://www.forestry.gov.cn/sites/main/main/gov/content.jsp?TID=2088, accessed on 5 May 2022.

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Article

The Distributional Effects Associated with Land Finance in China: A Perspective Based on the Urban–Rural Income Gap

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Abstract: Land finance has become an important way of generating fiscal incomes in developing countries, while the urban–rural income gap (URIG) in developing countries remains high. However, existing research has not paid much attention to the connection between land finance and the URIG. Therefore, this study used a fixed-effects model to test this relationship for 275 prefecture-level cities in China from 2014 to 2017. To identify the effects of the potential omitted variables, this study conducted additional robustness checks using placebo tests. The results showed that land finance significantly widened the URIG, and this finding was maintained after a set of tests. Further study found that the effect of land finance on the URIG showed significant heterogeneity. Land grants by tender, listing, and auction significantly widened the URIG, while land grants by agreement did not affect the URIG; the effect of land finance on the URIG was more significant in Eastern and Middle regions, but not marked in Western regions; and land finance had no impact on the URIG in large and medium-sized cities, while it had a significant impact in small cities. Based on the above results, this study offers recommendations to improve land fiscal policy and urban-biased development strategies, which aim to promote the equalization of the basic rights and interests of urban and rural residents and reduce the URIG.

Keywords: land finance; income distribution; urban–rural income gap; urban preference

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1. Introduction

With the rapid progress of global urbanization, it is a remarkable fiscal phenomenon to use land assets to raise extra-budgetary funds for the authorities in many developing countries [1]. Some examples include China, India, Viet Nam, and sub-Saharan Africa [2–5]. Land grant incomes and land taxes have turned into one of the main sources of income for local authorities, and this revenue strategy is often referred to as "land finance" [6]. The phenomenon of land finance is typical in China as the largest developing country. Although there are differences between other developing countries regarding the system and the institutional context in which land finance is established, there are many commonalities among them [2]. There is no doubt that the experience and exploration of land finance in China provide a valuable lesson for other developing countries.

Since the reform of the marketization of land transactions in 2004, land finance has been growing rapidly at an average annual rate of 20.7% over the past ten years, based on the Data of the Ministry of Finance [7]. In 2021, the scale of land finance reached USD 1.35 trillion, which accounted for 78% of local fiscal incomes. Land finance plays an essential role in regional socioeconomic development. On one hand, land finance increases the local authorities' income, accelerates the process of regional urbanization and industrialization [2,8], promotes the rapid development of infrastructure [9], and improves the regional economy [10]. On the other hand, the negative effects produced by land finance are also increasingly obvious. For example, it boosts the rapid growth of property prices [11], exacerbates the risk of regional debts [12], induces illegal land use [13], breeds corruption [14], and increases macroeconomic fluctuations, etc. [15].

A high dependence on land finance has kept income gaps at a high level for a long time in China. In the 21st century, the Gini coefficient in China has remained above the high level of 0.4 [16]. One study found that excessive income inequality may be harmful to social stability, hinder economic development, and weaken residents' sense of well-being [17]. Income inequality in China mainly stems from the URIG. For example, based on Wan's estimation, the URIG in China accounts for 70–80% of the total income gap [18]. In a later study, Chen et al. concluded that this ratio was 58% [19]. Figure 1 indicates that the per capita disposable income ratio of urban and rural residents stayed above 2.5 from 2013 to 2021, although it slightly decreased. Considering the welfare difference between urban and rural residents, this gap will continue to increase [20]. The huge URIG has also attracted the criticism that "the welfare of urban areas is built on the backs of farmers" [21].

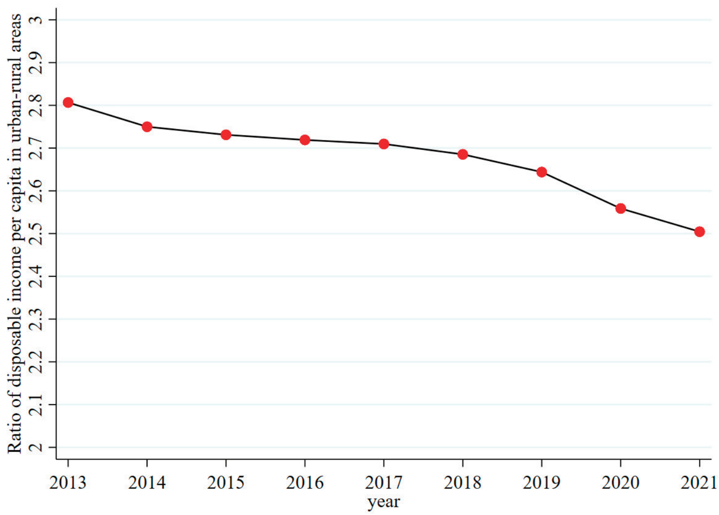

Figure 1. Ratio of disposable income per capita in urban–rural areas from 2013 to 2021.

The urban preference theory is often used to explain the URIG in developing countries, which attributes its cause to policies that favor the development of the urban sector [22]. Yang's study showed that urban preference policies, which include urban–rural labor market segregation, price control of agricultural commodities, discriminatory social benefits, and differentiated security systems, widened the URIG [23]. Sicular et al. found that the household registration system explained more than 50% of the middle-body income gap [24]. The household registration system distorts the labor market and helps urban residents obtain greater job opportunities with higher labor remuneration [25,26]. Moreover, the URIG, induced by a series of urban-preferred fiscal policies, including infrastructure investment, financial development, and education budgets, has been widely discussed [27–29]. Although the existing studies have analyzed the relationship between urban preferences, fiscal systems, and the URIG, there are few studies on the impact of land finance on the URIG. Land finance is dominated by the government with an obvious urban preference, and the government is probably contributing to the unequal distribution of factors between urban and rural areas through its intervention in land policy, which in turn affects income distribution [30]. Therefore, the relationship between land finance and the URIG needs to be further analyzed.

Based on the above background, this study analyzed the relationship between land finance and the URIG and tested this relationship using a fixed-effects model for 275 prefecture-level cities in China over the period 2014–2017, as well as an additional robustness test using a placebo test in order to identify the effects caused by the potential omitted variables. The results indicated that land finance significantly widened the urban–rural income gap, and the conclusion still stood after a set of tests. The results showed that land finance significantly widened the URIG. Further study found that the effect of land finance on the URIG showed significant heterogeneity. Land grants by tender, listing, and auction significantly widened the URIG, while land grants by agreement did not affect the URIG; the effect of land finance on the URIG was more significant in Eastern and Middle regions, but not in Western regions; and land finance had no impact on the URIG in large and medium-sized cities, while it had a significant impact in small cities.

The potential contributions of this study are as follows. First, it enriches the literature on the socioeconomic consequences of land finance, expanding the framework of land finance-related studies. Second, it integrates land finance and the URIG into a unified analytical framework, exploring the causes and mechanisms of the continuing widening of the URIG, and providing a new explanation for the understanding of China's URIG. Finally, it examines in detail the effects of land finance on the URIG, which deepens the understanding of the relationship between land finance and the URIG, proving that the exploration of policies can effectively promote the reform of the land system and reduce the URIG. This study also provides an empirical reference for other developing countries.

The remainder of the study is structured as follows. Section 2 describes the institutional background and theory analysis. Section 3 constructs the econometric regression model and describes the measurement of the date and variables. Section 4 shows the results of the empirical analysis. Section 5 discusses the implications of the empirical evidence and points out the shortcomings. Section 6 draws the conclusions and proposes relevant policy recommendations.

2. Institutional Background and Theoretical Analysis

2.1. Institutional Background

2.1.1. Land Finance in China

In the 1994 tax-sharing reform, taxes were classified into three categories: central taxes, local taxes, and shared taxes. While the largest of these, VAT (value added tax), was shared between the central and local governments at the ratio of 75% to 25%, the consumption tax of enterprises was included in the central tax. The income tax reform implemented in 2002 even changed the corporate income tax and the personal income tax from a local tax to a shared tax, which was shared 50%:50% between the central government and the local government. Since 2003, it has shifted to 60% to the central government and 40% to the local governments [31]. In 2016, China fully implemented the business tax compared to VAT and further reduced local government income by reducing VAT and double taxation [32]. However, the cost of public services and infrastructure borne by the localities was not reduced at the same time [6]. Local governments must find new ways of generating income to make up for the fiscal gap. The reform of the tax system also has a significant impact on the extra-budgetary and non-budgetary funds of local governments. In particular, agricultural coordination and land transfer income related to land development are not in the budget. There is no effective management system after tax reform, and the land transfer income is fully owned by the local government. Therefore, non-budgetary funds, especially land transfer income, have become the main source of financial growth for the local government [31].

In 2007, land transfer income and expenditure were fully incorporated into the budget management of local government funds. Compared to the general budget, it obviously reflected "weak constraints". The management of land grant revenues is still irregular, and expenditures are not transparent. Meanwhile, government officials, under the pressures of promotion and performance appraisal, must not only maintain a high GDP growth rate but also achieve higher rankings than the other candidates. As a result, they tend to adopt approaches that are inconsistent with the central government's policies and increase urban infrastructure investment through land finance to promote regional economic growth [32,33]. In addition, after the global financial crisis in 2008, local governments enhanced the role of local government financing platforms (LGFPs) to support infrastructure development [34] and used future land grant income as an invisible guarantee for debt financing. The Ministry of Finance announced in 2009 that "local governments are allowed to finance investment projects from essentially all sources of funds, including land income, budgetary income, and funds borrowed from local financing instruments," which also provided policy support for future invisible guarantees of land transfer income [35]. In 2014, to curb the risky rise of local financing platforms, the Chinese government amended its budget law to allow "provincial governments to raise capital for local investment in part by issuing local government bonds within the limits prescribed by the State Council". The Ministry of Finance (MOF) issued guidelines for local government bonds in 2015, which allowed local governments issuing special bonds to use cash inflows from future infrastructure projects and the government's future land sale income to repay the bonds, which also provided a formal legal link between local government land financing and debt financing [2], while strengthening the local government's reliance on land-based finances to maintain land finance at a high level.

2.1.2. Land Acquisition Strategies in China

China has adopted a dualistic land system divided into urban and rural lands, where urban land is owned by the state, and rural land is owned collectively by peasants. The Land Management Law (unrevised until 2020) provides that the state may acquire collective land in the "collective interest" by law [36]. In practice, most urban land needs to be acquired by the local government. Only after the change of ownership to state-owned land can the land be used for industrial, commercial, or infrastructure construction. These mechanisms strengthened the right of the government to manage and control land resources and achieve the monopolistic position of the government in the supply of urban land [37]. There are two ways for the government to obtain newly developed urban land. One is to transform the land owned by rural collectives into new developable urban land, whereby the government exchanges its rural land ownership by paying compensation to rural collectives and farmers. The second is to obtain the right to use urban land through compensation [2]. However, in terms of compensation standards based on the Land Management Law, land expropriation only reflects the value of the land before expropriation and does not take into account the value of the land after expropriation [30]. For example, based on the Land Management Law, compensation for expropriation of arable land consists of three components: land compensation (the monetary value of the average value of agricultural output over the past three years); compensation for resettlement (4–6 times the productivity of the derived land); and compensation for ancillary assets of the land [36]. The Ministry of Land and Resources (MLR) further stipulates that the maximum compensation for land expropriation cannot exceed 30 times the derived land's productivity. While the central government requires localities to dynamically update compensation standards to match the rate of economic growth, only a few provinces are raising compensation standards as recommended. The vast difference in the cost of land expropriation has led local governments to prefer expropriating rural collective land, which is cheaper. Local governments made huge profits by buying land at low prices and selling it at high prices. This mechanism is an important reason why local governments are able to implement land finance as well.

2.1.3. Local Government Income–Expenditure Structure of Land Concessions

Under the current financial framework of China, local governments have significant autonomy over the use of land concessions, and this autonomy of local governments has not been significantly limited, even though the full amount of income and expenditures from land concessions was incorporated into the budgetary management of local government funds in 2007. In 2008–2010, the average portion of land grant proceeds spent on cities was 69.56%, and the average portion spent on rural areas was 9.52% [38]. In 2010–2014, the cost expenditures for land acquisition compensation, and subsidies for expropriated farmers decreased from 80% to 20%, and the proportion of expenditures for rural development was smaller and has been decreasing constantly, creating a widening gap between expenditures on rural and urban development [30]. Overall, urban residents gain more than rural residents in land grant income expenditures, which highlights the urban bias in these expenditures.

2.2. Theoretical Analysis

Under government domination, the land finance development strategy has an obvious urban preference in terms of income and expenditure, which will inevitably have a negative impact on urban–rural income distribution. On the one hand, in the land expropriation procedure, collective landowners (rural residents) do not have the ability to negotiate directly with urban land users, nor can they directly transfer land ownership to urban land users, and the amount of compensation for land transfer is entirely unilaterally decided by the local authorities [36]. This directly leads to land compensation for farmers being far lower than the market price of the land [30]. In the meantime, urban residents are receiving higher compensation in the process of land expropriation. Local authorities have gained funds for urban development, promoted urban expansion, and increased the income of urban residents by selling expropriated collective land at high prices [39,40]. This huge gap between low compensation prices and high land premiums can widen the URIG [41].

On the other hand, the main source of the local authority's tax income has changed from an enterprise tax to a business tax, which is mainly collected from tertiary industries and the construction industry. With the construction industry being the main target of the business tax, it is logical that the local authorities allocate land grant income to the urban areas where the secondary and tertiary industries are concentrated [31]. This strategy of urban-oriented development significantly increases the provision of infrastructure and public services in urban areas [42]. Improvements in public services and infrastructure enhance the value of housing for urban residents, which increases the wealth of urban residents and increases their personal incomes through higher rates of return on capital [21,30]. However, rural residents are unable to trade their own houses and land freely due to institutional constraints, thus making it difficult for them to access the benefits of rising property prices, which in turn raises the cost of urban labor [43] and inevitably widens the URIG.

In addition, land is not only a factor in agricultural production, but it is also the basis of farmers' survival [44]. The expropriation of rural land means that rural residents will no longer own their production factors or housing, resulting in many rural residents migrating between urban and rural areas or choosing to settle in urban areas. This not only reduces the productivity of agriculture but also inhibits an increase in the income of rural residents who work at home [45]. At the same time, due to the poor education and skill levels of urban migrant workers, they are at an obvious disadvantage in the job market. Therefore, it is difficult for them to find employment, and they can only take up low-paid and high-risk jobs with insufficient labor protection, which results in a lower growth in wages than that of urban residents [36,46]. Moreover, rural residents who choose to settle in urban areas must often pay a mortgage from their labor income [47], and the rising prices of urban housing exacerbate this function, which is also not conducive to their employment choices and wage income [48].

As a result of the above analysis, this study puts forward the following hypothesis:

The dependence of local authorities on land finance will significantly widen the URIG.

3. Model, Variable and Data

To identify the relationship between land finance and the URIG and taking into account the type of data and the features of the variables, this study adopted the fixed-effects model, which is commonly used in economics and management to conduct such a test. The remainder of this section is arranged as follows. It first introduces the fixed-effects model, then describes the construction of the relevant variables, and finally explains the source and treatment of the data.

3.1. Fixed-Effects Model

The fixed-effects model is a panel data analysis method that is widely used in the fields of economics, sociology, and management by introducing dummy variables in the ordinary least squares regression model or using within-group de-meanings to prevent the endogeneity problem caused by omitted variables [49,50]. Usually, omitted variables affect the explanatory variables as well as the explained variables, leading to inaccurate estimation coefficients of the explanatory variables. Therefore, it is necessary to add more control variables. However, some of the control variables are unobservable, whereas the fixed-effects model can control the unobservable non-time-varying only-individual-varying omitted variables and the non-individual-varying only-time-varying omitted variables. The advantage is that it can largely mitigate the endogeneity problem caused by specific omitted variables, as well as eliminate inter-individual heterogeneity and improve the estimation efficiency and accuracy. The disadvantages are that it is unable to estimate the impact effect of the observable variables that do not vary over time, it cannot recognize inter-individual variability, and it may miss important differences between the individuals [51]. Taking into account the data features and variable features of this study, the fixed-effects model was used to test the relationship between land finance and the URIG. The specific form of the fixed-effects model is shown in Equation (1).

$$IG_{it} = \alpha_0 + \alpha_1 land\ fin_{it} + \alpha_2 X_{it} + \theta_i + \rho_t + u_{it}, \tag{1}$$

where IG indicates the URIG; $land\ fin$ indicates land finance; X indicates a set of control variables; θ indicates the city fixed effects used to control the omitted variables that vary only with the city and not with time, such as a city's geographic location; ρ indicates the time fixed effects used to control the omitted variables that vary only with time and not with cities, such as macro-level covariation; u indicates a random error term; and i and t indicate the city and year, respectively. The focus of this study was on the core index of α_1, which should be positive if the hypothesis is true. The coefficient estimation was carried out using the Stata 15.1 software.

3.2. Variable Description

3.2.1. Explained Variables

There are two main indicators commonly used to measure the URIG. One is the ratio of disposable income of urban and rural residents as a direct measure of the URIG [30,41]. The second is the Thiel index [20,52]. Compared to the Thiel index, the ratio of disposable income of urban and rural residents is more intuitive due to it being simple to measure. However, it ignores the proportion of urban and rural populations and fails to reflect the changes in mobility between urban and rural populations [20]. Therefore, we used the Thiel index, which better reflected the flow of urban and rural populations, to measure the URIG. Its formula is shown in Equation (2). In addition, the ratio of disposable income of urban and rural residents was used for the additional robustness test.

$$TL_{it} = \sum_{j=1}^{2} \left(\frac{P_{ijt}}{P_{it}} \right) \ln \left(\frac{P_{ijt}}{P_{it}} \Big/ \frac{Z_{ijt}}{Z_{it}} \right) \tag{2}$$

where TL_{it} indicates the Thiel index of city i in year t; $j = 1,2$ indicates the urban and rural areas, respectively; P_{ijt} indicates the per capita disposable income of city i in year t; P_{it} indicates the per capita disposable income of city i in year t; Z_{ijt} indicates the number of urban and rural resident populations of city i in year t; and Z_{it} indicates the total resident population of city i in year t. The larger the Thiel index, the larger the URIG.

3.2.2. Main Explanatory Variables

Land finance: Land finance income primarily includes land grant, land-related tax income, and land mortgage, where the land grant counts as the main part of land finance [53]. Therefore, this study took the ratio of land grant income to public finance income as a proxy variable for land finance. Moreover, this study constructed the ratio of land grant income to GDP and per capita land grant income to measure land finance for the robustness test.

3.2.3. Control Variables

To avoid the possible omitted variables, the following control variables were selected in this study. The level of economic development (econ): measured the level of economic development by using GDP per capita with natural logarithmic treatment; industrial structure (indus): measured the industrial structure by using the ratio of the gross domestic product of the secondary and tertiary industries to the regional GDP; financial development (fina): measured the financial development by using the ratio of the balance of deposits and loans of financial institutions to the GDP at the end of the year; the level of opening up: measured opening by using the ratio of the total amount of regional imports and exports to the regional gross domestic product; authorities' intervention (gove): measured the authorities' intervention by using the ratio of public fiscal expenditure to the regional GDP; education level (educ): measured the education level by using the number of students enrolled in general higher education institutions per 100,000 people with a natural logarithmic treatment. Since some cities did not have any higher education institutions, one was added to the original data before taking the logarithmic value.

3.3. Data Sources

The data used in this study were mainly from the *China Land and Resources Statistical Yearbook* and *China Urban Statistical Yearbook*, and some of the missing data were supplemented by local statistical yearbooks or statistical bulletins. In 2013, the National Bureau of Statistics launched a survey on the income, expenditure, and living conditions of urban and rural residents, and the survey methodology and caliber of urban and rural incomes were changed. Thus, the data after 2013 were not comparable with the previous data, and the *China Statistical Yearbook of Land and Resources* had only counted the data up to 2017. Therefore, this study selected the sample interval as 2014–2017. In addition, to avoid the influence of the price factor, the variables in the nominal value of money statistics were deflated using the GDP deflator and using 2003 for the base period. The descriptive statistics for each variable are shown in Table 1.

Table 1. Descriptive statistics.

Variable	Obs.	Min.	Max.	Mean	Std. Dev.
TL	1100	0.0045	0.252	0.074	0.0373
$land\ fin$	1100	0.0086	3.141	0.494	0.361
econ	1100	8.737	11.78	10.21	0.512
indus	1100	0.495	0.997	0.878	0.077
fina	1100	0.717	22.32	2.485	1.369
open	1100	0	10.61	0.178	0.47
gove	1100	0.0439	2.06	0.207	0.127
educ	1100	0	4.752	2.471	0.928

4. Results

4.1. Baseline Regression Results

The results of the base regression results of this study are shown in Table 2. Where column (1) only controlled for the time fixed effects and city fixed effects, the regression coefficient of land finance was 0.0024, and it was significantly positive at the 5% level. Column (2) added two control variables, which were the economic development level and industrial structure, and the results showed that the regression coefficient of land finance was 0.0028, and it was significantly positive at the 1% level. Column (3) added the financial development level and opening-up level based on column (2), and it was shown that the regression coefficient and significance level of land finance were not significantly changed compared to column (2). Column (4) added authorities' intervention and education level to column (3), and Table 2 shows that the regression coefficients and significance levels of land finance did not change significantly. According to the above results, land finance was indeed an important reason for the widening of the URIG in China, which initially verified the hypothesis of this study.

Table 2. Base regression results.

Variable	(1) TL	(2) TL	(3) TL	(4) TL
$land\ fin$	0.0024 ** (2.3654)	0.0028 *** (2.7604)	0.0027 *** (2.7272)	0.0028 *** (2.7960)
econ		−0.0161 *** (−3.0017)	−0.0165 *** (−2.8612)	−0.0158 *** (−2.8486)
indus		−0.0154 (−0.5697)	−0.0151 (−0.5611)	−0.0153 (−0.5617)
fina			−0.0002 (−0.6717)	−0.0004 (−1.2928)
open			0.0001 (0.3308)	0.0001 (0.3527)
gove				0.0047 (1.4958)
educ				−0.0015 (−1.6437)
_cons	0.0784 *** (121.2969)	0.2550 *** (4.4574)	0.2595 *** (4.2166)	0.2551 *** (4.2378)
Year fixed	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes
N	1100	1100	1100	1100
Adj. R2	0.289	0.325	0.324	0.326
F	82.0712	53.8820	40.4140	32.9928

Note: t statistics in parentheses (cluster in cities level). *** $p < 0.01$, ** $p < 0.05$.

4.2. Robustness Tests

4.2.1. Replace Relevant Variables

To verify the robustness of the results of the basic regression, robustness tests were conducted by replacing the variables. The results of the robustness tests are shown in Table 3. Column (1) was a measure of land finance using the per capita land transfer price, denoted by $land\ fin2$. The coefficient of $land\ fin2$ was 0.0037 and was significantly positive at the 5% level. Column (2) was a measure of land finance using the ratio of the land transfer price to GDP, and the coefficient of $land\ fin3$ was 0.0221 and was significantly positive at the 10% level. Column (3) was a measure of the URIG using the ratio of the disposable income per urban resident to the disposable income per rural resident (IR), and the coefficient of $land\ fin$ was 0.0316 and was significantly positive at the 5% level. The above results demonstrated that after replacing the main explanatory variables, the signs and significance of the coefficients were not significantly different from the basic regression, which further indicated that the empirical results were robust.

Table 3. Robustness test regression results.

Variable	(1) TL	(2) TL	(3) IR	(4) TL
$land\ fin2$	0.0037 ** (2.4686)			

Table 3. *Cont.*

Variable	**(1)** **TL**	**(2)** **TL**	**(3)** **IR**	**(4)** **TL**
$land\ fin3$		0.0221 * (1.9408)		
$land\ fin$			0.0316 ** (2.3153)	0.0014 (0.6646)
$land\ fin^2$				0.0007 (0.6863)
Control	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes
N	1100	1100	1088	1100
Adj. R2	0.323	0.322	0.228	0.326
F	34.4127	33.5594	15.6242	30.3025

Note: t statistics in parentheses (cluster in cities level). ** $p < 0.05$, * $p < 0.1$.

4.2.2. Non-Linear Regression

To verify the non-linear relationship between land finance and the URIG, the secondary term of land finance was also included in the regression equation in this section, and the regression results are shown in column (4) of Table 3. The coefficients of both the primary and secondary terms of land finance were positive and insignificant, and this result indicated that there was no non-linear relationship between land finance and the URIG.

4.2.3. Placebo Test

It is possible that, even after controlling for fixed effects and confounding variables, unobservable factors may still have affected the regression results. There may have been mechanisms that we could not observe that affected both land finance and the URIG, which could bias the estimated coefficients. Therefore, we used the placebo test to investigate whether the impact effect of land finance on the URIG stemmed from other unobservable factors. Referring to other placebo tests such as in La Ferrara et al. [54], the steps were as follows. First, the land finance data were randomly assigned to each city. Second, the regression was performed using Equation (1) to extract and preserve the regression coefficients of the land finance. Third, the above process was repeated 1000 times, and the regression coefficients extracted from these 1000 times were summarized and preserved. Finally, the 1000 regression coefficients were plotted according to the preserved kernel density distribution.

Figure 2 shows the distribution of kernel densities generated by the placebo test. The regression coefficients were approximated to a normal distribution with a mean of 0 and were mainly focused on the wings, while the absolute values of the 1000 regression coefficients were smaller than the base regression coefficients, which indicated that there was no effect related to virtual land finance. By inversion, the unobservable variables hardly affected the regression results.

4.3. Analysis of the Heterogeneity

4.3.1. The Heterogeneity of Land Grants for Industrial and Commercial/Residential Sites

In the process of land transfer, the authorities have adopted different modes of transfer for industrial land and commercial/residential land. In particular, the authorities usually grant industrial land at a low price, mainly by agreement, while they grant commercial and residential land at a higher and restrictive price, mainly by tender and auction. It is worthwhile to examine in detail whether this difference in the mode of land transfer may have different impacts on the URIG. Therefore, we used the agreement transfer transaction price as a proxy variable for the returns of industrial land, further exploring the impact of different land transfer returns on the URIG. We also used the tender and auction transfer transaction price as a proxy variable for the returns of commercial and residential land.

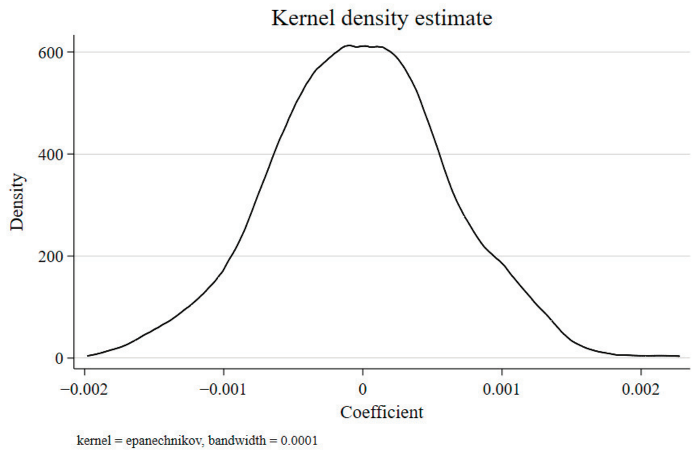

Figure 2. Placebo testing.

The regression results are shown in Table 3. Column (1) shows the regression results of the agreement to let, and column (2) shows the results of tender and auction. In column (1), the coefficient of agreement to transfer was −0.0017 but was not significant. In column (2), the regression coefficient of bidding, listing, and auctioning was 0.0034 and it was significantly positive at the 1% level. The above results showed that the proceeds from industrial land concessions by local authorities in the form of agreements did not have an impact on the URIG, while the proceeds from commercial and residential land concessions by means of tenders and auctions could aggravate the widening of the URIG.

4.3.2. Regional Heterogeneity

Due to the sheer size of China, there are large differences among regions. The land finance dependence varies from region to region, and the effect of land finance on the URIG may differ greatly. Therefore, this study further examined the effect on the URIG in different regions. The entire sample was classified into East, Middle, and West, according to the region, the regression tests were separately run, and the results are shown in columns (3–5) of Table 4. Column (3) shows the results for the East region, where the regression coefficient of land finance was 0.0037 and was significantly positive at the 1% level. Column (4) shows the results for the Middle region, where the coefficient of land finance was 0.0024 and was significantly positive at the 10% level. Column (5) shows the results for the West region, where the land finance coefficient was 0.0024 but was not significant. All these results indicated that in the Eastern and Middle regions, land finance widened the URIG while in the Western region, it had no significant effect.

Table 4. Heterogeneity analysis regression results for industrial and commercial/residential land.

Variables	(1) TL	(2) TL	(3) East	(4) Middle	(5) West
Agreement	−0.0017 (−0.9475)				
Tender and auction		0.0034 *** (3.4550)			
$land\ fin$			0.0037 *** (2.9845)	0.0024 * (1.8334)	0.0024 (0.6465)
Control	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes
N	1100	1100	384	400	316

Table 4. *Cont.*

Variables	(1) TL	(2) TL	(3) East	(4) Middle	(5) West
Adj. R2	0.320	0.328	0.295	0.531	0.439
F	33.8263	32.7332	20.6137	13.8762	16.5488

Note: *t* statistics in parentheses (cluster in cities level). *** $p < 0.01$, * $p < 0.1$.

4.3.3. Heterogeneity of City Size

There are large differences among Chinese cities in terms of functional positioning and resource concentration. Local authorities in different-sized cities differ markedly in their resource allocation rights, leading to differences in the impact of land finance on the URIG. Therefore, we further tested the effect of land finance on the URIG in different-sized cities. The Circular of the State Council on the Adjustment of the Standard for the Division of City Size classified city size into five types and seven levels. Considering that such a classification will lead to a reduction in the sample size, the city size was classified into three types in this study: cities with 500,000 or fewer residents were small cities, cities with 500,000 to 1,000,000 residents were medium cities, and cities with more than 1,000,000 residents were large cities. The city size was classified according to the 2014 resident population.

Table 5 shows the results for the different city sizes. In column (1), the coefficient of land finance was 0.0033 but was not significant in large cities. In column (2), the coefficient of land finance was 0.0011 and was not significant in medium cities. In column (3), the coefficient of land finance was 0.0035 and was significantly positive at the 5% level in small cities. All the results showed that land finance had no effect on the URIG in large and medium-sized cities, while in small cities, land finance had a widening effect on the URIG.

Table 5. Heterogeneity analysis regression results for city size.

Variables	(1) Large Cities	(2) Medium Cities	(3) Small Cities
$land\ fin$	0.0033 (1.1119)	0.0010 (0.5455)	0.0035 ** (2.5718)
Control	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
City fixed	Yes	Yes	Yes
N	252	372	476
Adj. R2	0.200	0.381	0.388
F	6.3603	12.7303	21.0853

Note: *t* statistics in parentheses (cluster in cities level). ** $p < 0.05$.

5. Discussion

This study theoretically analyzed and empirically tested the impact of land finance on the URIG in China, and we found evidence that land finance significantly widens the URIG. This finding not only helps us to understand the causes of the URIG in China and deepens our awareness of the income distribution effects of land finance, but also provides guidance for other developing countries. Nowadays, many developing countries are moving toward modernization and share many similarities with China in terms of the URIG [55,56]. Meanwhile, intense land expropriation is widespread [57]. This finding is a cautionary tale for other developing countries, who should be aware that rural residents whose land is expropriated bear the costs of urbanization, which is an important cause of frequent land conflicts [58]. Therefore, these countries should balance equity with the pursuit of efficiency in the future land development process to avoid infringing on the interests of rural residents, and they need to actively improve the current inequality.

This study found differences in the effect of land finance on the URIG depending on the way in which the land was granted. Specifically, it was found that land granting by tender and auction significantly widened the URIG, while land granting by agreement had no effect on the URIG. This was due to the local authorities granting industrial land at a low price by way of agreement, which decreased the gap between the land appreciation and the land compensation price. Meanwhile, industrial expansion also absorbed many rural laborers and increased their income [59]. On the other hand, the local authorities granted commercial and residential land at high and restrictive prices, which increased the cost and reduced the supply of housing, thus pushing up the price of houses. It was easier to increase the income of urban residents through the wealth effect and increase the cost of living of rural residents who work in the city [21,60].

This study found that in the Eastern and the Middle regions, land finance had a widening effect on the URIG, and the widening effect was more significant in the Eastern region, while it had no effect in the Western region. This ranking was consistent with the level of economic development of each region, where the Eastern region had the best level of economic development, the Middle of the country was second, and the Western region was the worst. Additionally, this ranking was consistent with the degree of dependence of local governments on land finance, which was also highest in the East, next highest in the Middle, and lowest in the West. The reason for this was that the higher the level of regional economic development, the higher the urban land premium, and that the larger the gap with the land compensation price, the more the dependence of the local government on land finance is intensified, which increases the urban–rural income gap. In turn, the higher the dependence of the local government on land finance, the more it could promote regional economic development. Thus, the urban–rural income gap gradually increased under this bidirectional feedback mechanism. In addition, the Western region tended to benefit from the central government due to its lower economic development, thus alleviating the financial pressure, which explained its lower dependence on land finance [46,61].

Furthermore, this study found that the effect of land finance on the widening of the URIG was more significant in small cities, while it had no effect in large and medium-sized cities. A larger urban population meant a higher level of local urbanization, which could absorb more rural surplus labor and increase farmers' income, thereby reducing the URIG [62,63]. The reduction in the urban–rural income gap as a result of urbanization weakened the role of land finance in widening the urban–rural income gap. Compared to large cities, small cities had fewer sources of fiscal income, which made them more dependent on land finance, thus leading to the widening effect of land finance on the urban–rural income gap being more significant. Another possible explanation is that the sample sizes of large cities were relatively smaller, which led to insignificant regression coefficients, which could be verified in future research by increasing the sample size.

6. Conclusions and Policy Recommendations

The phenomenon of land finance has become more widespread in developing countries, with profound impacts on local economic and social development. However, there are few studies focusing on the income distribution effects it induces. This study examined the impact of land finance on the URIG from the perspective of the URIG, based on panel data from 275 prefecture-level cities in China from 2014 to 2017.

In general, the results indicated that land finance significantly widened the URIG. Further study found that the effect of land finance on the URIG showed significant heterogeneity. From a methodology perspective, land grants by tender, listing, and auction significantly widened the URIG, while land grants by agreement did not affect the URIG. From a regional perspective, the effect of land finance on the URIG was more significant in Eastern and Middle regions, but not in Western regions. From the city size perspective, land finance had no impact on the URIG in large and medium-sized cities, while the impact was significant in small cities.

These findings have important policy consequences for the reform of the land regime and the promotion of fairness in income distribution. Firstly, the authorities should accelerate the market-oriented reform of land supply to remove the monopolistic status of local authorities in the primary land market, offer fair rights to rural residents in the land market, optimize the land income distribution system, ensure that rural residents receive fair and reasonable compensation for their landlessness under the market system, and rectify the uneven distribution of land premiums. Secondly, the authorities should change the present development strategy, accelerate the integration of urban and rural areas, and use the income from land concessions to enhance the public services provided in rural areas, providing the same opportunities for rural residents to obtain employment as urban residents and giving them the rights to the same public services. Lastly, authorities should actively promote the reform of the fiscal and taxation systems and change the local income structure to convert the income of local authorities from land transfer to stable and sustainable tax income. The dependence of local authorities on land finance must be removed at the source.

This study incorporated land finance and the URIG into a unified analytical framework, which deepened our comprehension of the relationship between land finance and the URIG, enriched the literature on the socioeconomic consequences of land finance, and provided empirical references for other developing countries. However, some shortcomings remained in the study that can be addressed in future research. First, this study only analyzed data from 2014 to 2017 due to the increasingly frequent adjustments in land finance policies in recent years with the continued advancement of urban–rural integration construction. In particular, with the revision of the Land Management Law in 2020, the government has strengthened the protection of rural residents' interests, and the effect of land finance on the urban–rural income gap may be transformed. Due to limitations on the availability of the data, this study did not discuss and test the change. However, future research can use this as an entry point and compare the changes in the impact of the policy before and after the revision. In addition, due to limitations on the available data, this study only analyzed the influence path of land finance on the URIG in theory. Lastly, this study did not explore the possible spatial spillover effects of land finance on the URIG, which will be the focus of our next phase of research. Further, the external validity of the results of this study has yet to be tested. The land acquisition and transfer mechanism has significant Chinese characteristics, and the institutional contexts of other developing countries will be markedly different from those of China, along with the resulting impacts. However, the development strategy of urban preferences is consistent, which is an important reason why other developing countries can learn from China's experience.

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Article

Spatio-Temporal Evolution and Multi-Scenario Simulation of Non-Grain Production on Cultivated Land in Jiangsu Province, China

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Abstract: Cultivated land plays a crucial role as the basis of grain production, and it is essential to effectively manage the unregulated expansion of non-grain production (NGP) on cultivated land in order to safeguard food security. The study of NGP has garnered significant attention from scholars, but the prediction of NGP trends is relatively uncommon. Therefore, we focused on Jiangsu Province, a significant grain production region in China, as the study area. We extracted data on cultivated land for non-grain production (NGPCL) in 2000, 2005, 2010, 2015, and 2019, and calculated the ratio of non-grain production (NGPR) for each county unit in the province. On this basis, Kernel Density Estimation (KDE) and spatial autocorrelation analysis tools were utilized to uncover the spatio-temporal evolution of NGP in Jiangsu Province. Finally, the Patch-Generating Land Use Simulation (PLUS) model was utilized to predict the trend of NGP in Jiangsu Province in 2038 under the three development scenarios of natural development (NDS), cultivated land protection (CPS), and food security (FSS). After analyzing the results, we came to the following conclusions:(1) During the period of 2000–2019, the NGPCL area and NGPR in Jiangsu Province exhibited a general decreasing trend. (2) The level of NGP displayed a spatial distribution pattern of being "higher in the south and central and lower in the north". (3) The results of multi-scenario simulation show that under the NDS, the area of NGPCL and cultivated land for grain production (GPCL) decreases significantly; under the CPS, the decrease in NGPCL and GPCL is smaller than that of the NDS. Under the FSS, NGPCL decreases, while GPCL increases. These results can provide reference for the implementation of land use planning, the delineation of the cultivated land protection bottom line, and the implementation of thee cultivated land use control system in the study area.

Keywords: cultivated land; non-grain production; spatio-temporal evolution; multi-scenario simulation; Jiangsu Province

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1. Introduction

Food security is a critical global issue that intersects with economies and people's livelihoods. It serves as a fundamental pillar of national security [1]. The foundation of food production lies in cultivated land, making it imperative to ensure the stability of both its quantity and quality to guarantee food security. However, China has witnessed a decline in the quantity and quality of cultivated land in recent years, primarily due to the increasing level of urbanization [2,3]. Meanwhile, various factors, such as the low efficiency of grain production, changes in dietary patterns, land property rights transfers, and the influx of industrial and commercial capital into rural areas, have compelled certain agricultural entities to prioritize maximizing their own profits. Consequently, they selectively choose crops based on profitability, leading to a significant portion of cultivated land being allocated for non-grain production (NGP) [4]. This disorderly expansion of NGP not only threatens food security by causing shortages and imbalances in grain supply, but also contributes to the degradation of cultivated land quality and environmental issues resulting from changes in land utilization practices [5–8]. Recognizing the implications of NGP, the Chinese Government has acknowledged its significance. In November 2020, the General Office of the State Council issued the "Opinions on Preventing the Non-Grain Production of Cultivated Land and Stabilizing Grain Production". This document summarized the manifestations of the "non-grain" use of cultivated land into three categories: "some localities have unilaterally interpreted agricultural structural adjustment as a reduction in grain production", "business entities have illegally planted trees and dug ponds on basic farmland", and "industrial and commercial capital has transferred cultivated land on a large scale to cultivate non-grain crops". It also emphasized that the use of cultivated land should not be determined purely on the basis of economic benefits and that limited cultivated land resources must be prioritized for grain production. Specifically, the government aims to stabilize the area allocated for grain production, with particular attention to safeguarding the planting area of the three major grains: rice, wheat, and maize.

Research concerning NGP dates back to the beginning of the 21st century [9]. Scholars at the time raised concerns about this pursuit of economic efficiency at the expense of food security. In recent years, with the widespread concern for food security, scholars have been studying NGP in further depth. Currently, there is no universally accepted definition of "non-grain" within the academic community. Some scholars define "non-grain" as the utilization of cultivated land for non-grain purposes by agricultural operators, including the cultivation of cash crops such as fruit trees and flowers, as well as the development of livestock and poultry breeding [10,11]. Others consider "non-grain" as the process of converting cultivated land that previously grew grain crops into land that now produces non-grain crops [12,13]. Regarding the measurement of NGP, various approaches have been used by scholars. Some calculate the level of NGP based on statistical data or sectoral surveys, using indicators like the ratio of non-grain crop area to total agricultural crop area [14,15]. Alternatively, remote sensing and GIS technologies have been employed by other researchers to identify NGP phenomena [16–18].Studies about the trends in land use change to NGP [19,20] and the drivers [21,22] and driving mechanisms [21,22] of NGP provide valuable insights into understanding its causes and mitigating its effects. These studies found that factors such as natural resources [23,24], socio-economics [21], transportation location [23], and policy considerations [21,25,26] may contribute to NGP. Considering previous research and the current agricultural production landscape in this study area, we defined NGP as the cultivation of crops other than rice, wheat, and maize on cultivated land. NGPCL is identified through the analysis of land use data and the spatial distribution of the three major grain cultivars. The ratio of NGP (NGPR) was then utilized to assess the level of NGP in the region. Subsequently, we analyzed the spatio-temporal evolution of the NGP. Finally, the evolution of the NGP under multiple development scenarios was projected. This study not only contributes to the theoretical and methodological aspects of NGP research but also offers insights into future developments, providing recommendations and counter measures for the sustainable use of cultivated land and the assurance of food security.

In order to reveal the issue of NGP and its implications for food security, this study focused on Jiangsu Province, a significant grain-producing province in China, which has consistently ranked among the top provinces in China in terms of grain sown, total grain output, and total output value. Based on the analysis of the spatial and temporal evolution of NGP in Jiangsu Province from 2000 to 2019, the Patch-Generating Land Use Simulation (PLUS) model [27], which is widely followed by scholars in the field of land simulation and is used to conduct a multi-scenario simulation to reveal the pattern of NGP under different development scenarios in 2038. The results of the study will provide a basis and reference for land managers to formulate policies, scientifically set the bottom line of NGP, and practically control the behavior of NGP in order to promote the rational use of cultivated land resources and guarantee food security.

2. Materials and Methods

2.1. Study Area

Jiangsu Province is situated in the eastern coastal region of mainland China, with latitude ranging from 30°45′ to 35°08′ N and longitude ranging from 116°21′ to 121°56′ E (Figure 1). As of 2020, the province had a total area of 102,521.20 km^2, with a cultivated land area of 62,773.09 km^2, accounting for 61.22% of the total area. Known for its flat terrain, favorable climate, and abundant water resources, Jiangsu Province is well-suited for agricultural production. Between 2000 and 2022, the sown area of grain in Jiangsu Province varied from 53,043.1 km^2 to 54,444.4 km^2. During this period, the total grain output is expected to change from 31,066,300 tons to 37,691,300 tons, and the total output value is anticipated to shift from USD 4379 million to USD 19,884 million. However, in recent years, rapid socio-economic development and increasing urbanization have led to the conversion of some of Jiangsu Province's cultivated land into artificial surfaces (ASs) like urban and rural residential land [28]. This, along with the prominent issue of NGP, has posed a serious challenge to food security in the region. Protecting cultivated land resources and ensuring stable grain production in Jiangsu Province are of utmost importance for national food security and the sustainable development of the national economy.

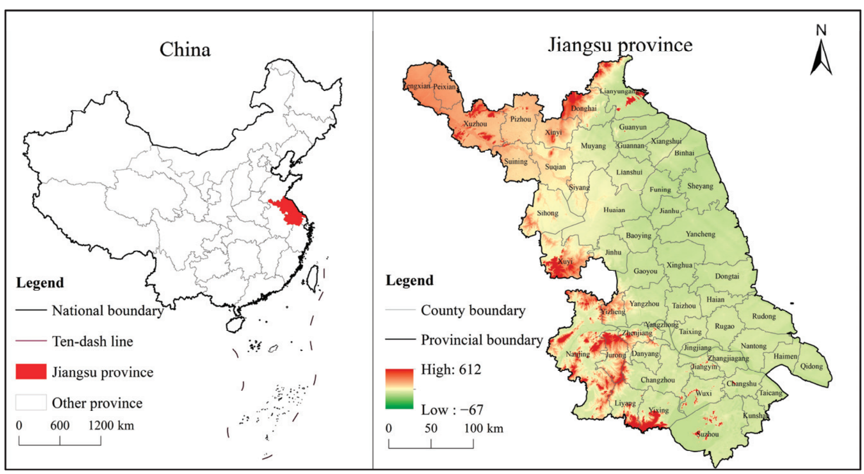

Figure 1. Location of the study area.

2.2. Data Sources and Pre-Processing

The data used in this paper include county-level administrative boundary data in Jiangsu Province, land use/land cover (LULC) data, grain cultivation spatial distribution data, meteorological data, DEM data, soil type data, road data, POI data, population density data, and GDP data (Table 1).

Given the extensive time span under consideration, the modifications to administrative divisions during the study period, and the presence of small-sized municipal districts, this study adopts the approach proposed by Li et al. [29,30] to merge these municipal districts and ultimately create 54 consolidated study units. Taking into account the situation of the study area and data availability, land use data from the Resource and Environment Science and Data Center (RESDC) were selected for five time points: 2000, 2005, 2010, 2015, and 2020; the spatial distribution data of grain cultivation at the five time points were obtained from the National Ecosystem Science Data Center (NESDC), which originated from Luo's study, which was based on cultivated land data and determined the spatial distribution of the cultivation of the three major grain crops in China according to the climatic characteristics of rice, maize, and wheat for the period of 2000–2019. The spatial distribution of cultivation of the three major grain crops in China was proved to be highly consistent with agricultural statistics ($R^2 > 0.8$) [31]; the meteorological dataset comprises annual precipitation (PRE), annual mean temperature (TEM), annual evaporation (EVP), and annual sunshine duration (SSD). This dataset was derived from daily observations collected at the meteorological element stations and utilizes the smoothing spline function integrated in the Anusplin 4.4 interpolation software to generate spatially interpolated data for each year's meteorological element [32]. We utilized Digital Elevation Model (DEM) data obtained from the US National Geological Survey (USGS). The slope and slope direction analysis functions in ArcGIS 10.7 software were employed to generate raster data representing slope and slope direction. Road data, including highways, primary roads, secondary roads, and railroad data, were sourced from Openmap. The Euclidean distance analysis function in ArcGIS was used to calculate distance data to all levels of roads. Government site data were derived from point-of-interest (POI) data collected by AMap, with distance data to government sites generated using the Euclidean distance analysis function in ArcGIS. Subsequently, all datasets were transformed into raster data and resampled to a resolution of 30 m.

Table 1. Data sources.

Name	Categories	Resolution	Source
Climate	raster	1 km	RESDC (https://www.resdc.cn (accessed on 1 April 2023))
DEM	raster	30 m	USGS (https://www.usgs.gov (accessed on 1 April 2023))
Soil types	vector plane	—	RESDC (https://www.resdc.cn (accessed on 1 April 2023))
Administrative boundary	vector line	—	RESDC (https://www.resdc.cn (accessed on 1 April 2023))
Land use	raster	30 m	RESDC (https://www.resdc.cn (accessed on 1 April 2023))
Grain cultivation spatial distribution	raster	1 km	NESDC (http://www.nesdc.org.cn (accessed on 1 April 2023))
GDP	raster	1 km	RESDC (https://www.resdc.cn (accessed on 1 April 2023))
Population density	raster	100 m	WorldPop (https://hub.WorldPop.org (accessed on 1 April 2023))
Roads	vector line	—	Openmap (https://openmaptiles.org (accessed on 1 April 2023))
Government sites	point	—	Amap (https://lbs.amap.com (accessed on 1 April 2023))

2.3. Methods

We analyzed the spatial and temporal evolution of NGP in Jiangsu Province from 2000 to 2019 and predicted the pattern of NGP under different scenarios for 2038. First, the spatial location of NGPCL was identified and the NGPR was calculated for each county. Then, land use transfer matrix, kernel density estimation (KDE), and spatial autocorrelation analysis were used to reveal the spatio-temporal evolution pattern of NGP. Finally, the PLUS model was used to simulate the different future scenarios of the NGP pattern. The general framework of the study is shown in Figure 2.

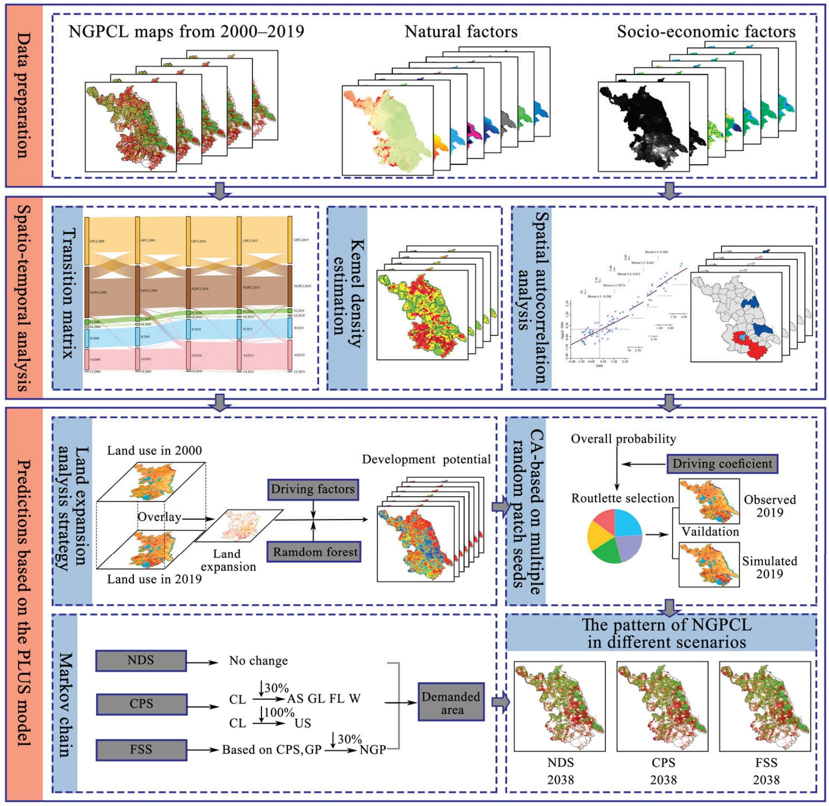

Figure 2. Study framework.

2.3.1. NGPR

The grain crops involved in this study include the three major categories of rice, wheat, and maize, and the cultivated land outside the three major categories of grain crops was defined as NGPCL. It should be noted that in identifying the 2019 NGPCL, we used 2020 land use data as a substitute due to the lack of 2019 land use data. The degree of regional non-grain was measured in terms of the NGPR with the following formula:

$$\mathrm{NGPR} = \left(1 - \frac{\mathrm{G}}{\mathrm{C}}\right) \times 100\% \tag{1}$$

where NGPR is the ratio of non-grain production; G is the sum of the area of wheat, corn, and rice; C is the total area of cultivated land.

2.3.2. Land Use Transfer Matrix

We categorized cultivated land into GPCL and NGPCL, and the land use maps of different time periods were spatially superimposed by using ArcGIS to derive the transfer matrix of the land use types in order to characterize the conversion between the land use types. The mathematical expression is as follows [33,34]:

$$\mathrm{P_{ij}} = \begin{bmatrix} \mathrm{P_{11}} & \mathrm{P_{12}} & \cdots & \mathrm{P_{1n}} \\ \mathrm{P_{21}} & \mathrm{P_{22}} & \cdots & \mathrm{P_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{P_{n1}} & \mathrm{P_{n2}} & \cdots & \mathrm{P_{nn}} \end{bmatrix} \tag{2}$$

where P denotes the area of each LULC type; i and j denote the area of LULC types at the beginning and end of the study period, respectively; and n denotes the total number of LULC types. Each row and column represents the outflow and inflow areas, respectively.

2.3.3. Kernel Density Estimate

Kernel Density Estimation (KDE) is a nonparametric method used to estimate the probability density function, which can effectively identify the spatial variability and continuity of the distribution of NGPCL and observe the agglomeration of their spatial distribution. In this paper, the raster data of NGPCL were converted to point data, and the kernel density value of NGPCL in Jiangsu Province was calculated with a kernel density bandwidth of 10 km [35]. The calculation formula is:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{d(x,x_i)}{h}\right) \tag{3}$$

where f(x) is an estimate of the NGPCL kernel density, n is the number of NGPCL point data in the bandwidth range, h is the bandwidth, k () is the kernel density equation, and $d(x,x_i)$ is the distance from the NGPCL point x to the sample point x_i.

2.3.4. Spatial Autocorrelation Analysis

We employed global spatial autocorrelation and local spatial autocorrelation to explore the spatial correlation of NGP.

Global spatial autocorrelation analyzes and describes the overall spatial characteristics of geographic elements within a study area and can visually represent the degree of spatial interdependence of geographic variables. A commonly used measure of global spatial autocorrelation is the global Moran's I, which has a value range of [−1,1]. A positive value indicates the existence of positive spatial correlation, i.e., the same trend between the research object and the neighboring objects; a negative value indicates the existence of negative spatial correlation, i.e., the opposite trend between the research object and the neighboring objects; and a value equal to zero indicates no spatial correlation. We took the NGPR of the Jiangsu county-level administrative units as an observational variable and used the global Moran's I to determine its overall spatial characteristics. Its calculation formula is:

$$I = \frac{N\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\right)\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2} \tag{4}$$

where I is the global spatial autocorrelation coefficient; x_i and x_j are the observed values of NGPR at the location of objects i and j in the study area; N is the number of county units; and w_{ij} is the spatial weight matrix.

Local spatial autocorrelation explores spatial correlation features from the local scale to identify spatial clustering or spatial anomalies of geographic elements. In this paper, local Moran's I was used to identify the spatial association patterns of NGPR, which is calculated by the expression:

$$I_i = \frac{x_i - \bar{x}}{\sigma^2}\sum_{j=1}^{N} w_{ij}\left(x_j - \bar{x}\right) \tag{5}$$

where I_i is the local spatial autocorrelation coefficient at location i in the study area; x_i and x_j are the observed values of NGPR at the locations of objects i and j in the study area; $\bar{x}$ is the mean value of x; σ^2 is the variance of x; w_{ij} is the spatial weighting matrix; and the range of values of I_i is the same as that of the global Moran' s I.

Local spatial autocorrelation involves four distinct patterns: high-high agglomeration (H-H), low-high agglomeration (L-H), low-low agglomeration (L-L), and high-low agglomeration (H-L). H-H and L-L signify positive spatial correlation, indicating clustering of similar high or low values, whereas H-L and L-H suggest negative spatial correlation, reflecting dissimilar neighboring values. We utilized Moran scatter plots and LISA clustering diagrams to provide a comprehensive analysis of the local spatial correlation attributes in the context of NGP.

2.3.5. NGP Simulation

1. PLUS model. The PLUS model, introduced by the HPSCIL@CUG laboratory team at China University of Geosciences (Wuhan, China) in 2020 [27], is a patch-based land-use change simulation model that operates on raster data. This model effectively identifies the driving forces behind land expansion and landscape modifications, enabling a more accurate simulation of the progression of land-use patches. The PLUS model comprises two key components:
   - Land Expansion Analysis Strategy (LEAS): This strategy involves extracting various land use expansion areas between two stages of land use change. It then selects from the expanded areas, using the Random Forest algorithm to identify the influencing factors and driving forces behind each type of land use expansion individually. This process allows for the determination of development probabilities and the contribution of driving factors for all types of land use expansion during the specified period.
   - Cellular Automata based on multiple random patch seeds (CARS) model: The PLUS model integrates random seed generation and a threshold-decreasing mechanism to dynamically simulate the automatic generation of patches in space under specific development probability constraints.

In the study, the land use expansion between the years 2000 and 2019 was extracted, and the expansion areas were sampled in the LEAS module. The parameters of the LEAS module were set as follows: 50 decision trees, a sampling rate of 0.01, 15 training features, and the outputs include the probability of development for each class and the contribution of driving factors to the expansion of the site. We selected 15 driving factors from natural and socio-economic factors based on previous research (Table 2). These factors were used to determine the probability of development and the contribution of each factor to the expansion of the land. The PLUS model requires that the interval between the projection year and the end year should be the same as, or an integer multiple of, the interval between the start year and the end year. The time interval for this study was 19 years, so we used CARS to predict the 2038 landscape based on the information and analysis obtained from the LEAS module.

Table 2. Driving factors.

Variable Type	Name	Bibliography
Natural factors	DEM	[35,36]
	Slope	[35,36]
	Slope direction	[37]
	EVP	[35]
	PRE	[35]
	SSD	[38]
	TEM	[35]
	Soil types	[39]
Socio-economic factors	Population density	[36]
	GDP	[5,36]
	Distance to government departments	[39,40]
	Distance to highway	[35]
	Distance to primary road	[35,36]
	Distance to secondary road	[35,36]
	Distance to railroad	[35]

Pontious et al. [41,42] found that the Figure of Merit (FoM) index is superior to the Kappa coefficient in evaluating the accuracy of the simulated changes, so the FoM index was used for the accuracy evaluation of the simulations. Its calculation formula is:

$$\mathrm{FoM} = \frac{\mathrm{B}}{\mathrm{A} + \mathrm{B} + \mathrm{C} + \mathrm{D}} \tag{6}$$

where A represents the number of pixels that are predicted not to change and actually change; B represents the number of rasters that are accurately predicted; C represents the number of pixels that are predicted incorrectly for the land-use type; and D represents the number of pixels that are predicted to change and actually do not change. According to previous studies, when the calculated value of FoM is small, it indicates that the simulation accuracy is low. Conversely, when its value is larger, it suggests that the simulation accuracy is higher. An FoM value greater than 0.1 can be considered indicative of good simulation accuracy.

We set the neighborhood weights according to the proportion of the expansion area of different land types to the total area. After repeated debugging, the attenuation threshold was set to 0.9, the diffusion coefficient was set to 0.1, and the probability of random seeds was set to 0.001. At this time, the FoM index reached 0.29, indicating that the simulated 2019 NGPCL was highly consistent with the real situation and was able to meet the research needs.

2. Scenario analysis. Based on the documents "Jiangsu Province Land Spatial Planning (2021–2035)" and "Jiangsu Province 14th Five-Year Plan Grain Industry Development Plan", as well as drawing insights from previous studies [43–45], the study established three development scenarios as follows:
    - Natural development scenario (NDS): Based on the change rule of land use in Jiangsu Province from 2000 to 2019, the distribution of NGPCL under the natural growth scenario in 2038 was simulated without any constraints.
    - Cultivated land protection scenario (CPS): Considering the requirements of "stabilizing the amount of cultivated land, optimizing the layout of cultivated land, and strictly controlling the occupation of cultivated land by non-agricultural construction" mentioned in the land space planning of Jiangsu Province (2021–2035), this scenario reduced the probability of transferring cultivated land to construction land, forest land, grassland and water by 30% and 100% to unutilized land based on the probability of the natural development scenario to simulate the protection of cultivated land by land managers.
    - Food security scenario (FSS): Considering the requirements of "Strictly controlling non-grain production and guaranteeing food security" mentioned in the "Jiangsu Province Land Space Planning (2021–2035)" and the "14th Five-Year Plan for the Development of Grain Industry in Jiangsu Province", this scenario reduced the probability of transferring GPCL to NGPCL by 30% based on the probability of the CPS to simulate the control measures taken by the land managers on the NGP.

3. Results

3.1. Timing Evolution of NGP in Jiangsu Province

Between 2000 and 2019, the cultivated land area in Jiangsu Province decreased from 69,910.29 km^2 to 62,777.79 km^2. The NGPCL decreased by 18.67% from the initial year, while the NGPR decreased from 51.48% to 46.63% (Figure 3). The temporal evolution characteristics of NGP suggest two phases during the study period.

1. From 2000 to 2010, the province's NGPR declined by 6.59%. This decline can be attributed to China's active implementation of agricultural policies and reforms in the grain circulation system after 2003. In addition, in 2004, Jiangsu Province introduced supportive policies such as grain subsidy policies and agricultural tax reductions and

exemptions. This has boosted grain production and increased farmers' incentives to cultivate grain. Consequently, the dominance of grain production increased, leading to a decline in the NGPR during this period.

2. In the period from 2010 to 2019, the NGPR in Jiangsu Province experienced a slight increase, primarily due to declining grain prices. The continuous decrease in grain prices, particularly rice prices, exhibited a downward trend from 2012, reaching CNY 2.4/kg in 2019. This decline in the profitability of grain cultivation prompted some farmers to shift towards planting cash crops with higher economic returns. The average annual increase in the NGPCL rate in Jiangsu Province during this period was 0.17%, with an average annual increment in the area of NGPCL amounting to 51.32 km^2.

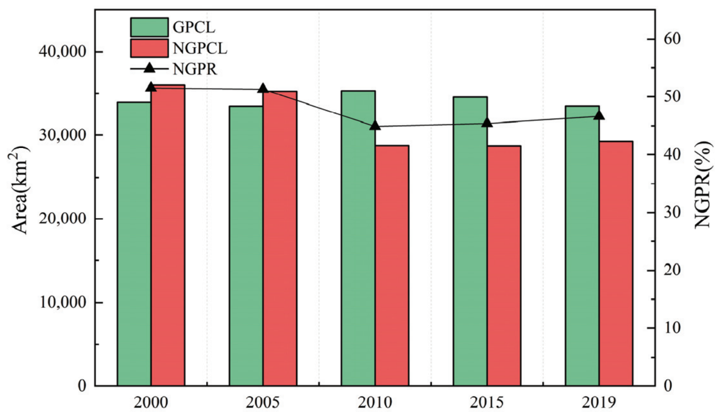

Figure 3. Temporal changes in NGPCL area and NGPR in Jiangsu Province.

During the study period, both the area of GPCL and NGPCL experienced a decrease, with the reduction in NGPCL surpassing that of GPCL. This led to a decline in the NGPR, aligning with the conclusions drawn by Wang et al. [46]. This observation indicated that despite the decrease in NGPR in Jiangsu Province, concerns regarding food security persist, particularly given the rising demand for grain within the province [47,48].

The data presented in Figure 4 indicate that the mutual transformation between NGPCL and GPCL was a common occurrence across all time periods studied. The data from Table 3 reveal that during the period of 2000–2019, NGPCL accounted for 76.33% of the transfer out of GPCL to other land categories, while the conversion of NGPCL to GPCL represented 63.18% of the outward transfers from NGPCL. Additionally, the conversion of cultivated land to AS constituted a significant proportion, with 20.69% of GPCL outward transfers and 30.86% of NGPCL outward transfers resulting in AS. These findings suggested that the expansion of AS during the study period led to a common occurrence of cultivated land being converted, with NGPCL being more prone to transformation into AS compared to GPCL.

Table 3. Land use transfer matrix for Jiangsu Province, 2000–2019.

Area in 2000/km^2	Area in 2019/km^2							
	GPCL	**NGPCL**	**FL**	**GL**	**W**	**AS**	**UL**	**Transfers Out**
GPCL	—	8892.66	14.73	7.03	321.69	2410.33	3.82	11,650.26
NGPCL	10,681.86	—	105.15	47.07	831.04	5217.69	23.03	16,905.84
FL	60.73	191.45	—	6.46	21.30	170.44	30.09	480.47
GL	28.64	204.68	4.05	—	453.08	89.80	2.94	783.19
W	78.36	320.25	7.61	242.18	—	441.41	22.29	1112.09

Table 3. *Cont.*

Area in 2000/km^2	Area in 2019/km^2							
	GPCL	NGPCL	FL	GL	W	AS	UL	Transfers Out
AS	389.27	576.18	22.97	16.42	829.22	—	7.02	1841.09
UL	0.02	0.15	1.57	0.06	2.20	1.59	—	5.59
Transfers in	11,238.88	10,185.39	156.08	319.22	2458.51	8331.26	89.19	—

"FL" indicates forest land; "GL" indicates grassland; "W" indicates water; "AS" indicates artificial surface; "UL" indicates unutilized land.

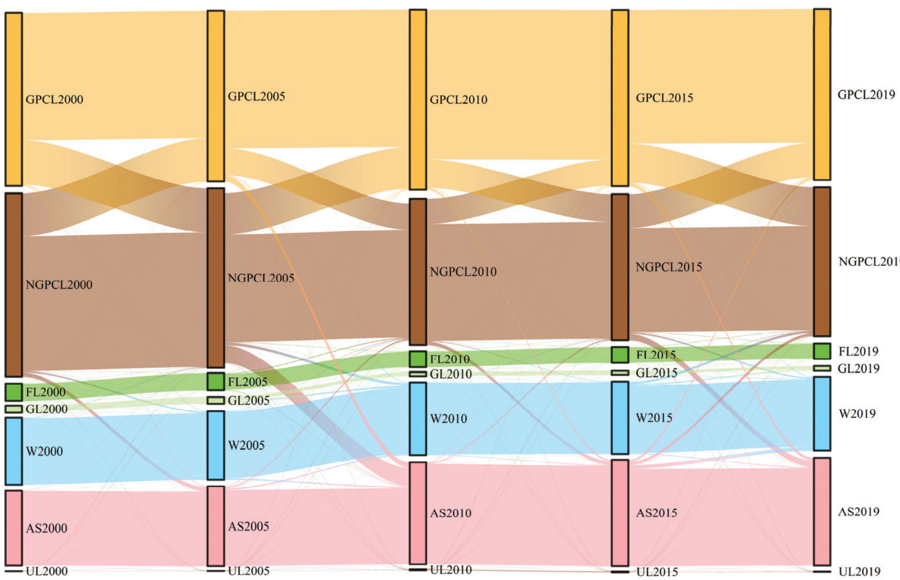

Figure 4. Land use transfer Sankey map of Jiangsu Province, 2000–2019.

3.2. Spatial Evolution of NGP in Jiangsu Province

The spatial distribution of NGPCL in Jiangsu Province is depicted in Figure 5. Across all counties in Jiangsu Province, NGPCL distribution exhibited clear spatial differentiation characteristics. Southern Jiangsu emerged as a focal point for NGPCL concentration throughout the study period, boasting the highest NGPR in the province. Central Jiangsu has experienced a notable increase in NGPCL from 2000 to 2019, accompanied by a rise in the NGPR. Conversely, northern Jiangsu has witnessed a decline in NGPCL and a corresponding decrease in NGPR, alongside a resurgence in grain cultivation activities. By 2019, Jiangsu Province had established a spatial pattern characterized by a "high prevalence of NGP in the central and southern regions, with lower levels in the northern areas".

As shown in Figure 6, the patches with decreasing NGPCL were mainly located in Lianyungang, Guanyun, and Gunnan in northeastern Jiangsu and Nanjing, Suzhou, and Wuxi in the south, while the areas with increasing NGPCL were mainly located in Rugao, Taixing, and Xinghua in central Jiangsu and Fengxian, Peixian, and Pizhou in the northwest.

3.2.1. Spatial Clustering Analysis of NGPCL

We utilized KDE to quantitatively illustrate the aggregation of NGPCL, as depicted in Figure 7. The results are segmented into three levels based on the natural breakpoint method: the low-value zone (0–22.84/km^2), the medium-value zone (22.84–43.78/km^2), and the high-value zone (43.78–97.08/km^2).

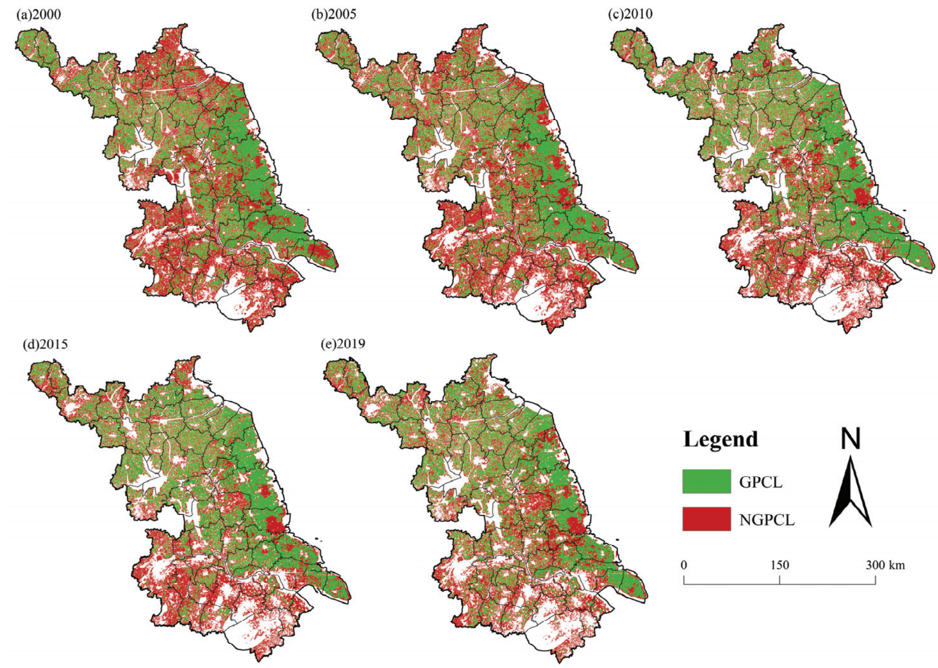

Figure 5. Spatial variation map of NGPCL in Jiangsu Province.

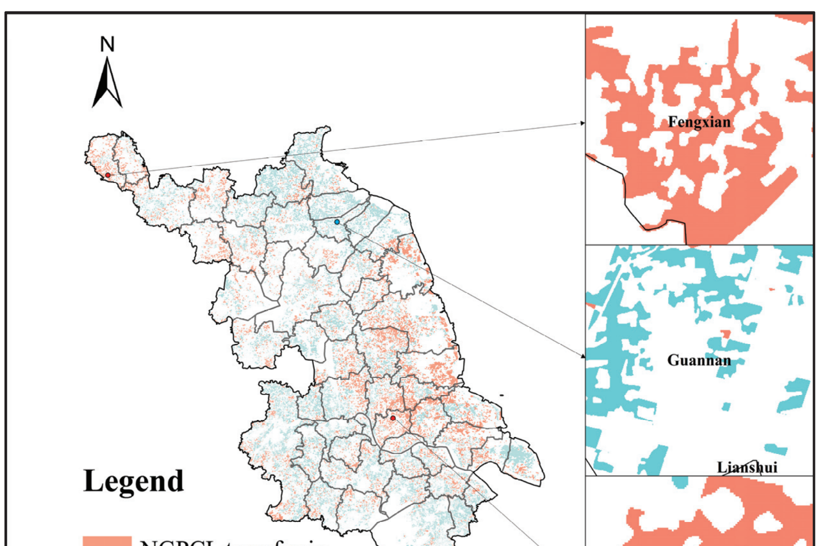

Figure 6. Distribution of transfer-in and transfer-out for NGPCL in Jiangsu Province.

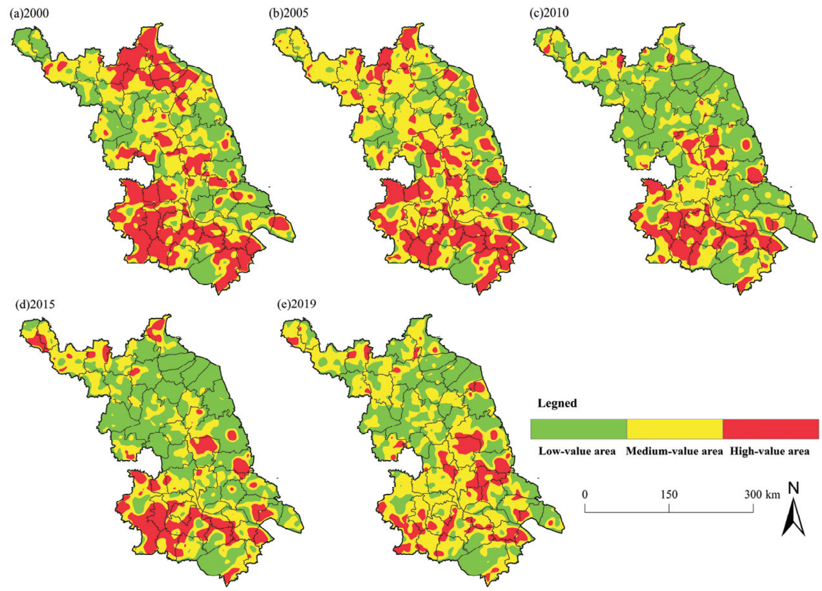

Figure 7. Spatial variation in KDE grade of NGPCL in Jiangsu Province.

Over the study period, the spatial distribution of NGPCL underwent a gradual transition from being "dense in the northeast and south and sparse in the center" to "dense in the middle of the south and sparse in the north". Initially, high-value areas were predominantly concentrated in Nanjing, Wuxi, and Suzhou in the south, as well as Lianyungang, Guanyun, and Gunnan in northeastern Jiangsu Province, indicating a high degree of NGPCL concentration in these regions.

Throughout the study period, the high-value zones in northeastern Jiangsu experienced a contraction, with low-value zones expanding and a decrease in NGPCL concentration. In central Jiangsu, high-value zones expanded, particularly in areas like Haian and Taizhou, indicating an increase in NGPCL concentration in the central region over time. In southern Jiangsu, high-value zones decreased, leading to the dominance of medium-density and high-density zones by the end of the study period, maintaining a relatively high level of NGPCL concentration.

3.2.2. Spatial Evolution of the NGPR

The county NGPR was used to classify the 54 county units into low-value areas (40% $\leq$ NGPR), medium-value areas (40% $\leq$ NGPR $\leq$ 58%), and high-value areas (NGPR $\geq$ 58%) based on the natural breakpoint method, as shown in Figure 8. Throughout the study period, the high-value zones decreased from 24 in 2000 to 15 in 2019, while the medium-value zones increased by 6, and the low-value zones increased by 3. In terms of spatial distribution, Jiangsu Province underwent a shift from "high NGPR in the north and south and lower in the center" to "high NGPR in the south and center and lower in the north". Across the entire study period, the southern part of Jiangsu exhibited a higher degree of NGP, primarily concentrated in the high-value areas. Cities like Nanjing and Suzhou remained in the high-value area for an extended period. In central Jiangsu, the NGPR was lower in 2000 but increased over time. Cities such as Taizhou and Taixing transitioned from the low-value area to the middle-value area, while Xinghua and Haian shifted from the middle-value area to the high-value area. In the northern part of Jiangsu, the NGPR was higher in 2000 but experienced a decline over time. Locations like Donghai, Guanyun, and Gunnan shifted from being high-value areas to low-value areas during this period.

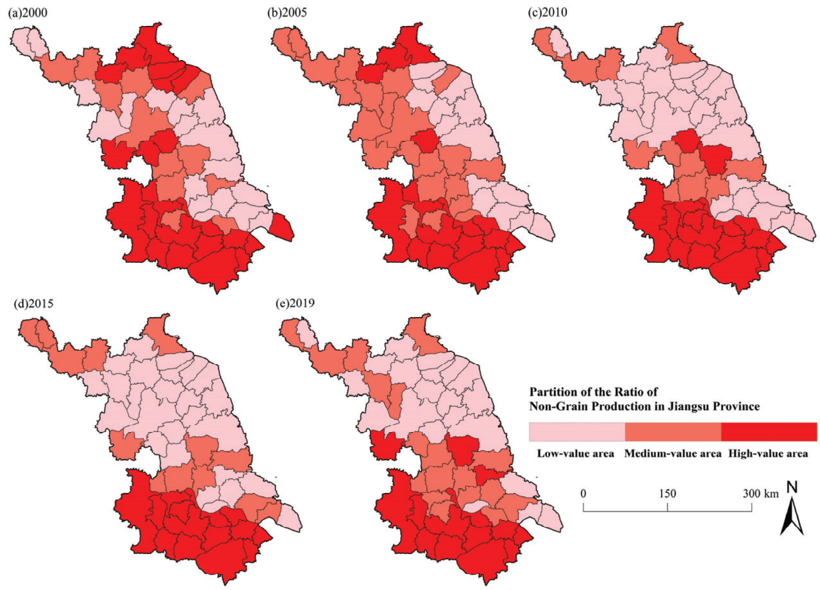

Figure 8. Spatial evolution of county NGPR in Jiangsu Province.

The spatial evolution of the NGPR in Jiangsu Province highlighted a clear development trend where the NGP level was higher in the southern regions and lower in the northern areas, which is consistent with the findings of previous studies conducted by Li et al. [46,49]. This pattern was influenced by the diverse geographic locations and variations in social and economic factors between the north and south of Jiangsu. The higher levels of urbanization and economic development in southern Jiangsu drove a greater demand for NGP crops, especially cash crops. Farmers in the southern region were more inclined towards NGP practices due to economic incentives. The process of urbanization in these areas created more job opportunities in secondary and tertiary industries, reducing the dependence of farmers solely on agriculture for their livelihoods and leading to a higher prevalence of NGP. The central region of Jiangsu benefited from its proximity to the well-developed southern part of the province, underwent rapid urbanization and economic growth, and resulted in an increasing trend in NGP levels over the study period. On the contrary, the northeast, although it had a high degree of NGP in 2000, had a relatively low potential return on NGP due to relatively lagging social and economic development. As a result, the region experienced an increase in the status of grain cultivation and a decrease in the NGPR during the study period.

3.2.3. Spatial Correlation of NGP

The analysis presented in Figure 9 demonstrates that the global Moran's I for each year in Jiangsu Province was consistently greater than 0 and passes the 99% confidence test. This indicates a strong positive correlation in the spatial distribution pattern of the NGPR over the five years under study. The small change in Moran's I suggests that the global characteristics exhibit a relatively smooth transition over time. The results of the global spatial autocorrelation analysis point towards a strong radiation effect in the NGPR distribution, indicating that the trend of NGP in one area drove NGP in neighboring regions.

The spatial correlation pattern of the NGPR in Jiangsu Province, as illustrated in Figure 10, was characterized by a prevalence of H-H agglomeration and L-L agglomeration. High H-H agglomerations were predominantly situated in the southern region of the study area, while L-L agglomerations tend to concentrate gradually in the northeastern part of the province. The number of H-H agglomerations remained constant from 2000 to

2019, primarily clustered in the economically developed southern Jiangsu Province, where urbanization and agricultural diversity contribute to a high NGPR. In contrast, the number of L-L agglomerations increased and shifted towards the northeast of Jiangsu, an area marked by slower economic growth but favorable agricultural conditions conducive to grain crop production, resulting in a lower NGPR.

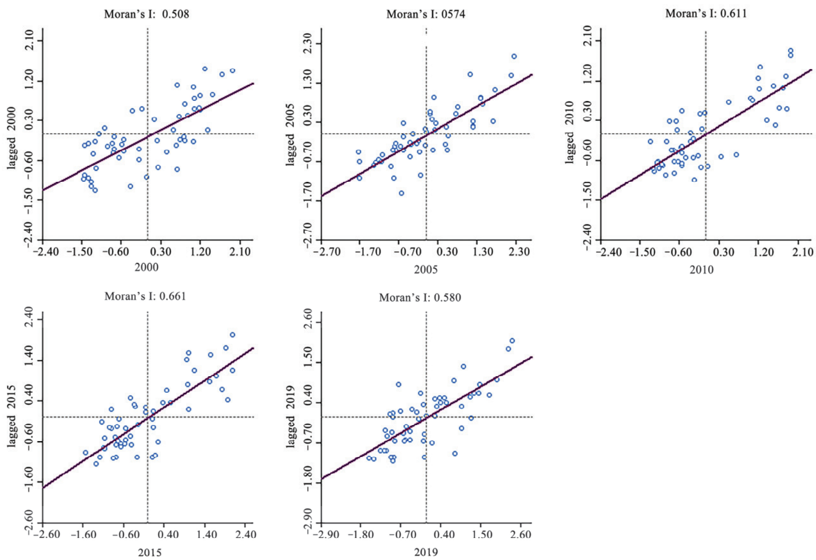

Figure 9. Moran scatterplot of NGPR in Jiangsu Province.

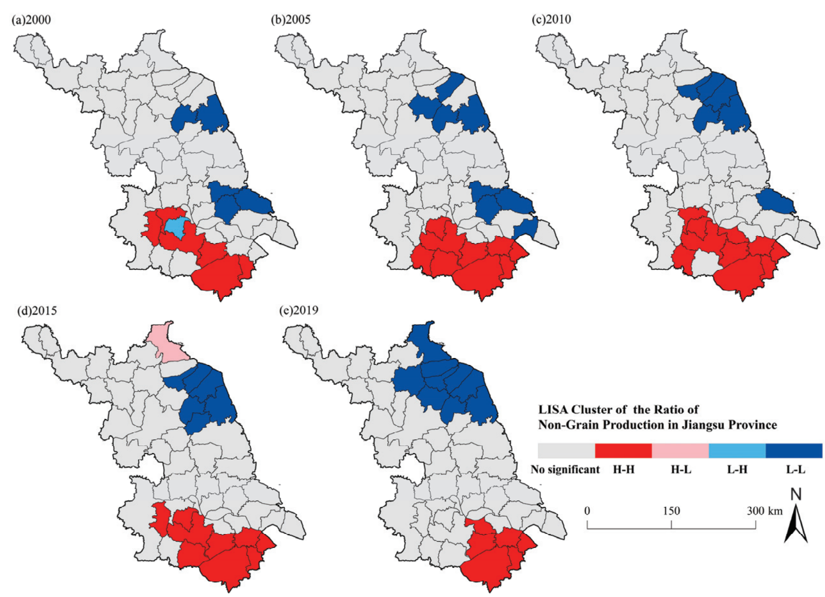

Figure 10. LISA clustering map of NGPR in Jiangsu Province.

3.3. Multi-Scenario Simulation Results for NGP in Jiangsu Province

The contribution of the drivers of NGPCL could be derived from LEAS (Figure 11). EVP, SSD, TEM, GDP, PRE, and population density had a high contribution to NGPCL, while distance to government departments, soil types and distance to roads at all levels also had a certain influence on NGPCL, and topographic factors had the lowest driving force for NGPCL.

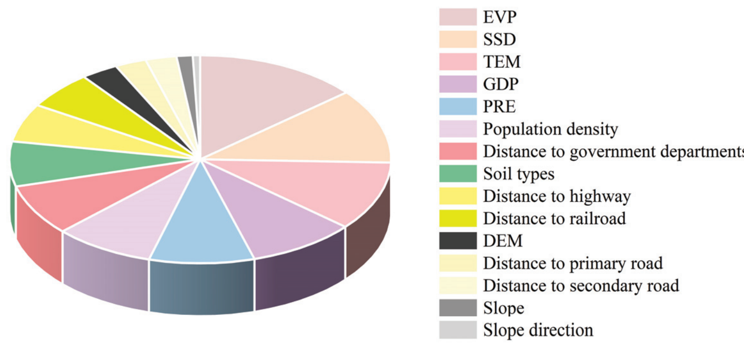

Figure 11. Distribution of contributions to driving factors of NGPCL.

The significant difference in the development trend of the NGP in Jiangsu Province under different scenarios is depicted in Figures 12 and 13.

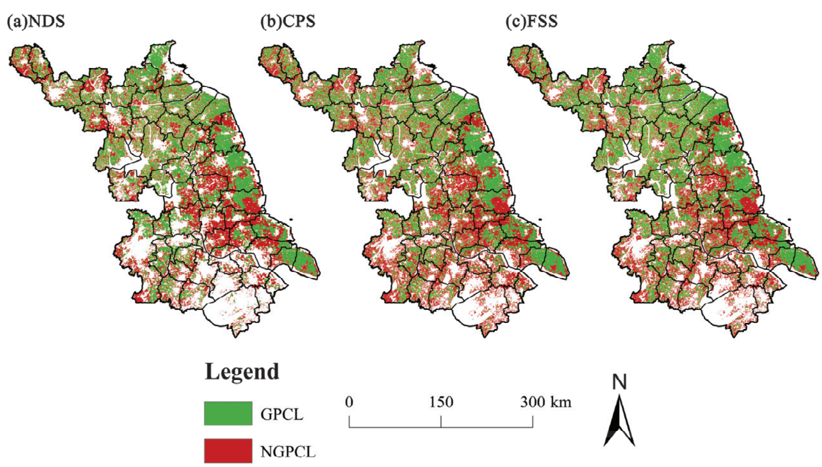

Figure 12. Spatial distribution of NGPCL under multi-scenario simulation.

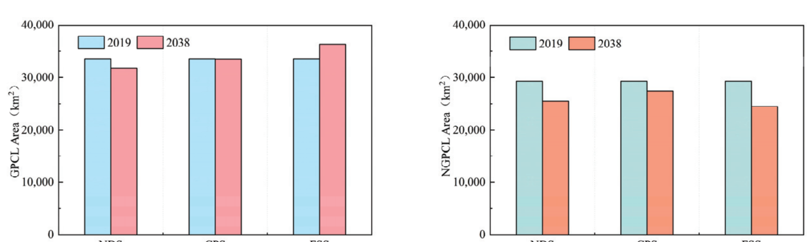

Figure 13. Area statistics of GPCL and NGPCL under multi-scenario simulation.

Under the NDS, the constraints imposed by land managers on the reduction in cropland and the NGP were not considered, and only the future development of NGPCL driven by a combination of socio-economic and natural factors was considered. Under this scenario, the area of cultivated land will decrease by 5569.77 km^2, with NGPCL decreasing by 12.96% and GPCL decreasing by 5.31% from 2019. Spatially, the distribution of NGPCL continued the characteristics of 2019, with more densely populated economically developed areas in central and southern Jiangsu and new NGPCL. Fengxian and Suining counties in northwestern Jiangsu have relatively poor conditions for grain production due to the limitations of precipitation, evaporation, and average temperature and also had some new NGPCL. In addition, there will be a clear mutual transformation between GPCL and NGPCL, which will be consistent with the trend of change from 2000 to 2019.

Under the CPS, land managers will rigorously enforce the compensation system for cultivated land occupation and the fundamental farmland protection system. They enhance cultivated land protection through the development of high-standard basic farmland and regulate the conversion of cultivated land to other land uses. In comparison to the NDS, the decline in cultivated land will diminish significantly, particularly as the encroachment of AS on cultivated land shows a notable decrease. In this scenario, the reduction in cultivated land amounts to 1915.27 km^2, with a 6.4% decrease in NGPCL and a 39.19 km^2 decrease in GPCL. Spatially, NGPCL will be predominantly concentrated in economically developed and urbanized areas such as Taicang, Changshu, Dongtai, and Haian in the southern and central regions of Jiangsu Province.

Under the FSS, land managers will not only impose restrictions on the conversion of cultivated land to other land types but also control the transformation of GPCL into NGPCL through various policies like cultivated land use control, NGP monitoring, and grain cultivation subsidies. This approach will lead to a decrease in the addition of new NGPCL and a reversal in the declining trend of GPCL. Cultivated land will diminish by 1931.08 km^2 in this scenario, with NGPCL decreasing by 16.40% and GPCL increasing by 2868.68 km^2. Notably, regions like Lianyungang, Guanyun County, and Xiangshui will witness substantial growth in new GPCL, aligning with local initiatives such as the grain industry development plan and the promotion of high-standard farmland construction. In addition, this is in line with the requirements of strengthening the construction of grain bases in the northern part of Jiangsu Province and steadily increasing the grain capacity, as mentioned in the Jiangsu Province Territorial Spatial Planning (2021–2035). Overall, this scenario will effectively maintain the quantity of GPCL, ensuring food security by slowing down the conversion of GPCL to NGPCL while safeguarding cultivated land.

The NGPR under the three scenarios was divided according to the previous grading (Figure 14). The distribution of the NGPR in Jiangsu Province under the three scenarios will maintain the overall distributional characteristics of 2019, with higher NGPR in the south and center and lower in the north.

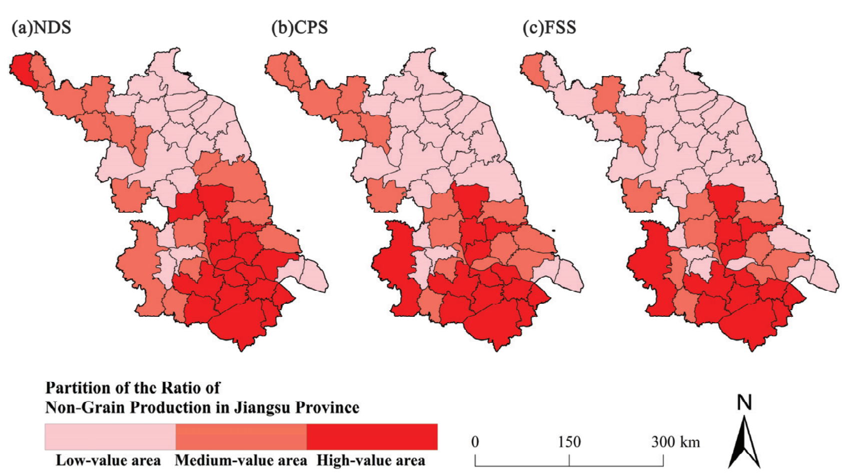

Figure 14. NGPR for counties in multi-scenario simulations.

Under the NDS, the overall NGPR will decrease, which is due to the fact that the rate of decrease in NGPCL will be larger than that of GPCL. The high-value areas of the NGPR are Taizhou, Taixing, and Kunshan, while the medium-value areas will mainly be located in Dongtai and Yangzhou, and the low-value area areas are Lianyungang and Guanyun.

Under the CPS, the reduction in both GPCL and NGPCL is mitigated. In this scenario, the high NGPR zones will mainly be located in Changshu and Kunshan, the medium zones will mainly be located in Yangzhou and Dongtai, and the mild NGPR zones will mainly be located in Guannan and Guanyun.

Under the FSS, the conversion of GPCL to NGPCL is limited and the NGPR will be further reduced. The high-value areas of the NGPR in this scenario will be Suzhou and Taicang, the medium-value areas are mainly distributed in Yangzhou and Gaoyou, and the low-value areas will be Lianyungang and Guanyun.

4. Discussion

4.1. Research Significance

NGP has a negative impact on the stabilization of grain output. NGP takes away the cultivated land for grain production, which may lead to a shortage of grain planting areas and thus trigger a decline in grain production and quality [14]. Furthermore, the shift to non-grain crops can alter the irrigation and drainage systems [6], making them more suitable for the growth of non-grain crops or even causing complete destruction. Some non-grain crops, like fast-growing poplar and eucalyptus, can contribute to soil infertility and acidification [10]. If there is a need to revert to planting grains in the future, significant economic investment may be required to restore the irrigation and drainage systems and address soil degradation issues caused by non-grain crop cultivation.

The decline in grain output caused by the NGP may lead to a decline in per capita grain availability, as well as an increase in grain prices, threatening human health and the stability of society [50]. While dietary adjustments, such as increasing the consumption of meat and meat products, can alleviate some dependence on grains, the demand for grain crops for human consumption and livestock feed will persist over the long term [51,52]; cross-border and inter-provincial grain trade can support the demand for grain up to a certain extent, but it is unstable due to transportation costs, market price fluctuations, adjustments in policy factors, and changes in international relations [10]. Therefore, it is crucial to control the unregulated expansion of NGP to stabilize grain yields.

The evolution of NGP is a complex and dynamic process, and it is difficult to comprehensively characterize the evolution of NGP by relying on the analysis of historical data only, and it lacks the consideration of multiple development scenarios in the future. The NGPCL prediction under multi-scenario simulation can complement the understanding of the spatial and temporal evolution characteristics of NGPCL. Meanwhile, the simulation of different future NGPCL distribution patterns based on different development goals such as cultivated land protection and food security also provide an important reference for the current land management and cropland utilization in the region.

4.2. Exploration of Driving Mechanisms

We found that climatic factors contributed more to NGP, probably because grain production requires better water and heat conditions, and areas with poorer water and heat conditions tend to favor NGP. Jiangyan, Rugao, and Taixing had higher EVPs and lower PREs, and water resources were relatively scarce, leading to poorer conditions for grain production, so these counties experienced a significant trend of NGP change during the study period, with more newly added NGPCL. Soil types affects the suitability for grain production, which in turn affects the potential benefits of grain production and therefore also has an impact on the degree of NGP.

GDP and population density reveal the level of economic development and urbanization in the counties, and central and southern Jiangsu have a higher level of development than northern Jiangsu and therefore a higher degree of NGP. In developed regions, consumption tends to be more diverse, with a higher demand for cash crops. At the same time, increased employment opportunities in secondary and tertiary industries have shifted farmers' focus away from viewing agricultural production as their sole livelihood. These reasons significantly reduced farmers' incentives to produce grain, leading to a higher likelihood of NGP. The proximity to various levels of roads reflects the convenience of transportation. The enhancement of the transportation system has accelerated the integration of urban and rural areas, fostering stronger inter-regional exchanges and communication. This development has also provided transportation facilities for the movement of cash crops, particularly those with shorter storage times like vegetables and fruits. As a result, farmers are more inclined towards pursuing NGP due to the comparative advantages and economic interests associated with these cash crops.

4.3. Policy Implications

Jiangsu Province holds a crucial position as a significant grain-producing region in China. It is imperative to address the uncontrolled expansion of non-grain crops and stabilize grain yields to ensure food security in Jiangsu Province and the nation as a whole. To achieve this goal, the following suggestions were proposed:

1. The AS has indeed resulted in the reduction of cultivated land in Jiangsu Province. Without effective restrictions, the trend of AS occupying a significant amount of cultivated land is likely to persist in the future. By enhancing the protection of cultivated land and imposing strict controls on the conversion of cultivated land to other land categories, such as, agricultural resources can be protected and a balance between urban development and agricultural production can be achieved. These measures are essential for ensuring food security, promoting sustainable land use practices, and preserving the long-term productivity of Jiangsu Province's agricultural sector.
2. The NGP is a result of farmers weighing various factors, including natural conditions, economic considerations, and other influences. To mitigate the impact of NGP, governmental intervention is crucial. Firstly, the government should implement financial policies such as subsidies and preferential loans for farmers and enhance the purchase price of grain crops to encourage their cultivation. Secondly, attention should be paid to guiding farming methods, and planting conditions should be improved by such means as strengthening the construction of water conservancy facilities. It should also build a production system that integrates grain processing, transportation, storage, and marketing in order to reduce production costs and increase income from grain production. Lastly, it is imperative to limit NGP through a comprehensive system of land use control.

4.4. Limitations and Future Prospects

1. The grain cultivation spatial distribution data were extracted from the 1 km resolution land use data provided by RESDC, which came from the same data source as the 30 m resolution land use data we used and had the same decoding method and classification method (we validated the two sets of data and obtained an overall accuracy of 94.57% and a kappa coefficient of 0.90 [53,54]). But when defining the NGPCL and the GPCL, there is still a certain degree of error, and subsequent studies should improve the resolution of the spatial distribution data of grain cultivation in order to identify NGPCL more accurately.
2. The evolution of NGPCL is affected by a variety of factors, including natural factors such as EVP and PRE, as well as socio-economic factors such as GDP and population density. In our study, we did not include factors that are difficult to quantify, especially policy factors, and due to the limitations of the PLUS model [27], we could only consider the driving factors as static factors. Future studies should aim to include policies as drivers and consider their dynamics.

5. Conclusions

Based on the spatio-temporal analysis of NGP in Jiangsu Province, we conducted a multi-scenario simulation of the pattern of NGP in 2038, and came up with the following conclusions.

1. From 2000 to 2019, the degree of NGP in Jiangsu Province decreased, with NGPR decreasing by 4.85%, the area of NGPCL decreasing from 35,991.07 km^2 to 20,270.21 km^2, and GPCL decreasing from 33,916.99 km^2 to 33,505.61 km^2. Meanwhile, interconversion of NGPCL and GPCL was common in Jiangsu Province. In addition, the transformation of cultivated land to AS was also more common, and NGPCL was more likely to be transformed to AS than GPCL, which was a phenomenon that deserves the attention of land managers.
2. During the study period, Jiangsu Province exhibited a pattern of high NGPCL densities in the central and southern regions, with lower densities in the northern areas. In this paper, the NGPR of county units in Jiangsu Province was measured, and the evolution of NGPR illustrated the tendency for the level of NGP to be greater in the south and central Jiangsu Province than in the north. The results of spatial autocorrelation illustrated the spatial correlation of NGPR in Jiangsu Province, and the tendency of NGP drove and influenced the NGP in the surrounding areas. The NGPR was dominated by H-H agglomerations and L-L agglomerations, and H-H agglomerations were located in the southern part of Jiangsu Province, where the economy and urbanization are high, while L-L agglomerations were gradually concentrating in the northeastern part of Jiangsu Province.
3. Climatic factors, GDP, and population density contributed more to NGP in Jiangsu Province, while distance to government departments, soil types, and distance to all levels of highway also had some influence on NGP, and topographic factors drove NGP the least.

NGPCL will broadly maintain its current spatial pattern under the three scenarios, with denser concentrations in the south and center and sparser distribution of NGPCL in the north. In the NDS, there will be a large reduction in both NGPCL and GPCL; in the CPS, the reduction in NGPCL and GPCL will be somewhat suppressed; and in the FSS, the trend of reduction in GPCL will be reversed and the degree of NGP will be further suppressed.

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Data Availability Statement: Data available in a publicly accessible repository that does not issue DOIs: Publicly available datasets were analyzed in this study. This data can be found here: http://www.nesdc.org.cn (accessed on 1 April 2023).

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

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Article

Disembedding and Disentangling Grassland Valuation: Insights into Grassland Management Institutions and Ecological Research in China

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Abstract: After two decades of implementing top-down grassland restoration projects focused on reducing livestock numbers and pastoralist populations, the Chinese government's well-funded efforts have not significantly reversed grassland degradation. This study reviews the institutional changes in grassland management over the past forty years, highlighting the Livestock and Grassland Double Contract Household Responsibility System of the early 1980s and the Grassland Ecological Reward and Compensation Policy introduced in 2011. It demonstrates how these institutional transformations have shaped pastoralists' evolving understanding of grassland value and reveals that commodifying grassland's economic and ecological value has led to the capitalization of nature, disembedding husbandry from grassland production, and undermining the effectiveness of conservation projects. This article also showcases the development of grassland ecology research in China, noting its increasing detachment from a holistic understanding of ecosystems and the interdisciplinary needs of management practices. The disjunction between grassland ecology research and practical management has resulted in a lack of techniques aligned with local ecological and socioeconomic contexts. This article champions active engagement with and protection of pastoralist communities to reintegrate grasslands' true economic and ecological value into management practices, thereby effectively restoring degraded grasslands and achieving sustainable management.

Keywords: grassland degradation; social–ecological system; commodification; capitalization; ecological restoration

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1. Introduction

To address the issue of grassland degradation in China, which became evident in 2000, the central government has invested substantial funds and resources in a series of grassland protection projects [1,2]. These projects have been based on the simplified logic that overgrazing is the direct cause of grassland degradation [3]. Consequently, the restoration of degraded grasslands has been pursued through the enclosure of grassland and efforts to reduce livestock numbers [4]. The value of grassland has been monetized to facilitate this reduction, and pastoralists are supposed to receive ecological compensation to make up for their lost income [1,3]. However, despite the compensation provided to pastoralists, livestock numbers have not decreased as expected, and the degraded grasslands have not recovered as planned [1,5]. To understand why these well-intentioned projects have failed to restore degraded grasslands, it is essential to investigate pastoralists' views on the changing ecological value of grassland and, subsequently, their perceptions of grassland conservation measures. This understanding has the potential to bridge the gap between policy implementation and on-the-ground realities and holds promise for more effective and sustainable grassland management strategies.

1.1. Simplified Logic of the Recovery Method: Grazing Ban and the Invalid Results

Since 2000, the issue of grassland degradation has garnered significant public attention due to several widespread sandstorms originating from degraded grasslands and extending southward and eastward, even reaching Korea and Japan [6]. These events highlighted the severity of the problem at that time. According to the Third National Grassland Resource Survey, approximately 38.67 million hectares of grassland in the Inner Mongolia Autonomous Region, accounting for 56.9% of the available grassland area, are moderately or severely degraded. The productivity of natural grasslands has generally decreased by 30% to 70% [7]. Overgrazing, attributed to pastoralist activities, has been identified as the primary cause of grassland degradation [8].

In response to this pressing issue, the Chinese central government has spearheaded a series of projects aimed at restoring degraded grasslands. The flagship initiative, the Returning Grazing Land to Grassland (RGLG) project, was launched in 2003. This comprehensive project is designed to curb overgrazing through various measures, including year-round and spring grazing bans. The government has committed significant resources, including manpower, fencing materials, and financial investments, to this project. By 2018, the central government had poured a total of USD 3.84 billion into the RGLG project [9]. In addition to the RGLG project, the Beijing and Tianjin Sandstorm Source Control Project and the Public Welfare Forest Conservation Project were rolled out in 2002 and 2004, respectively. In 2011, the Grassland Ecological Reward and Compensation Policy (GERCP) was introduced, with the total investment exceeding USD 19.5 billion to compensate pastoralists for reducing their livestock through grazing bans, making it the largest Payment for Ecosystem Services (PESs) project in China [10].

However, despite the substantial efforts and investments, the situation on the ground does not seem to be improving as expected. The number of livestock has not decreased, even with the compensation allocated to alleviate grazing pressure on grasslands. In fact, in Inner Mongolia, the livestock numbers have continued to rise, from 99.3 million sheep units in 2015 to 102.3 million in 2017 and a staggering 109.3 million in 2022. This trend of 'partial improvement but overall deterioration' in terms of China's grassland degradation has not been fundamentally reversed [11]. This begs the question: despite the significant investments in terms of fiscal transfer funds and human power, why has the situation in terms of grassland degradation not been fundamentally addressed?

1.2. Grassland Ecology in China: Payment for Ecosystems as a Solution

Amplified concerns regarding escalating environmental crises have led to evolving strategies to meticulously quantify the cost of environmental degradation (value lost) and monetize the benefits (value gained) derived from nature, which are increasingly being integrated into decision-making frameworks. These approaches serve as potential tools to enhance both social and ecological sustainability through a proper valuation of the resources [12–14]. The ecosystem services model supposedly signifies a shift from traditional hierarchical, directive management to more decentralized, ostensibly voluntary decision frameworks that enable policymakers and resource managers to integrate environmental externalities into market transactions [13,15,16]. In recent decades, an intriguing phenomenon has emerged among Chinese grassland scholars, who have become increasingly captivated by the concept of payment for ecosystem services as an innovative policy remedy for the rampant degradation of grasslands. By financially incentivizing local communities and stakeholders to engage in sustainable practices, PESs schemes present a novel paradigm that supposedly harmonizes ecological stewardship with economic benefits, mitigates environmental degradation, and fosters a synergistic relationship between human activity and ecological preservation.

Conservation experts from various fields support assigning a monetary value to the environmental benefits that contribute to human well-being. This approach can be incorporated into policy decisions alongside traditional market values and thereby, lead to the creation of market-based tools, such as PES schemes. These tools provide compensation to natural resource managers for implementing environmentally friendly management practices [15,17]. Furthermore, these schemes may include conditional agreements, payments only if a service is successfully delivered, or penalties for failure to adhere to agreed-upon service provisions [16,18–20]. Although these schemes are theoretically appealing, they often encounter practical difficulties, including high transaction costs and power imbalances between the negotiating parties, and often involve the state mediating to ensure service delivery through a mix of voluntary and regulatory mechanisms [15,16,21].

The practical implementation of PESs often significantly diverges from idealized models. A substantial body of critical literature contends that PESs schemes may perpetuate social and environmental injustices by altering traditional livelihoods and excluding Indigenous and long-tenured groups from their lands [16,22]. Moreover, these schemes have been criticized for commodifying nature, which oversimplifies the intricate ecological and social dynamics involved. This could result in policy decisions that prioritize economic efficiency at the expense of ecological health and human well-being [16]. As PESs has become a cornerstone of global environmental governance, the social and ecological implications of these models warrant careful consideration and adjustment to ensure their positive contribution to a just transition and environmental sustainability.

In China, researchers are increasingly attracted to PESs as a policy solution to overgrazing due to its potential to foster long-term ecological resilience and socioeconomic prosperity, while aligning with the country's highly interventionist environmental regulatory framework [23]. This model regards environmental governance and ecology as a state-led development project and is a pivotal element of the broader ecological modernization initiative [23,24]. This regulatory approach positions the state as a mediator between environmental and economic concerns, incorporating critical imperatives, such as revenue generation, poverty alleviation, environmental protection, and legitimation, into comprehensive national ecological reforms [25,26].

The state's top-down implementation model internalizes environmental issues by emphasizing the technocrats' quantification of natural resources and environmental externalities, which, although effective, may inadvertently perpetuate social inequities [27]. The advent of remote sensing technology has further reduced the costs associated with environmental monitoring and has improved the accountability of policy outcomes by providing large-scale, continuous, and repeatable observations. Remote sensing offers significant advantages, including monitoring extensive and inaccessible areas, delivering real-time data, and minimizing the necessity for extensive fieldwork [28]. The synergy between earth system sciences and grassland ecologists has bolstered the implementation of this top-down, interventionist conservation strategy [29].

However, the top-down environmental regulatory regime is not merely an arbitrary administratively managed system, but a comprehensive system that merges legal, economic, and political instruments to enhance regulatory enforcement [25,30]. This interventionist state approach, driven by the development of ecological sciences, provides an epistemological foundation for legitimizing state-led technocratic practices involving socioenvironmental engineering and naturalizing social inequalities between urban and rural populations [31]. Consequently, the perpetuation of PESs has become central to environmental governance, state formation, and the continued uneven valuation and stratification in the use of land resources in the grassland regions of China [23]. One example of how this technocratic approach may result in the uneven utilization of land resources in China is the limitation of relying solely on remote sensing technology to assess the progress of grassland restoration projects. A primary critique of remote sensing is the absence of ground truth data, which is crucial for validating and calibrating remote sensing measurements [32]. Without ground-based verification, the measurement accuracy and reliability of satellite-derived data remain questionable. Moreover, relying exclusively on remote sensing data neglects the disconnect between the stated goal of grassland protection against overgrazing and the on-the-ground techniques local officials use to assess and monitor grassland degradation [33]. While remote sensing and test plot measurements are explicitly geared towards monitoring grass production, the carrying capacity of local grasslands cannot be accurately assessed without systematically coupling data on forage growth with data on livestock numbers.

Additionally, information gathered locally is often compiled solely to fulfill short-term policy goals, which frequently change according to the formation of different green development agendas [34,35]. This information blockage results in the viewpoints of rational planners and technicians employed by the central state taking precedence over those of local pastoralists. Consequently, the goals of conservation programs shift towards fulfilling program quotas set by the bureaucracy, rather than achieving long-term ecological sustainability and economic viability for local communities [30,35]. As such, it is important to hear the perspectives of pastoralists on the causes of grassland degradation and the value of grassland ecology, which will be explored in the following sections.

1.3. Pastoralists' Perceptions on Grassland Value: A Missing Perspective

Undoubtedly, the perceptions of pastoralists regarding grassland conservation measures are crucial to the success of these policy programs. Grassland serves as a home, production resource, or base for compensation requests for pastoralists. The differing views on the functions of grassland and the value they generate are decisive in determining whether grasslands can be truly and sustainably protected. It should be noted that the change in valuation by pastoralists for grassland conservation is not solely triggered by PESs-based policy projects. In fact, pastoralists' perceptions of the value of grassland have been gradually transforming since the implementation of the Livestock and Grassland Double Contract Household Responsibility System (LGDCHRS) in the early 1980s, which brought fundamental changes to the grassland property rights regime.

Various scholars have provided explanations from different perspectives for the failure of grassland restoration projects, which can be categorized into the following three aspects. The first and mainstream explanation, as articulated by the Deputy Director of the Grassland Supervision Center of the State Forestry and Grassland Administration in 2018, is overgrazing. Consequently, the foremost conservation measure is to eliminate overgrazing [8]. Overgrazing is seen as a characteristic of traditional nomadic animal husbandry. More than 80% of China's natural grassland has degraded due to this practice, leading to low productivity and production methods that, at the expense of ecology, have rendered the grassland an unsustainable, severely degraded, and economically depleted ecosystem [36].

The second explanation posits that these conservation projects oversimplify the complexity of the social–ecological system of grasslands. For example, the appraisal mechanisms at the national level fall short of capturing most of the value of pastoral systems because they operate with simplifications that focus on market exchanges and the formal economy [37]. These projects do not consider the variability and uncertainty of the dryland environment but tend to use impractical and generalizable solutions by simplifying the analysis of complex problems, such as imposing a unified carrying capacity standard for each pastoral household within a township [23,38].

The third explanation is the "tragedy of commodity", whereby the implementation of PESs has altered local internal conservation mechanisms [1,39]. These mechanisms include disrupting the mutual dependence between livestock and vegetation, excluding pastoralists from grassland conservation and supervision, and encouraging both pastoralists and outsiders to engage in activities harmful to grasslands, such as digging for desert stones, medicinal herbs, and catching *Mesobuthus eupeus* to sell [40]. One criticism of PESs is that it may shift people's decision-making logic from considering actions that benefit the social–ecological system to those that are most advantageous for individuals [41].

Over the past four decades, a series of institutional and policy changes have significantly altered pastoralists' perceptions of the value and significance of grasslands. However, few scholars have explored the reasons for grassland degradation and slow recovery from this perspective. This article aims to elucidate the shifts in the perceived value of grasslands among pastoralists and examine how these shifts influence the implementation of grassland conservation policies in China. By analyzing these changes, this study seeks to provide a deeper understanding of the complex interplay between local knowledge systems and policy frameworks. The insights gained from this analysis will offer more effective strategies for sustainable grassland management by integrating local knowledge and practices within ecological studies. The objective of this study is to emphasize the necessity of holistic and adaptive management strategies that account for the variability and complexity of grassland ecosystems. Engaging pastoralists in the decision-making process and ensuring their active participation in conservation efforts are critical factors for achieving effective outcomes.

2. Methods and Data

This study utilizes data from government documents, policy papers, and official statistics to examine the implementation of LGDCHRS since the 1980s and PESs in the Inner Mongolia Autonomous Region of China, from 2011 to 2022. The policy on grassland management has transitioned from a decentralized governance model to a more top-down administrative approach imposed by the Chinese central government. We selected and analyzed the planning and implementation guidelines of grassland management policies on the Xilingol grassland of Inner Mongolia. This analysis aids in understanding the formal approaches to ecological zoning and grassland preservation, as well as the local practices used to deliver compensation for ecosystem services and enforcement.

We conducted over 200 in-depth interviews with pastoralists, village cadres, and banner husbandry officials in the Xilingol grassland (Figure 1), during multiple field trips between 2001 and 2022. These interviews, conducted with consent, were recorded for subsequent analysis. The survey questionnaire addresses several key issues: the implementation process of grassland contracting, changes in water resource utilization, impacts of climate change, costs and benefits of pastoral livestock management, strategies and costs of pastoralists in coping with natural disasters, changes in cooperative and reciprocal practices among pastoralists in terms of livestock management and disaster resilience, the impact of fencing on livestock management and grassland protection, the effects of payments for ecosystem services (PESs) on pastoral livelihoods, and the perceptions of pastoralists towards PESs. The qualitative data from these interviews reflect pastoralists' evolving perspectives on grassland conservation programs and the varying informal practices that grassroots cadres employ to enforce compliance. The qualitative longitudinal interviews comprehensively portray how grassland management policies have affected pastoralists' perceptions of grassland value and modified their herding practices. This, in turn, has shaped the evolving socioeconomic and human–nature relations in the grassland regions of Inner Mongolia.

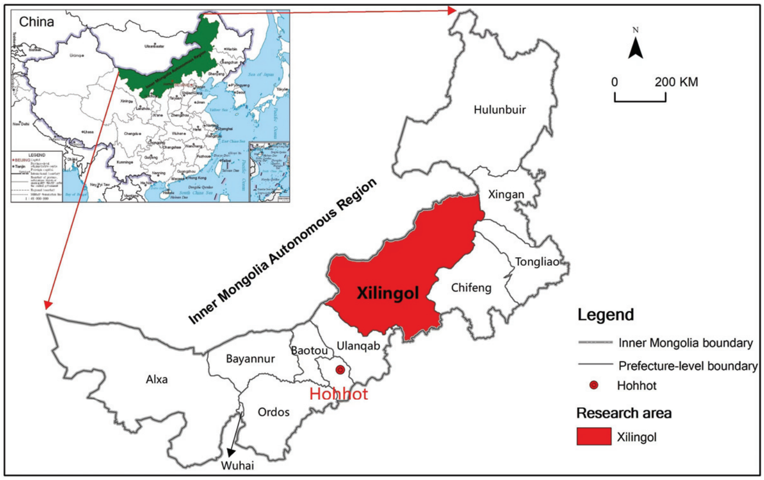

Figure 1. Research Area in Inner Mongolia, China.

To extend the robustness of our analysis, we employed a mixed methods approach. Quantitative data from official statistics published in the Animal Husbandry Yearbook (1985–2022) were triangulated with qualitative insights from policy documents (See Table 1) and interviews to ensure a comprehensive understanding of the policy impacts. We categorized different codes to identify recurring themes and patterns within the qualitative data, providing a nuanced view of the local implementation practices and the resulting socio-ecological changes. This methodology allows for a detailed examination of both the formal policy frameworks and the grassroots-level responses, offering insights into the effectiveness and challenges of grassland conservation efforts in Inner Mongolia.

Table 1. Grassland Management Policies and Guidelines in China.

Year	Policy and Guidance Documents	Issuing Agencies
1982	Summary of the National Rural Work Conference	Central Committee Document No. 1
1983	Several Issues on Current Rural Economic Policies	Central Committee Document No. 1
1996	Regulations on Further Implementing and Improving the "Double Rights and One System" of Grasslands in Inner Mongolia Autonomous Region	Inner Mongolia Autonomous Region, No. 168
2011	Guidance on the Implementation of the Grassland Ecological Protection Subsidy and Reward Mechanism Policy for 2011	Ministry of Agriculture, Ministry of Finance
2016	Notice on Issuing Opinions on Improving the Separation of Ownership Rights, Contracting Rights, and Management Rights of Rural Land	General Office of the Central Committee of the Communist Party of China, General Office of the State Council, No. 67
2016	Guidance on the Implementation of the New Round of Grassland Ecological Protection Subsidy and Reward Policy (2016–2020)	Ministry of Agriculture, Ministry of Finance
2021	Guidance on the Implementation of the Third Round of Grassland Ecological Protection Subsidy and Reward Policy	Ministry of Finance, Ministry of Agriculture and Rural Affairs, National Forestry and Grassland Administration
2021	Opinions on Deepening the Reform of the Ecological Protection Compensation System	General Office of the Central Committee of the Communist Party of China, General Office of the State Council

3. Results

3.1. An Overview of Grassland Management Institutions in Inner Mongolia

Since the establishment of the People's Republic of China in 1949, there have been two significant changes in grassland management institutions in Inner Mongolia. The first major change occurred with the implementation of LGDCHRS in 1984, which transformed the collective property rights of grassland into private use rights [38] (pp. 96–97) [42] p. 12. This shift led to the transition from traditional nomadic livestock husbandry to a sedentary system, effectively halting seasonal movement [38] (pp. 96–97). The second major change was the introduction of PESs in 2011. This program provides pastoralists with relatively high compensation, encouraging them to reduce their livestock numbers or even cease animal husbandry and relocate to urban areas [43,44]. The specific grassland management institutions during these three stages are detailed below.

3.1.1. Before the LGDCHRS

For a long history, the ownership of grassland in Inner Mongolia was held by feudal nobles, temples, or the state. Generally, pastoralists did not possess individual land ownership; however, they had certain recognized rights to use grassland for grazing their own livestock and the herds of local nobles [38] p. 93. During the collective economy period from the 1950s to the 1970s, when grassland was collectively owned, pastoralists established mutual assistance groups. Households voluntarily moved together to jointly use grassland and manage livestock based on labor division and cooperation [38] (pp. 95–96). Subsequently, some groups were combined into larger communes, each with its own allocated grassland. Livestock grazing was restricted by the boundaries of the commune's grassland, and the transhumance of animals throughout the four seasons was arranged by the commune [38] p. 96. Due to the common use of grassland, the daily grazing radius of livestock was relatively extensive, with horses, cattle, and sheep having a grazing radius of 30 km, 20 km, and 10 km, respectively [42] p. 37. In 1980, Xilinhot, located in the center of the Xilingol grassland, had established five communes, one of which comprised 503 pastoralists and 87,999 livestock. To establish this commune, each household had to sell their livestock at a discount of 20–30% of the total price to the commune, with the remaining 70–80% of the livestock value used as shares to join the commune. At the end of each year, pastoralists received 3% of the value of their livestock as a dividend [38] p. 96.

3.1.2. The Implementation of LGDCHRS

Following the implementation of the household contract responsibility system in agricultural areas, LGDCHRS was introduced in the 1980s in pastoral areas of Inner Mongolia. This system distributed livestock and grassland to individual pastoral households. LGDCHRS aimed to address the "*Daguofan*", a term describing the tragedy of the commons, where every livestock grazes on communal grassland. Grassland management was reorganized into smaller, contracted areas for each pastoral household. The most direct result was the cessation of seasonal movement, leading to a significant reduction in the daily grazing radius of livestock, for example, 3–3.5 km for horses, 2 km for cattle, and 1.5–2 km for sheep, in eastern Inner Mongolia [42] p. 37.

These changes have been recognized as progress in the discourse, which claims that backward nomadism, characterized by "following water and grass to breed livestock", should be replaced by intensified livestock breeding dependent on infrastructure, including sheds, wells, artificial grassland, high-yield feed fields, and storage facilities. Consequently, the grassland landscape was gradually fragmented by fences. The risk of grass availability, previously mitigated by mobility, has increased sharply due to the cessation of seasonal movement. Grazing impacts caused by the same number of livestock on grassland during droughts exemplify and exacerbate overgrazing and grassland degradation. Moreover, the labor division and cooperation among pastoralists diminished, requiring pastoralists to become "versatile" in managing their own livestock and building infrastructure [45]. The roles of village leaders and experienced pastoralists in arranging grassland utilization and livestock breeding at the village scale have been abandoned. This includes managing seasonal movements, improving livestock breeds, and responding to natural disasters. Consequently, one of the key principles of adaptive governance of grasslands, action on the ecological scale, has been lost [46].

3.1.3. The Implementation of PESs

In 2011, the Grassland Ecological Reward and Compensation Policy (GERCP) was initiated across the entire pastoral area of China, encompassing 13 provinces. This policy operates on a five-year cycle and aims to encourage pastoralists to reduce their livestock numbers and protect grasslands by providing compensation for grazing bans and rewards for maintaining livestock numbers within the grassland carrying capacity [3]. The GERCP project recognizes pastoralists' efforts to provide grassland ecosystem services and offers compensation as payment for these services. The policy measures include: (1) for grasslands with very harsh living environments, severe degradation, and unsuitable conditions for grazing, a grazing ban and enclosure were implemented, with the central government subsidizing pastoralists at the rate of USD 11.7/ha/year; (2) for usable grasslands outside the grazing ban area, based on the approved reasonable livestock carrying capacity, the central government provided rewards for maintaining a balance between grass and livestock to pastoralists who did not exceed the carrying capacity, at a rate of USD 2.9/ha/year [47]. This mechanism attempts to compensate pastoralists who contribute to grassland conservation through government subsidies. During the first round of policy implementation from 2011 to 2015, satisfactory results were achieved, such as poverty elimination and a reduction in grassland exploitation [10]. However, the livestock numbers did not decrease as expected. For instance, in Inner Mongolia, during the first three years of PESs, the number of livestock decreased from 96.94 million sheep units in 2010 to 93.4 million sheep units, a decrease of 4%. However, by 2014, the number of livestock had increased to 97.7 million sheep units, surpassing the 2010 levels before the implementation of PESs.

3.2. Changes in the Pastoralists' Perceptions of Grassland Value

Based on the above analysis, the implementation of LGDCHRS and PESs has significantly changed grassland management in Inner Mongolia [1]. It is crucial to recognize that these policies and projects have also profoundly influenced pastoralists' attitudes towards grassland, affecting the effectiveness of these initiatives [23,39]. This section will explore the changes in pastoralists' perceptions of grassland value from three perspectives: the nature of grassland, the ownership of grassland, and the purpose of grassland conservation. Although there may be an element of romanticism in describing the collective period, the statements in regard to these three aspects are fundamentally accurate.

3.2.1. What Is Grassland for Pastoralists?

Before the implementation of LGDCHRS, the grassland was both the homeland and the most important asset for pastoralists. Mongolian singer Tengger encapsulates this sentiment in his song "Heaven," where he describes the grassland as "home" with its blue sky, clear lake, and green expanses. From an external perspective, pastoralists rely on grassland because they are dispersed in remote areas, isolated from political and economic centers, and have no other industries to depend on. However, from the pastoralists' perspective, the grassland resembles a mother, a metaphor frequently found in Mongolian songs and proverbs [48]. A Mongolian proverb states, "The first-class rich have friends, the second-class rich have knowledge and wisdom, and the third-class rich have cattle and sheep, but the greatest wealth is still the grassland" [45]. This comparison implies that wealth is not merely economic but is foundational to the pastoralists' way of life.

After grassland was contracted to individual households, it transformed into a means of production. Once pastoralists left livestock husbandry, the grassland became an asset that could be rented out for income. This transformation did not occur overnight. Initially, during the implementation of LGDCHRS, pastoralists found it difficult to accept the construction of fences on grassland. As an elderly Mongolian woman remarked, "If the grassland was divided like a spider web, then there must be a problem with the grassland". However, driven by the market economy, such as the sharp rise in cashmere prices in the 1980s, pastoralists were motivated to increase their goat herds, believing "it meant losing money if we did not increase goats" [49] (pp. 153–157). Consequently, grassland became a means of production that facilitated income generation. In the collective economy, pastoralists had to consider grassland and livestock use value. Post-LGDCHRS, the value of grassland and livestock became intertwined with market transactions. In essence, exchange value became the core concern for pastoralists after the implementation of LGDCHRS.

Following the implementation of PESs in 2011, the grassland became a voucher for some pastoralists to receive compensation [1,23]. On the one hand, the high compensation prompted some pastoralists to completely abandon the grassland and move to towns; on the other hand, it attracted a few pastoralists who had left grassland and livestock breeding for years, to return and reclaim their abandoned grassland. These individuals primarily sought a paper certificate, which they could use to apply for compensation, regardless of the location or health of the grassland [39]. The previously mentioned exchange value required pastoralists to actively work on their grassland. Under the concept of exchange value, pastoralists had to manage their livestock well, while protecting the use value of the grassland. Even when renting the grassland to others, they needed to consider its health. However, under PESs, pastoralists can receive compensation merely for having a nominal contracted area of grassland and a contract certificate [1,35]. Thus, aside from exchanging compensation for PESs, the exchange value of grassland has diminished further in the eyes of some pastoralists.

3.2.2. Who Does the Grassland Belong to?

As stated above, the grassland is often compared to "Mother Earth". Before the implementation of LGDCHRS, pastoralists believed that the grassland was jointly owned by all pastoralists. This common ownership was guaranteed by a series of institutional arrangements. There were many beliefs and rules emphasizing conservation in the use of grassland [45]. For example, Prof. Liu Shurun's research in the Hulunbuir grassland in Inner Mongolia revealed the role of a "*nutugchin*", a coordinator of grassland management and livestock breeding, who played a crucial role in conserving grassland and local knowledge. "Nutug" means "hometown" in Mongolian, and "chin" means "the person of. . .". Thus, it can be literally translated as "the person who guards the grassland hometown". Before the implementation of LGDCHRS, "nutugchins" were nominated at all administrative levels of leagues, banners, and *sumus* (counties). In some areas, they were referred to as *galin ah*, especially where camel breeding was prevalent. "*Nutugchins*" were primarily responsible for arranging grassland use and livestock movement [45]. Importantly, during this period, leaders at all administrative levels and pastoralists respected and obeyed the commands of "*nutugchins*". As the Mongolian proverb says: "The horse who eats *artemisiae herba* will brim with energy and vitality, and the person who listens to the old man will have wisdom growth". With these experienced individuals guarding the grassland, the "grassland mother" could be protected, while nourishing the material and spiritual lives of pastoralists [45] (pp. 126–131).

At the beginning of LGDCHRS implementation in the 1980s, even though the use rights of grassland were distributed to individual households, most pastoralists did not immediately change their mindset. This is also the reason why Inner Mongolia implemented the second round of grassland contracting in 1995. For herders, using grasslands on a household basis presents many difficulties. It was difficult for them to imagine how to graze livestock within a fixed, fenced, and much smaller grassland area [38] p. 101. However, under various influences, they gradually adopted the "my grassland" concept and put up fences around their contracted areas to protect their use rights. A primary factor was the increase in livestock, which led pastoralists to realize the necessity of using fences to "protect their own grassland from others' livestock" [45] (pp. 126–131). From 1984 to

1999, favorable weather conditions and market prices, particularly the rapid increase in cashmere prices, led to a significant increase in livestock numbers in Inner Mongolia, with sheep numbers increasing by 56% from 23.77 million in 1984 to 37.03 million in 1999 [50]. The widespread growth in livestock numbers made pastoralists understand the need to build fences to keep neighbors' cattle and sheep out, or else they would suffer ecological and economic losses. Different regions in Inner Mongolia experienced varying modification processes. For instance, Zhang [49] (pp. 127–132) noted in her research on the Ordos grassland in western Inner Mongolia that local pastoralists began building fences around 1990, gradually shifting the meaning of grassland from "collective" and "public" to "private". However, Li and Zhang [38] p. 101 found that most fences in central Inner Mongolia's Xilingol grassland were constructed after 2000. With the entry of state-owned or private capital for activities such as mining, road construction, agricultural planting, and later wind and solar power development, which occupied grassland, pastoralists needed fences to assert their use rights and receive compensation. Consequently, under internal and external pressures, pastoralists established and exercised their grassland use rights by constructing fences. However, in response to external pressures, pastoralists often used fences merely to obtain compensation rather than to genuinely protect their use rights.

Although the use rights of grassland still belong to pastoralists, the implementation of PESs has generally increased the perceived instability of these rights. The top-down policy enables every pastoralist to participate in the project, with the price of receiving compensation being the imposition of certain restrictions, such as a seasonal or year-round grazing ban. PESs further promotes the diversification of pastoralists, who can be roughly divided into four categories. The first category comprises households with no livestock or a few livestock, who leave the grassland and move to towns, relying on the compensation to make a living [1]. Under relatively loose supervision, some of them rent out their grassland to earn additional income. The second category includes outsiders who take this opportunity to use the grassland to raise livestock [1,39]. The third category consists of moderately wealthy and wealthy households, who continue to engage in animal husbandry with increasing costs, loans, and risks [51]. The fourth category includes a small number of pastoralists, who have left the grassland for years but return to claim their share of the grassland due to the compensation benefits.

The question of who owns the grassland has become more ambiguous. Pastoralists who leave the grassland with compensation or reclaim their share of grassland solely to obtain compensation do not care about the grassland beyond their contract certificate, which allows them to earn compensation. They do not consider the health status or even the specific location of their grassland. Outsiders who rent grassland are primarily interested in the immediate benefits of animal husbandry, often leading to overuse of the contracted grassland. If this grassland becomes unusable, they simply rent another piece. Only the local pastoralists who continue to engage in animal husbandry care about the health of their grassland. However, under the pressures of climate change, grassland degradation, and loan burdens, they also tend to raise more livestock than their grassland's sustainable carrying capacity [1,23].

3.2.3. For Whom Is Grassland Conservation?

Before the implementation of LGDCHRS, pastoralists primarily relied on grassland animal husbandry for their livelihood and believed that sustainable grassland use was essential for their own well-being. The pastoral areas were remote from agricultural zones and even more distant from industrial centers. At that time, life was simple; there was little need for cash, and local income came almost entirely from animal husbandry, with the grassland serving as its foundation [52] p. 7. The transhumance system, which involved the seasonal migration of livestock, operated like a complex mechanism, with numerous interlocking components. Each pastoralist household or group functioned as a small gear, contributing to the overall operation of the system. This complete dependence on grassland resources compelled every pastoralist to engage in grassland conservation.

After the grassland was contracted to individual households, pastoralists initially had a strong desire to protect it. However, various restrictions rendered them increasingly powerless [52] p. 23. Firstly, since different households were allocated specific grassland parcels, moving livestock to other pastures became difficult unless arrangements and payments for rent were made. Secondly, prior to settlements, when pastoralists lived in yurts, there were few paths, and both people and livestock could move freely without the constraints of fences. After settlements, multiple roads emerged in front of each house, and numerous routes between fences became severely degraded due to over-trampling. Thirdly, compared to the cooperative and straightforward tasks arranged during the collective era, pastoralists had to become versatile after LGDCHRS [52] p. 23. Their adaptive governance, which respected natural grassland laws, was replaced by unreasonable practices that ignored the grassland ecosystem's characteristics. Traditional grazing knowledge became obsolete, necessitating the acquisition of new skills, such as driving, feeding livestock with forage, and using the Internet [52] p. 33. Additionally, the cost of purchasing fodder and forage has increased, forcing pastoralists to increase their livestock numbers to repay bank loans. Some even resort to usurious loans, creating a vicious cycle. Despite knowing that the degraded grassland cannot support so many livestock, pastoralists must maintain high livestock numbers to meet their financial obligations. Without sufficient funds to buy fodder and forage, both livestock and livelihoods are jeopardized [45] (pp. 126–131).

The implementation of PESs further transformed pastoralists' moral sentiment towards grassland conservation. For some, the grassland's meaning shifted from being a homeland to a voucher for obtaining compensation [1]. The ecological service function of "grassland as an ecological barrier in northern China" gained prominence, and various conservation projects were implemented, primarily through grazing bans [2]. However, the role of "grasslands as a homeland for pastoralists" was neglected. Firstly, PESs directly compensated pastoralists, fostering dependency and increasing the number of individuals who relied on compensation and grassland rents rather than engaging in livestock rearing [52]. This attracted outsiders seeking short-term benefits, exacerbating overgrazing issues. Secondly, PESs schemes distributed compensation to individuals rather than collectives, undermining the collective action needed for effective grassland ecological function maintenance. This led to the fragmentation of local social systems and the abandonment of community cooperative rules for rational grassland use [39]. Lastly, compensation encouraged irrational consumption and disrupted family unity. For instance, a village leader in eastern Inner Mongolia noted that over twenty SUVs appeared within a month of compensation distribution. Many pastoralists lacked plans for reasonable use of the compensation. The implementation of PESs also led to the division of large families into smaller units, further fragmenting the ecosystem and creating more social problems [23,39]. Overall, while LGDCHRS and PESs schemes aimed to improve grassland management and pastoralist livelihoods, they introduced new challenges and complexities that require careful consideration and adaptation to ensure long-term sustainability and social cohesion in pastoral communities.

3.3. Characteristics of Grassland Ecological Research in China

As mentioned above, the commodification of both ecosystem services and economic value has profoundly altered the social–ecological system in pastoral areas, including relationships among pastoralists and between humans and nature. Despite continued state investment, the resulting social disorganization and grassland degradation persist [35,44]. However, reflection on this issue should not end here; it must extend into the field of grassland ecology as an academic discipline. Grassland ecology in China, developed since the 1950s, has played a crucial role in grassland management. Reflecting on this field can provide a foundation for the future management of pastoral areas. As Beck emphasized in his "Risk Society" [53] p. 79, while the misapplication of scientific rationality has caused numerous problems, it should still be used to correct errors. Therefore, this section further analyzes the dilemma faced by grassland management and pastoral areas, by exploring the development of grassland ecology in China over the past four decades, focusing on potential solutions.

Research on grassland ecology in China began in the 1950s and has gained increased attention since the late 1970s. According to interviews with pioneers in livestock and grassland science, including Zhang Zutong, Fu Xiangqian, Chen Shan, and Liu Shurun (July 2008), early grassland ecological research in China was closely linked to livestock and animal husbandry studies. The first grassland major in China, established in 1958, was established by the Department of Animal Husbandry and Veterinary Medicine at Inner Mongolia University. Later, influenced by Prof. Wang Dong and Prof. Ren Jizhou, a grassland major was established at Gansu Agricultural University, maintaining a strong connection with animal husbandry [38] p. 40. The Department of Ecology at Inner Mongolia University was established in 1957, led by Prof. Li Jidong, one of the founders of modern Chinese ecology, who relocated the ecology and geobotany team from Peking University to Inner Mongolia University. In 1977, Inner Mongolia University established China's first undergraduate major in ecology. Field research has been a significant focus in the development of grassland ecology. An ecological research station was established in Xilingol grassland in 1979, concentrating on monitoring, research, and demonstration. It had natural advantages in terms of conducting grassland research, because it was the closest research station to grassland and pastoralists at that time. Based on an analysis of the annual meeting records from 1981 to 1998 at the research station, as well as 11 collected paper publications during this period [54], early grassland ecological research exhibited two main characteristics. These early efforts laid the groundwork for understanding and addressing the complex challenges in grassland management, providing essential insights that remain relevant in developing effective strategies for sustainable pastoralism and ecological conservation in China's grassland regions.

3.3.1. Losing the Understanding of the Complexity and Integrity of Grassland Ecosystems

Early research from the ecological research station reveals a shift in research direction, with a decreased focus on the overall grassland ecosystem and an increased focus on detailed studies, such as plant succession, plant physiology, and photosynthesis. This trend aligns with Lin and Fyles' findings, which highlight the limitations of an overemphasis on technical knowledge [55]. While this approach has facilitated a deep understanding of the technical aspects of plants and land, it falls short of comprehending the holistic complexity of the ecosystem. When research began at the station in 1980, 28 topics were identified and categorized into seven areas: plants, animals, soil, water, material cycles, grassland utilization, and database construction. For instance, the fifth edition of "Research on Grassland Ecosystem," published in 1997, included detailed studies on the effects of grazing on soil physical properties, soil nutrients, soil microorganisms, and the locust community response. However, notably, it lacked articles addressing the overall impact of grazing on vegetation [56].

3.3.2. Taking an Engineering Approach to Grassland

These studies also reflect an increasingly distant approach from nature and a focus on artificial interventions. Since 1981, the annual meetings have proposed establishing and studying artificial grassland. Based on the author's analysis of the summaries from the working meetings of the positioning station from 1981 to 1998, by 1984, various experiments on artificial grassland began to appear in the collection of papers. These experiments included studies on the biological characteristics of *Leymus chinensis* under cultivation, the establishment of *Leymus chinensis* artificial grassland, winter-snow-layer fertilization of *Artemisia frigida* communities, background investigations on cutting grass succession test areas in *Leymus chinensis* grassland, and cutting grass succession tests on artificial *Leymus chinensis* grassland. Since then, studies on natural grassland have significantly diminished. The few studies that focus on natural grassland often emphasized its backwardness and lack of artificial modification, critiquing the unreasonable utilization of natural grassland

(1985) [57] and its management practices (1981) [58]. These studies continued to advocate for an eco-developmental logic underpinning systems science approaches to environmental management as not just techniques of managing natural resources, but as the very foundation of the progress of China's grassland region, a notion of utmost importance to development and legitimacy [23]. Emphasizing human control of nature through technical management, these studies advocate for the technoscientific control of socio-natural systems and portray ecology as both malleable and that it can be altered through human intervention and the correct calculation of its ecological functionality [23,30,59]. This logic posits that ecological engineering through environmental modeling and functional land zoning will transform a herding society into an ecologically modern society and pave the way for a "healthier" grassland region and community [26,59].

4. Discussion

4.1. The Capitalization of Nature and the Two Disembedding Processes in Regards to Grassland Value

As we examine the evolving significance of grassland for pastoralists, it becomes apparent that nature is increasingly "cut" and "extracted" from the social life of local people within the developed market mechanism. Implementing the LGDCHRS and PESs has precipitated two disembedding processes within the grassland social–ecological system. The first process involves the commodification of the grassland's economic value, a direct consequence of the LGDCHRS. This commodification leads to the economic value being disembedded from the grassland's ecological, social, and cultural dimensions. The second process, stemming from the implementation of PESs, concerns the commodification of the grasslands' ecological value, where only a portion of this value is harnessed to provide ecological barrier services in central China. This selective commodification alters the moral inclinations of pastoralists towards grassland protection.

4.1.1. Disembedding Process of Grassland Economic Value

In her research conducted in western Inner Mongolia, Zhang ([49] p. 191) introduces the concept of "Disembedding 'Nature'" to elucidate the transformation in the relationship between nature and humans following the implementation of the LGDCHRS. This paradigm shift is marked by the transition from a relationship characterized by integration and symbiosis to one of division and opposition, with nature increasingly objectified by human actions. This transformation is primarily evident in the subdivision of grasslands into smaller, tradable plots, a change that many pastoralists find difficult to accept. This resistance stems from alterations to their longstanding grazing practices and, more significantly, from a profound conflict of beliefs. As pastoralists articulate, "The grassland is our mother earth and cannot be dismembered and divided by her children" [45] (pp. 126–131).

Despite the challenges, grassland contracting has been implemented across Inner Mongolia, facilitated by the region's relatively flat terrain and the absence of insurmountable natural barriers. Typically, grasslands are divided based on family size and livestock numbers according to specific standards, whether applied to pastoralist groups or individual households. In 1996, Inner Mongolia launched a second round of LGDCHRS implementation, during which grassland previously contracted to pastoralist groups was further distributed among individual households [38] p. 71. While some areas retain common grassland, the more prevalent arrangement now involves fragmented grassland utilized by individual households. Consequently, the relationship between pastoralists and the grassland has evolved from adaptation to active construction and transformation [38] p. 71. The increasing prevalence of fences, motor-pumped wells, forage planting, silage pits, warm sheds, and various mechanical facilities, underscores this shift. Pastoralists are compelled to become multifaceted workers to cope with these changes in livestock management post-LGDCHRS [45] (pp. 126–131).

Meanwhile, the relationships among pastoralists have also changed accordingly. First, contradictions have emerged within families and between neighbors. These include disputes over the fairness of grassland division, livestock encroaching on neighbors' grassland, and fences blocking access routes. Secondly, income from renting grassland, especially to outsiders, weakens the moral incentive for pastoralists to abide by social norms and promote common interests [60]. Thirdly, the original reciprocal support among pastoralists in the face of disasters has been replaced by economic transactions. Renting other people's grassland at high prices and even paying for livestock's drinking water from wells during droughts has made pastoralists more calculating. Finally, in the era of the collective economy, pastoralists could rely on the leadership of *nutugchins* and village leaders for winter and disaster relief. Now, pastoralists must rely on themselves. Facing increased uncertainty, they feel confused and uncertain about their future, making them more focused on short-term benefits rather than long-term sustainability. All these changes have led to the gradual physical and emotional division of pastoralists by fences, which creates physical distance, contradictions, and mutual distrust. This has given rise to a "fencing society" that physically and emotionally divides pastoralists [61].

The emergence of a "fencing society" has significantly altered the relationship between people and grassland. As previously mentioned, nature is increasingly objectified by human actions. As a result of the increasingly developed market mechanism, nature is "cut" and "extracted" from the social life of local people, endowed with a standardized market value, becoming a profitable economic production factor, while losing its vibrant vitality and original rich connotation. This process is the capitalization of nature. In Mongolian society, this represents a profound shift in the cultural significance of nature, accompanied by environmental consequences [49] p. 153. For pastoralists, the grassland is now seen primarily as a productive resource. Elvin noted that failing to exploit this resource economically results in lost potential wealth. The term "the cash-in imperative" encapsulates this notion [62] p. 2. This perspective also sheds light on why pastoralists, despite knowing that outsiders might overexploit the grassland, still choose to rent out their contracted land. Furthermore, the cashmere price surge in the 1980s led pastoralists to increase their goat herds, operating under the belief that reduced grazing equates to financial loss.

4.1.2. Disembedding Process of Grassland Ecosystem Service Value

Based on our research in a township in the south-central Xilingol grassland in Inner Mongolia, it is demonstrated how the implementation of PESs in the 2010s led to the collapse of the local co-management mechanism that had protected grazing lands for 30 years [1]. This collapse precipitated a tragedy of the commons, characterized by outsiders bringing in their livestock and local pastoralists indefinitely increasing their herds. Prior to the implementation of PESs, even households with no or a few livestock depended on livestock breeding and pastoral communities for their livelihood. The future of pastoralists hinged on the sustainable use of grassland, reinforced by local regulations that prohibited renting grassland to outsiders. During this time, community support mechanisms were also in place, such as earning income through shepherding or protecting grassland for mowing. However, post-PES implementation, households with minimal or no livestock received compensation based on their grassland contracting certificates, despite often being unaware of the specific locations of their grazing lands, since these were commonly used. After completing market transactions for ecosystem services, these households relocated to towns, severing ties with the community's mutual support systems. Under lax supervision, they began renting their grazing lands to outsiders, without regard for the consequences, exacerbating the livestock influx. This situation led other households to abandon the norms on controlling livestock numbers and protecting grassland, instead using compensation funds to secure loans for increasing their livestock numbers.

Therefore, the commodification of ecosystem services fails to reflect the broader value of the ecosystem as it strips away the social and ecological dimensions embedded in these services, which are crucial at varying scales [63] (pp. 172–174). In this case, the original grazing land co-management and livestock quantity control mechanisms were the most directly and significantly affected elements. PESs may shift people's decision-making rationale from considering what practices fit the community social-ecological system to considering what is most beneficial for individuals [1]. The process of commodification has led to the disorder of social metabolism, resulting in unsustainable social and ecological outcomes, thus leading to the tragedy of commodification [63] (pp. 172–174).

4.2. Research on Grassland Ecology and Its Detachment from Grassland Management

The studies on grassland ecology often focus on technological and technocratic solutions, while overlooking traditional grassland management practices. The research can be divided in regard to the following two aspects.

4.2.1. Disentangling Research on the Natural Grassland Ecosystem

This research typically assumes that traditional animal husbandry, which relies entirely on natural grassland, is backward and lacks stable, high-quality, and high-yielding grazing land. For example, a 1988 study argued that traditional livestock herds grazed year-round lack a comprehensive scientific breeding and management system, impeding increased production in animal husbandry. Ironically, the "movement" of herds allows pastoralists to maintain stable, high-quality, and high-yielding grazing land, requiring "no supplemental feeding" [64] p. 47. While "no supplemental feeding" was assessed as a lack of scientific management systems, it indicates the full and rational use of natural grassland, reducing costs. Therefore, supplemental feeding does not represent advanced methods, but rather signifies grassland degradation and increased costs. The belief that supplemental feeding creates "improved livestock" overlooks the fact that livestock raised on supplemental feeding may be unfit for natural conditions, weak, and sickly, thus requiring supplemental feeding. Pursuing more meat, milk, and cashmere production based on "improved" livestock often ignores other significant drawbacks. Based on these misconceptions, it was proposed that "if China's animal husbandry wants to significantly improve production efficiency, it must combine artificial grassland with natural grassland and transition to semi-domesticated grazing on the basis of planting artificial pasture and concentrated feed" [65]. However, decades of practice have shown that abandoning natural advantages and transforming landscapes into artificial spaces for animal production creates numerous problems [38] p. 110; [66] (pp. 47–54).

4.2.2. Disentangling Research on the Pastoralists' Knowledge and Practice

Grassland contracting, in essence, is a "mandated marketization" reform based on two erroneous assumptions: the tragedy of the commons and the backwardness of nomadism [38] (pp. 62–69). From the perspective of the tragedy of the commons, traditional grassland management and animal husbandry were misunderstood as a situation of "no owner of the grassland, no boundary for grazing, no rules for management, no responsibility for construction, and no guilt for destruction" [38] p. 68. This view contributed to the belief that it caused grassland degradation and desertification. Those who assert the backwardness of nomadism claim that traditional animal husbandry relied mainly on "raising livestock by relying on nature" and "extensive management methods", which depend solely on natural conditions and focus only on livestock quantity, rather than quality [49] (pp. 214–216). Researchers from outside often fail to understand why herds are constantly relocated and why pastoralists do not plant forage grass. If there had been better communication with local pastoralists, these misunderstandings could have been resolved, revealing that pastoralists manage their animals within their ecosystems more holistically.

Both scholars and policymakers have underestimated the knowledge and experience of traditional pastoralists, valuing technical interventions instead. While data are valuable, we should also seek insights from modern Leopold foresters, farmers, and indigenous elders, who have spent their lives observing the land, and ask them what they see [55]. As previously discussed, pastoralists have always been practitioners of land ethics, respecting, relying on, and protecting the grassland. They learn from livestock, understanding whether forage is toxic, or delicious, and nutritious, and mastering livestock management skills on grassland [45] (pp. 126–131). Ecology provides a model for a more vibrant and harmonious human community, and ecological theory must be holistic rather than simplified, neglecting the system's complexity [67] (pp. 493–499). This article emphasizes that local people, who have long been involved in the operation of this system, cannot be ignored.

This article illustrates the changing perceptions of pastoralists regarding the social, economic, and ecological value of grassland, by presenting the implementation of grassland contracting, which has led to the dominance of anthropocentrism in grassland management and replaced the original ecological ethics of pastoralists. This view is entirely based on considerations of technical production improvements, ignoring the diversity and complexity of ecosystems and the traditional knowledge on those systems. Faced with widespread grassland degradation, scientific rationality has once again prevailed, asserting that degraded grassland can be restored if livestock grazing is reduced. To this end, various conservation projects and the largest PESs project have been implemented. The overall trend in ecological development has been to abandon a holistic viewpoint and an interdisciplinary approach. The narrative in this article is just one example of humanity's advocacy for scientific rationality and its immersion in conquering and transforming nature. This article emphasizes the importance of the pastoralists' perspective by highlighting how their views on grassland's social, economic, and ecological value have evolved. Only through actively understanding, learning from, and protecting the grassland can we re-embed and realize the true economic and ecological value of the grassland.

5. Conclusions

Our findings underscore the critical importance of integrating local knowledge into policy frameworks for grassland conservation. Institutional transformations in China's grassland management policies have significantly shaped pastoralists' evolving understanding of grassland value. The commodification of grassland's economic and ecological value has led to the capitalization of nature, disembedding husbandry from grassland production and undermining conservation efforts. This article chronicles the trajectory of grassland ecology research over the past four decades, highlighting its increasing detachment from a holistic understanding of ecosystems and the interdisciplinary needs of management practices. This study reveals that the disjunction between grassland ecology research and practical management has resulted in a lack of techniques aligned with local ecological and socioeconomic contexts. Consequently, this research advocates a collaborative approach involving all stakeholders to develop and implement effective and sustainable solutions to grassland degradation in China.

This research is unique in two significant ways. First, it offers a continuous historical perspective, comprehensively reviewing policy changes over the years, rather than focusing on a single period. Second, it highlights pastoralists' perspectives, particularly their attitudes and actions regarding recent ecological compensation policies, which are often overlooked. This study examines the transformation of pastoralists' perceptions on ecological compensation within the context of successive conservation programs. Due to data constraints, this study focuses on one region in Inner Mongolia as a case study. However, the diverse pastoral regions of China may experience varying effects, and generalizing the insights and suggestions requires caution. This research emphasizes an evidence-based approach rather than starting from theoretical assumptions, contributing significantly to understanding pastoral areas, pastoralists, and pastoralism.

Our findings demonstrate that the concept of "my grassland" among pastoralists did not form immediately after grassland contracting but developed gradually due to the need to prevent others' livestock from encroaching on their grassland. Analyzing the changing value of grasslands from the pastoralist's perspective is crucial, especially given their lack of voice in policy formulation. This article suggests that policies should be formed that create space for local pastoralists to make informed decisions about the rational use of grasslands, emphasizing confidence in their cultural knowledge, rather than relying solely on externally imposed technology. Policymakers should understand how pastoralists form ecological value instead of relying on technocrats' abstract reification. This study suggests that policymakers consider how subsidies are distributed and utilized, giving local stakeholders a voice to address regional needs and improve fund utilization efficiency. PESs schemes require complementary measures, such as restricting the entry of outsiders and providing compensation for ecological services generated by community-level collective actions. It is crucial to align ecological protection with pastoralists' livelihoods rather than view them as opposing forces.

This article is an exploratory study to provide a localized understanding of how pastoralists in Inner Mongolia perceive ecological value. However, there is much to consider regarding how capital and social networks shape specific implementation methods. Addressing these issues is fundamental, especially under conditions of climate change and socioeconomic development, which increase the complexity and uncertainty. Further research is needed to explore situations in other regions of China. In conclusion, actively engaging with and learning from pastoralists is vital to realizing the true economic and ecological value of grasslands. This article suggests more nuanced and effective strategies for sustainable grassland management, through comprehensive and collaborative efforts.

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Contribution of Rare Earth Elements Is Key to the Economy of the Future

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Abstract: An econometric model was developed to analyze the contribution of various factors to the gross value added to the agricultural, manufacturing, and service sectors in the United States. The study found that variables such as rare earth element mining, the employment it generates, the domestic consumption, imports, and prices of certain elements significantly impact economic sectors. The models showed a good fit and met the necessary statistical assumptions. Rare earth elements are essential for a wide range of technological products, with China being the leading producer and consumer. This has raised concerns about the dependence on other countries. These elements significantly impact the economy's primary, secondary, and tertiary sectors used in agriculture, manufacturing, and services. Rare earth elements' mining and processing are complex and expensive processes, and demand is expected to continue to increase in the future.

Keywords: rare earth elements; critical elements; next-generation markets; economy

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1. Introduction

Rare earth elements are 17 chemical elements found in the Earth's crust in minimal quantities, between 10 and 100 parts per million. Rare earth elements are found in a wide range of rocks but are concentrated in a few minerals, such as monazite, bastnäsite, and xenotime [1]. Recent years have seen a surge in research on how geopolitical events influence energy and resource prices [1,2]. Nassar et al. [2] were among the first to demonstrate that world governance, political stability, the absence of violence, and global supply concentrations have a more significant impact on rare earth elements' prices when global supply is limited. Building on this, Ref. [3] found that periods of economic turmoil and geopolitical unrest lead to increased "spillover" effects, meaning that price fluctuations in oil markets can have a greater impact on financial markets, and vice versa.

The principal rare earth elements' deposits are in China, Australia, the United States, Brazil, and Russia [4]. China is the leading producer and consumer of rare earth elements. These are essential elements for manufacturing a wide range of products, including electronic devices, automobiles, defense equipment, and clean energy [4].

The importance of rare earth elements has increased in recent years due to the growth of the global economy and the increasing demand for products that depend on them [5]. Rare earth elements are essential for developing critical energy, transition technologies, and digitalization technologies, such as electric motors, wind turbines, and batteries [5].

High-tech devices, medical equipment, and military systems all rely heavily on rare earth elements (REEs) [6]. These elements are becoming even more critical as clean energy technologies develop [6]. As the demand for clean energy surges in the coming decades, so will the demand for REEs, placing a strain on the current supply chain [6].

Rare earth elements (REEs) are like wonder materials for modern technology. Their unique electronic, optical, catalytic, and magnetic properties allow them to solve a range of technological challenges [7]. While there is no single way to categorize their uses, REEs are generally employed in nine main sectors as catalysts, polishing compounds, glass, phosphors and pigments, metallurgy, batteries, magnets, ceramics, and others [7]. In 2015, the global consumption of REEs reached an estimated 119,650 metric tons of REO, with their biggest use as catalysts, followed by magnets, polishing, and others (Figure 1). Experts predict a 5% annual growth rate in global REE demand by 2020, with clean energy's booming market expected to further propel this growth for years to come [8]. This surge in demand puts a strain on the global REE supply chain, creating a significant challenge [8].

The push for cleaner energy through decarbonization and electrification is skyrocketing demand for neodymium (Nd). The International Energy Agency (IEA) predicts demand could double or even triple in the next few decades, with clean energy becoming a major consumer of rare earth elements (REEs), potentially exceeding 40% of total demand [9]. This economic importance, coupled with potential supply disruptions, has countries scrambling for sustainable REE sources. As a result, we have seen a recent surge in REE exploration projects and processing plants [9].

Nations around the world have come together to address climate change by setting a goal of limiting global warming to be below 2 °C compared to pre-industrial levels. This effort is called the Paris Agreement. To achieve this goal, countries are implementing strategies to reduce emissions' "mitigation" and prepare for the effects of climate change "adaptation" [10].

Mitigation efforts include transitioning to cleaner energy sources like solar and wind power, which are becoming increasingly cost-effective. Rare earth elements, which have unique properties that make them essential for many renewable energy technologies, are also in high demand [10].

The transition to renewable energy is happening rapidly, with the share of renewables in electricity generation expected to reach over 60% by 2030 and 88% by 2050. Solar and wind power are expected to become the leading sources of electricity [11].

Transportation is another major source of emissions, and electric vehicles are seen as a key part of the solution. In a scenario where emissions are reduced to net zero, electricity is projected to be the primary fuel for transportation by 2040 [12].

Given this evolving landscape, a timely analysis of global REE resources and potential supply chains is critical for stakeholders. This study provides a comprehensive overview, including a compilation of ongoing rare earth element projects, innovative supply chain designs, and highlights regions with the most promising REE potential [12].

China currently dominates the global REE market, producing roughly 85% in 2016, with Australia following at 10% [6]. However, there is good news: despite limited production, the world has a wealth of REE resources. As of 2017, there were 178 identified REE deposits scattered around the globe, containing an estimated total of 478 million tonnes (Mt) of rare earth oxides (REOs). Over half (58%) of these deposits hold more than 0.1 Mt of REOs, and nearly 60 have undergone technical assessments [6].

Rare earth elements, a critical strategic resource, have become a subject of intense research due to concerns about China's influence. Scholars like [13,14] worry that China might leverage its dominant position to gain geopolitical advantages.

Beyond physical disruptions, research by [15] highlights how societal and geopolitical factors like speculative markets, export bans [16], and environmental regulations can impact supply [16]. Since downstream applications hold more power in the global market [17], China's policies significantly influence prices. The authors of [18] even found that increased trade policy uncertainty in the US benefits the rare earth element market by potentially boosting demand, while such uncertainty in China might restrict supply [12].

Further research by [19] suggests a positive correlation between geopolitics and import prices, but a negative correlation with overall import value. This complexity highlights the interplay of factors like rising anti-globalization sentiment and the COVID-19 pandemic, influencing the rare earth element market in unpredictable ways [20].

At the current production rate, these resources could supply the world for over a century. However, there is a catch. Clean technologies are expected to require a significant amount of specific REEs, particularly neodymium (Nd) and dysprosium (Dy). By 2030, these two elements are projected to make up 75% and 9% of the clean tech REE demand, respectively [19,21]. This is concerning because they only represent 15% and 0.52% of global REE resources. This imbalance means that neodymium and dysprosium will likely be major factors driving the development of new REE exploration projects and clean energy technologies in the coming years.

The extraction and processing of rare earth elements is a complex and expensive process. The extraction and processing processes of rare earth elements can be divided into the following stages [22]:

- Prospecting: This stage consists of searching for rare earth element deposits.
- Exploitation: This stage consists of extracting rare earth elements from deposits.
- Concentration: This stage consists of the concentration of rare earth elements.
- Purification: This stage consists of the purification of rare earth elements.

The scarcity of deposits around the world in which it is profitable to extract these materials is a source of tensions between the central technology-producing countries.

This article aims to evaluate the implications of rare earth elements on the gross value added and break it down for primary, secondary and tertiary sectors. Also, it is expected that this analysis can evaluate the global potential of REE resources, evaluate the economic viability of current advanced REE projects, and analyze the medium- and long-term demand (2016–2030) for REEs from clean energy technologies. The relevance of this research is to establish a foundation to quantitatively analyze future opportunities, challenges, and constraints within the global REE supply chain and demand landscape.

This article follows the following structure. The introduction is followed by a theoretical framework that puts us in the situation of the current discussion in the scientific field, specifying its contribution to the three main sectors of the economy, the primary, secondary, and tertiary sectors.

The materials and methods are explained below, including data collection and the econometric model used, followed by the results obtained, the discussion, and conclusions. This study ends with the bibliographic references cited in the article.

1.1. Theoretical Framework

The 17 chemical elements that make up rare earth elements are Lanthanum (La), Cerium (Ce), Praseodymium (Pr), Neodymium (Nd), Promecium (Pm), Samarium (Sm), Eudimium (Eu), Gadolinium (Gd), Terbium (Tb), Dysprosium (Dy), Holmium (Ho), Erbium (Er), Thulium (Tm), Ytterbium (Yb), Lutecide (Lu), Scandium (Sc) and Yttrium (Y). These elements are found in the periodic table in group 3 and are characterized by their magnetic, optical, and catalytic properties [23].

Rare earth elements are crucial materials in electronics, optics, or magnetism and are currently irreplaceable. Small amounts of up to 16 or 17 components are usually present in our mobile phones, except for the average. In short, they are used in circuits, speakers, and screens in all device parts [24]. They are vital for electric vehicles and electronic devices, but we also find their use is transcendental in the weapons industry, such as in missile guidance systems, radar-invisible aircraft, or nuclear submarines [24]. This industry is currently on the rise due to the Russia–Ukraine conflict, Chinese rearmament, and the fear that the United States will lose its role in world hegemony [25].

The use of rare earth elements is not only used to take lives but also to save them. The role of these chemical elements is fundamental in medical applications. For example, they are found in contrast injections to see the functioning of an organ or an X-ray [26].

Scandium is a non-lanthanide rare earth element used to strengthen metal bonds. We can find it in low-consumption lights and modern televisions. Scandium, a valuable element used in applications, is typically difficult to extract [27]. This research explores a promising method for obtaining scandium from bauxite residue, a waste product from aluminum production. The technique utilizes high-pressure sulfuric acid leaching to achieve high yields of scandium while minimizing the extraction of iron and aluminum, which are also present in the residue [27,28].

Yttrium is a non-lanthanide rare earth element used in superconductors, pulsed light lasers, drugs in chemotherapy and rheumatoid arthritis treatment, and surgical supplies. It is also used in low-consumption light bulbs or camera lenses. Beyond traditional mining, lanthanides and yttrium can be extracted as valuable byproducts from processing other minerals [29]. These include apatite mining and uranium tailings. Notably, red mud, a waste product from the Bayer process for aluminum production, is enriched with lanthanides and yttrium. In Greece alone, 5 million tons of red mud are produced annually, and this material contains a significant concentration of these elements—exceeding 0.1% in total [29].

Lanthanum is used in the manufacturing of lenses for cameras and telescopes. It can also be used in wastewater treatment and oil refining. Lanthanum has a strong attraction to phosphate, binding it to form insoluble $LaPO_4$. This compound sinks to the bottom and cannot be absorbed by algae or aquatic plants. One major advantage of lanthanum is its effectiveness across various environmental conditions. Traditionally, aluminum (Al) or iron (Fe) were used for phosphorus control, but their success heavily depended on factors like water pH, oxygen levels, alkalinity, and the presence of other minerals and organic matter. Lanthanum's broader applicability makes it a more reliable solution [27,30].

Cerium is the most abundant rare earth element. It has many uses, including being used as a catalyst in catalytic converters in vehicle exhaust systems to reduce emissions. It is widely used to manufacture magnets and create alloys with iron, magnesium, and aluminum. Cerium (Ce), a member of the lanthanide group on the periodic table, made its debut in 1803. Discovered in its oxide form by researchers in both Sweden and Germany, the oxide was later named "ceria" by Swedish scientist Jons Jacob Berzelius [29,31].

Praseodymium is used in pigmentation for glass and gems and in the manufacturing of magnets. We can find it when creating high-strength metals, such as those used in aircraft engines [27]. Praseodymium stands out among the rare earth elements due to its unique ability to exist in multiple chemical states. This versatility translates to praseodymium-based catalysts excelling at both capturing and activating CO_2. Additionally, these catalysts boast superior stability compared to their copper and iron counterparts, making them a promising option for CO_2 conversion technologies [27]. The decrease in the size of electronic devices has been possible thanks to the magnetic properties of ytterbium and terbium.

Another element that is part of the rare earth elements group is neodymium. It is present on mobile phones or headphones, not only on those devices. It is a colorant in ceramic glazes and manufactures' welding glasses and lasers. Neodymium allows us, through alloys with boron and iron, to create a neodymium-iron-boron magnet, which is currently the most powerful magnet. The magnetic properties of rare earth elements make a high demand for them [32]. This magnet type represents one of the most powerful permanent magnets used in electric motors, vital for the transition toward electric vehicles (see Tables 1 and 2). In a couple of decades, more than a million electric vehicles are expected to be on the roads of the United States, increasing the demand for neodymium exponentially. Demand exceeds production by around 2 or 3 thousand tons annually. Neodymium is a strategically important resource and an essential element in modern societies. It is a key enabler of the energy transition due to its application in electric motors and wind turbines [33].

Table 1. Uses of rare earth elements (La, Ce, Pr, Nd, Pm, Sm, Eu, Gd, and Tb).

	La	Ce	Pr	Nd	Pm	Sm	Eu	Gd	Tb
Permanent Magnets	✗	✗	✗	✗		✗		✗	
Ceramics	✗	✗	✗	✗	✗	✗	✗	✗	✗
Batteries	✗	✗	✗	✗		✗		✗	
Construction Materials	✗	✗	✗	✗	✗		✗		✗
Lasers					✗		✗		✗
Aircraft Alloys									
Optical Glasses									
Catalysis									
Magnetism									

Note: "✗" are the different use of rare earth elements, according to the "World Production of Rare Earths" report by the United States Geological Survey [27].

Table 2 shows us the following rare earth elements.

Table 2. Uses of rare earth elements (Dy, Ho, Er, Tm, Yb, Lu, Sc, and Y).

	Dy	Ho	Er	Tm	Yb	Lu	Sc	Y
Permanent Magnets	✗							
Ceramics	✗	✗	✗	✗	✗	✗		
Batteries	✗							
Construction Materials		✗	✗	✗	✗	✗		
Lasers		✗	✗	✗	✗	✗		
Aircraft Alloys							✗	
Optical Glasses							✗	✗
Catalysis							✗	✗
Magnetism								✗

Note: "✗" are the different use of rare earth elements, according to the "World Production of Rare Earths" report by the United States Geological Survey [27].

According to the "World Production of Rare Earths" report by the United States Geological Survey [27], the central producing countries of rare earth elements in 2023 were the following (see Table 3).

Table 3. Countries producing or exploiting rare earth elements.

Country	Production (Metric Tons)
China	210,000
United States	43,000
Australia	18,000
Myanmar	12,000
Thailand	7100
Vietnam	4300
India	2900
Russia	2600
Madagascar	960
Brazil	80
Malaysia	80

China has been the leading producer of rare earth elements for decades, accounting for more than 69% of global production. The authors of [23] report that the United States is the second largest producer in the world (14%), followed by Australia (6%), Myanmar (4%), and Thailand (2%).

The production of rare earth elements has increased in recent years due to the increased demand for these elements to manufacture technological products. Demand for rare earth elements is expected to continue to rise in the coming years as technology develops and the global economy expands [34].

China's dependence on rare earth element production is a matter of growing concern. China has used its control of the rare earth element market as an instrument of political pressure. It has led to efforts to diversify the supply of rare earth elements and reduce dependence on China [25,26].

In recent years, significant investments have been made in rare earth elements exploration and development projects in countries outside of China. These projects aim to increase rare earth element production in these countries and reduce dependence on China [32].

However, diversifying the supply of rare earth elements is a complex and challenging process. Rare earth element deposits are relatively scarce and difficult to extract. Additionally, the mining and processing of rare earth elements can have a negative impact on the environment [22].

1.2. Contribution of Rare Earth Elements to the Sectors of the Economy

Rare earth elements significantly impact the primary sector, as they are used in various products and applications essential for agriculture, forestry, and fisheries. Among the main uses that are addressed in previous research are the following:

Neodymium is used to manufacture phosphate fertilizers, an important source of phosphorus for crops. Phosphorus is an essential nutrient for plant growth. Praseodymium is used to manufacture pesticides such as insecticides and fungicides. These pesticides control pests that attack crops [27,35].

Terbium is used to manufacture electric motors for agricultural machinery, such as tractors and combines. Electric motors are more efficient than internal combustion engines and produce fewer polluting emissions [29,36].

Gadolinium manufactures sensors for forestry equipment, such as distance and motion sensors. These sensors are used to monitor the operation of forestry equipment. Dysprosium is used to manufacture some pesticides, such as insecticides and fungicides [27,37].

These pesticides are used to control pests that attack forests. Erbium is used to manufacture wood products such as furniture and construction boards. These wood products are used in construction and furniture. Thulium is used to manufacture electric motors for fishing equipment such as boats and nets. Electric motors are more efficient than internal combustion engines and produce fewer polluting emissions [29].

Yttrium is used to manufacture navigation instruments, such as Global Positioning Systems (GPSs). These instruments are used to navigate the sea. Scandium is used in the manufacture of fileting machines for fish processing. These machines cut fish into filets [27,38].

Rare earth elements are the invisible raw materials that power many of the technologies that shape our world. Their unique properties drive innovation and enable the development of a more sustainable future and a modern manufacturing industry [39]. Their main uses include the following:

Neodymium is the element most used in the manufacturing of permanent magnets. These magnets are used in various applications, such as electric motors for automobiles, hard drives for computers, and speakers for audio equipment [40].

Cerium is used as a catalyst in the production of sulfuric acid, an important chemical used in a wide range of applications, such as fertilizers, detergents, and batteries [41].

Yttrium is used in the manufacturing of optical glasses for lenses and filters. These lenses are used in cameras, telescopes, glasses, and other optical devices. Scandium is used in alloys with aluminum to improve its strength and ductility. These alloys are used to manufacture airplanes, automobiles, ships, and other structures [39].

The main applications to the third sector of the economy include the following:

Neodymium is used to manufacture permanent magnets for electric motors in mobile phones, computers, and televisions. Gadolinium is used to manufacture MRI contrast agents, which are used to diagnose diseases [42].

Dysprosium is used to manufacture permanent magnets for wind turbines, essential for renewable energy generation. Terbium is used to manufacture electric motors for electric vehicles, which are more efficient and produce fewer polluting emissions than internal combustion vehicles. Yttrium is used in the manufacturing of missiles, which are used by armies to attack targets [43].

2. Materials and Methods

The research objectives are met by applying the following methodology and verifying the empirical assumptions analyzed for the object of study.

2.1. Data Source and Variables

The data were obtained from the Rare Earth Statistics and Information issued by the National Minerals Information Center. This information is regulated by the U.S. Geological Survey acts as the scientific arm of the Department of the Interior, providing up-to-date scientific information relevant to an ever-changing world. It responds to society's evolving needs by offering a wide range of data and expertise in geology, water, biology and cartography. This information supports decision-making on environmental, resource, and public safety issues in the United States [44].

The reports were reviewed and the information was extracted from the Mineral Commodity Summaries and Minerals Yearbook from 1990 to 2022, thus providing 33 observations. The prices of the leading rare earth elements and the gross value added to the primary (agricultural), secondary (manufacturing), and tertiary (services) sectors of the United States of America were extracted (see Table 4).

The trade restriction variable was a dummy variable where 0 was used for the years in which there were no restrictions and 1 was used for the year's corresponding to the restrictions initially imposed by the administration of President Donald Trump.

Table 4. Model variables.

Symbology	Variable	Measurement	Variable Type
Y_1	Primary Gross Added Value	Log (% Total GDP)	Explained-Endogenous
Y_2	Secondary Gross Added Value	Log (% Total GDP)	Explained-Endogenous
Y_3	Tertiary Gross Added Value	Log (% Total GDP)	Explained-Endogenous
X_1	Rare earth elements' exploitation	Log (Metric Tons)	Explanatory-Exogenous
X_2	Employment generated by rare earth elements	Log (Annual average)	Explanatory-Exogenous
X_3	Domestic consumption of rare earth elements	Log (Metric Tons)	Explanatory-Exogenous
X_4	Import of rare earth elements	Log (Metric Tons)	Explanatory-Exogenous
X_5	Dysprosium	Log (Average Price)	Explanatory-Exogenous
X_6	Europium	Log (Average Price)	Explanatory-Exogenous
X_7	Neodymium	Log (Average Price)	Explanatory-Exogenous
X_8	Terbium	Log (Average Price)	Explanatory-Exogenous
X_9	Trade restriction	Dummy	Explanatory-Exogenous

The data for this study were processed using JASP v.0.17.2.1 [45], a comprehensive and user-friendly statistical software package developed by the JASP Team at the University of Amsterdam. JASP offers a wide range of statistical analyses suitable for various research designs, from basic descriptive statistics to complex modeling techniques. In this study, we utilized JASP version 0.17.2.1, which incorporates the latest advancements and bug fixes to ensure the accuracy and reliability of our statistical analyses.

JASP is used because it uniquely offers both Bayesian and Frequentist statical approaches, allowing users to compare and contrast results from different perspectives and gain a more comprehensive understanding of their data. This flexibility is particularly valuable in fields where both approaches are prevalent.

Figure 1 shows the behavior over time of the gross value added to each sector of the economy. It can be seen that the primary GVA is maintained over time, while the manufacturing sector has a slight decrease and in the case of the tertiary sector, an increase is seen.

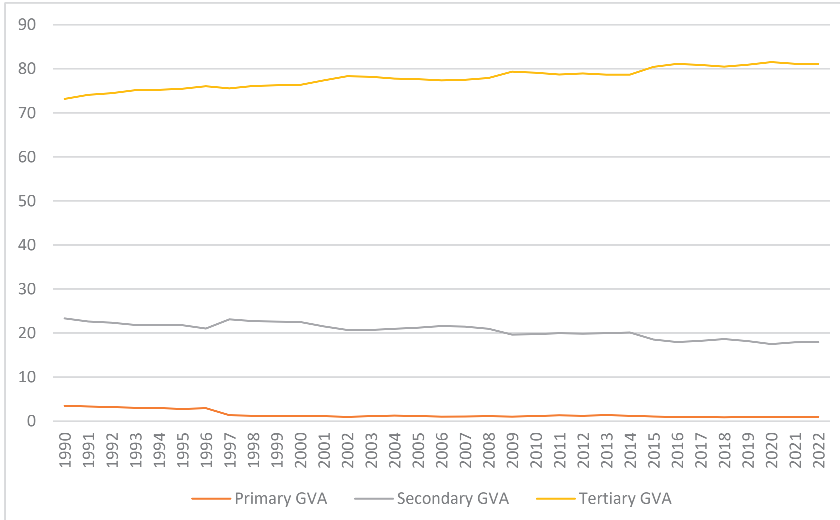

Figure 1. GVA sector.

Figure 2 shows the behavior of the rare earth element industry from exploitation to consumption or export, depending on the case. It can be seen that both the exploitation of rare earth elements and their exportation have a structural upward trend in the last seven years.

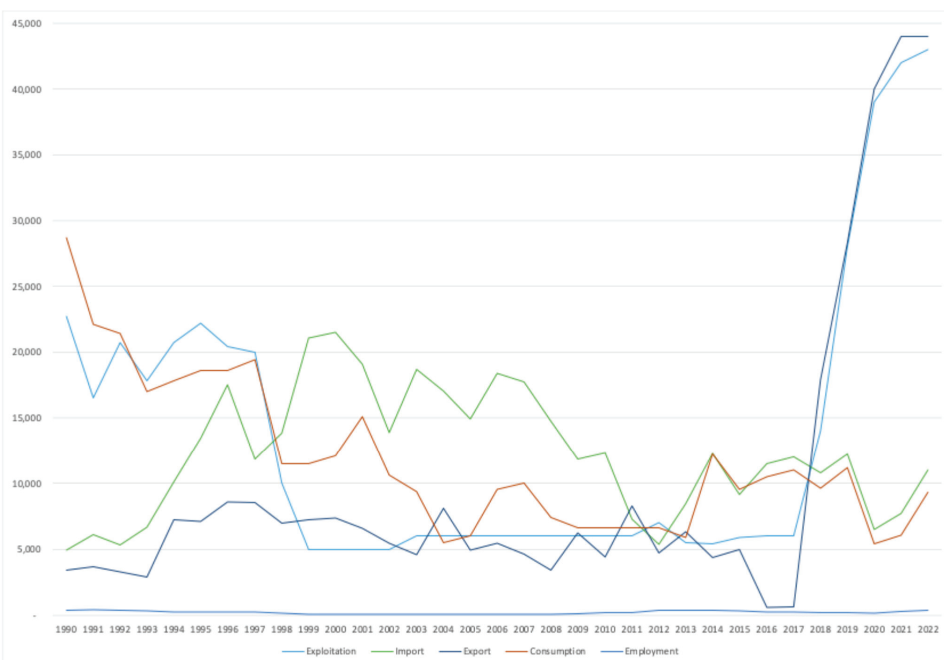

Figure 2. Rare earth elements' market behavior.

In Figure 3, you can see the prices of rare earth elements over time. It can be seen that the prices decreased in the nineties, but in recent years they have been on the rise.

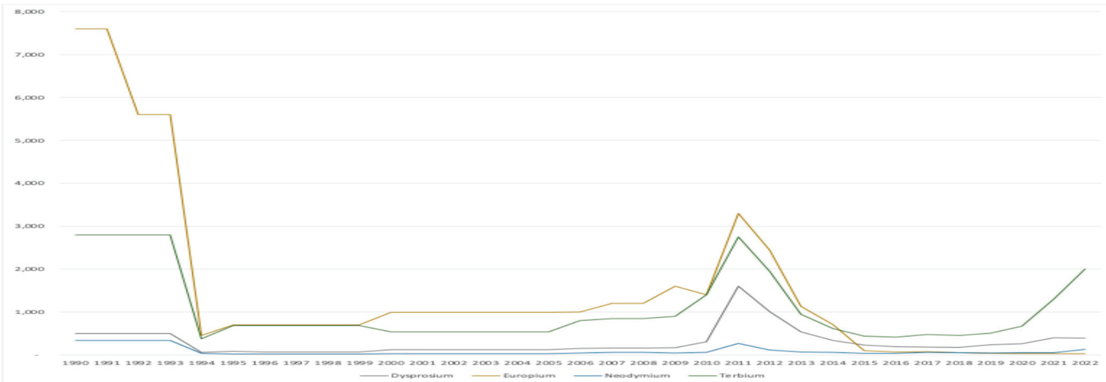

Figure 3. Dysprosium, Europium, Neodymium, and Terbium prices.

2.2. Econometric Model

The econometric model meets the article's objective to analyze the contribution of various factors in the gross value added to the economic sectors in agriculture, manufacturing, and services. The mathematical expression of the model is shown in Equation (1).

$$Y_t = f(X_1, X_2, \ldots X_n) \quad (1)$$

where Y_t represents an endogenous or explained variable, while the X_n are the variables that indicate the explanatory or exogenous factors.

Consequently, to correctly explain the empirical content, three models are proposed that are expressed in Equations (2)–(4).

$$Y_1 = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + \mu_i \quad (2)$$

$$Y_2 = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + \mu_i \quad (3)$$

$$Y_3 = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + \mu_i \quad (4)$$

where each model represents each economic sector of the economy of the United States of America. Now, the term disturbance or random error is μ_i. This term groups all the variables not included in the model but can explain the object of study [46]. Each b_n represents the explanatory variables described in Table 4.

3. Results

Table 5 shows the description of the variables and their main statistics. It allows us to analyze the absence of outliers and evaluate the normality of the data and the number of observations.

Table 5. Descriptive statistics.

Variable	N	Mean	SE
Primary GVA (Y_1)	33	0.304	0.078
Secondary GVA (Y_2)	33	3.020	0.015
Tertiary GVA (Y_3)	33	4.355	0.005
Exploitation (X_1)	33	9.232	0.127
Employment (X_2)	33	5.270	0.101

Table 5. *Cont.*

Variable	N	Mean	SE
Consumption (X_3)	33	9.272	0.079
Import (X_4)	33	9.335	0.073
Dysprosium (X_5)	33	5.313	0.144
Europium (X_6)	33	6.410	0.285
Neodymium (X_7)	33	4.031	0.152
Terbium (X_8)	33	6.755	0.112
Trade restriction (X_9)	33	0.152	0.364

Table 6 shows the coefficients of the models explained in the Materials and Methods, with the standard deviation and the plausible significance of the variable in the models in parentheses. The latter is represented as a measure of probability that the coefficient of the variables is different from zero. For this, the significance is represented when it is less than 0.00 with (***) and 0.05 with (**).

Table 6. Model coefficients.

Variable	Model 1 (Y_1)	Model 2 (Y_2)	Model 3 (Y_3)
Intercept	−3.896 (0.823) ***	1.854 (0.357) ***	4.678 (0.039) **
Exploitation (X_1)	0.346 (0.077) ***	0.021 (0.014) **	
Employment (X_2)	0.302 (0.075) ***		
Consumption (X_3)		0.061 (0.017) ***	−0.028 (0.005) ***
Import (X_4)		0.032 (0.027) **	
Dysprosium (X_5)	−0.211 (0.092) ***		0.013 (0.004) ***
Europium (X_6)	0.281 (0.086) ***	0.034 (0.019) ***	−0.007 (0.004) ***
Neodymium (X_7)	0.196 (0.115) ***	−0.022 (0.015) ***	
Terbium (X_8)	−0.307 (0.129) ***		−0.013 (0.005) ***
Trade restriction (X_9)	0.088 (0.085) *	0.045 (0.058) **	0.012 (0.013) ***

Note: *, **, *** are the significance levels of 10%, 5% and 1% or less respectively.

Table 7 shows the additional adjustments to validate the model, showing acceptable collinearity indices. The last two adjustments were made to verify that the models do not present problems in which two or more variables are highly correlated.

Table 7. Models' goodness of fit.

Fit	Model 1 (Y_1)	Model 2 (Y_2)	Model 3 (Y_3)
R^2	0.896	0.884	0.919
RMSE	0.161	0.032	0.009
Tolerance (Colinearity)	***	***	***
VIF (Colinearity)	***	***	***

Note: *** is the significance level of 1% or less.

The models meet the statistical parameters and assumptions of the variables' linearity, exogeneity, homoscedasticity, normality, and independence.

This plot compares the quantiles (percentiles) of two datasets. In this case, one dataset represents the quantiles of your standardized residuals, and the other represents the quantiles of a theoretical normal distribution.

For the specified model 1, the Q–Q plot of standardized residuals presents strong evidence supporting the normality of the distribution of the residuals. The points on the graph are aligned approximately along a straight diagonal line, indicating a notable similarity between the observed distribution of standardized residuals and a theoretical normal distribution (see Figure 4).

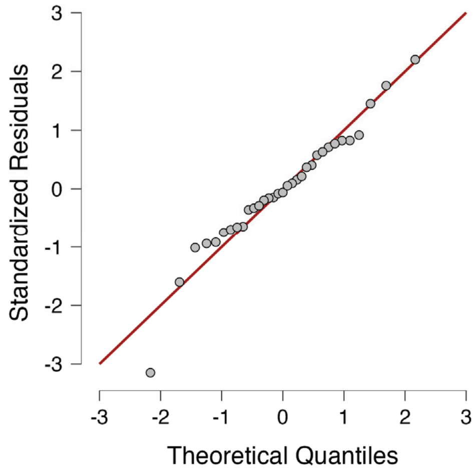

Figure 4. Q–Q plot of standardized residuals for Model 1.

Importantly, no curved patterns or significant deviations from the diagonal line are observed in the Q–Q chart. This reinforces the idea that there is no evidence to suggest a non-normal distribution of the residuals (see Figure 5).

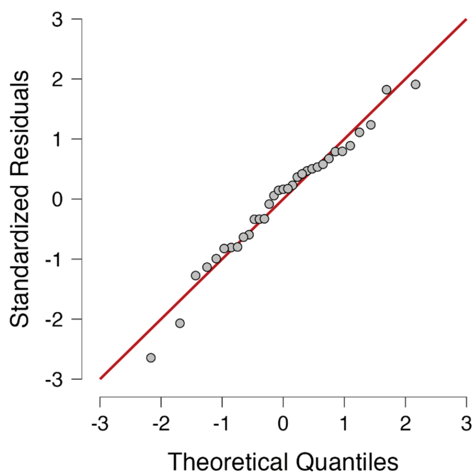

Figure 5. Q–Q plot of standardized residuals for Model 2.

Based on the evidence provided by the Q–Q plot, we can analyze that the residuals of the specified model follow a normal distribution (see Figure 6). This conclusion has important implications for the reliability of the statistical analysis performed.

The plot of residuals versus predicted values for the specified model provides strong evidence supporting the adequacy of model fit. In this graph, the points are randomly distributed around a horizontal line in the center, exhibiting no discernible patterns. This random distribution suggests that the model effectively captures the relationship between the dependent and independent variables and that there are no significant violations of the assumptions of the linear regression model (see Figure 7).

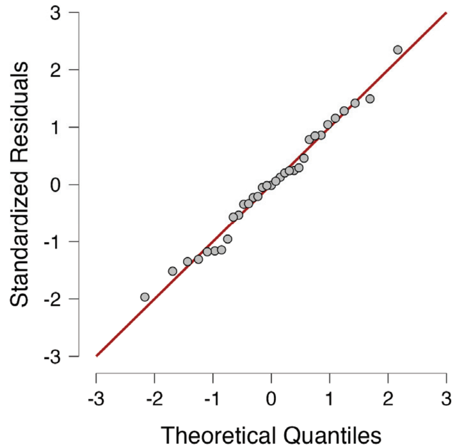

Figure 6. Q–Q Plot Standardized Residuals Model 3.

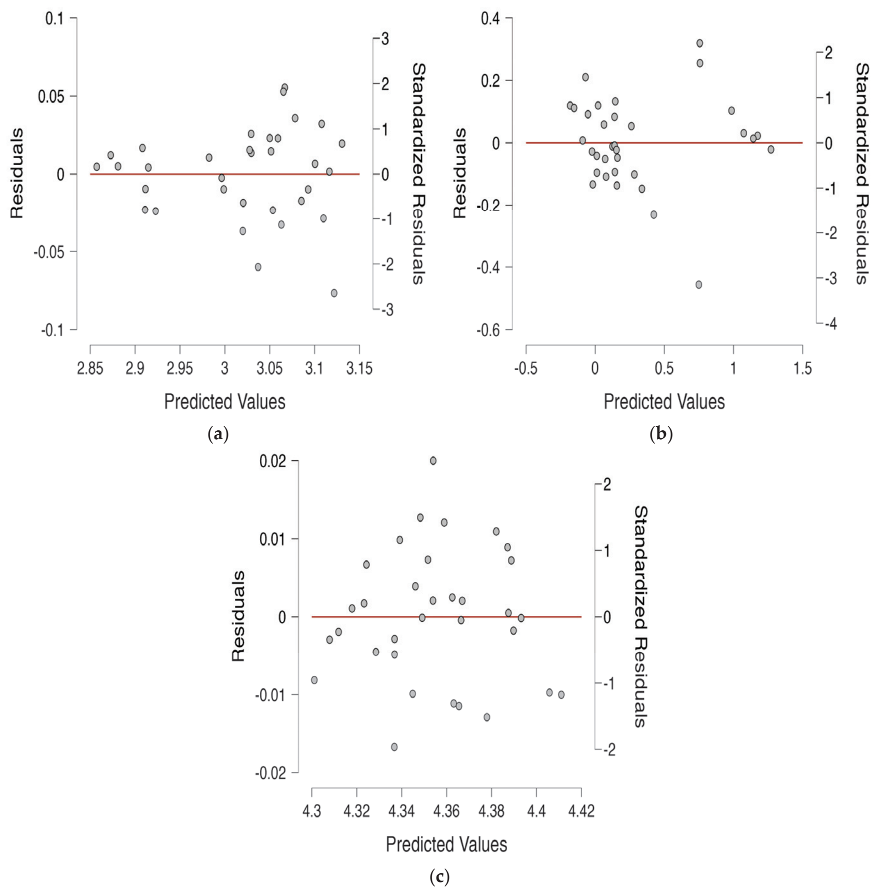

Figure 7. Plot of residuals vs. predicted values. (**a**) Model 1, (**b**) Model 2, (**c**) Model 3.

The plot of residuals vs. predicted values provides compelling evidence that the specified model adequately fits the data. The random distribution of residuals supports the validity of the model assumptions, strengthening confidence in the predictions, inferences, and interpretations obtained from the analysis. This graphical analysis complements the evaluation of the model and contributes to the robustness of the conclusions derived from the study.

4. Discussion

This study employed an econometric model to systematically investigate the influence of various factors on the gross value added (GVA) to the agricultural, manufacturing, and service sectors in the United States. The model's findings unveil statistically significant impacts of rare earth element (REE) exploitation, utilization, domestic consumption, imports, and the prices of specific REEs (e.g., Dysprosium, Europium, Neodymium) on sectoral GVA. These results corroborate prior research highlighting the pivotal role of REEs in modern economies, stemming from their extensive application in technological advancements [26,46]. Notably, the control variable representing restrictions on REE trade suggests a stronger influence of REEs on the primary (agricultural) sector compared to the manufacturing sector. This aligns with prevailing concerns regarding overreliance on a single source, particularly China's dominant position in REE production and consumption [47,48]. While potential alternatives to mitigate this concentration are acknowledged, long-term monitoring and evaluation are imperative to assess their effectiveness and implications.

The econometric analysis extends beyond the manufacturing sector, revealing that REEs exert a pervasive influence across the primary and service sectors as well. Their diverse applications in agricultural practices, manufacturing processes, and various service industries underscore the multifaceted economic importance of REEs [49,50]. However, the model also sheds light on the challenges associated with REE extraction and processing, including their complex and costly nature [51,52]. These factors, coupled with the projected surge in REE demand [53], necessitate the development of robust strategies to address the sustainability and security of supply concerns. Ensuring a stable and sustainable supply of these critical elements is paramount for fostering long-term economy growth, resilience, and environmental stewardship.

The findings of this study have significant implications for policymakers, industry leaders, and researchers engaged in the sustainable management of REE resources. Policymakers can leverage the study's insights to formulate informed policies that promote the efficient and environmentally responsible utilization of REEs while mitigating the risks associated with overreliance on a single supplier. Industry leaders can utilize the research findings to guide their strategic decision-making processes, ensuring the sustainable sourcing, processing, and application of REEs throughout their value chains. Researchers can build upon the study's methodology and findings to further investigate the intricate dynamics between REEs, economic development, and environmental sustainability.

The study's contributions extend beyond the realm of resource economics, offering valuable insights for broader economic discourse. The identification of REEs as critical factors influencing sectoral GVA highlights the interconnectedness of modern economies and the need for holistic approaches to economic development. Moreover, the study underscores the importance of considering environmental and social sustainability dimensions alongside economic growth objectives. By recognizing the multifaceted impacts of REE utilization, policymakers and industry leaders can strive for a more sustainable and equitable distribution of the benefits associated with these critical resources.

Future research directions can further enhance our understanding of the complex relationship between REEs, economic development, and sustainability. One avenue for exploration lies in conducting comparative studies across different countries and regions to identify factors that influence the effectiveness of REE-related policies and practices. Additionally, in-depth analyses of specific REE-intensive industries can provide granular insights into the economic and environmental implications of REE utilization. Furthermore, research examining the potential for substitution of REEs with alternative materials can inform strategies for reducing reliance on these critical resources.

This study unveils the profound influence of rare earth elements on the gross value added of various economic sectors, highlighting their critical role in modern economies. The findings underscore the need for comprehensive strategies that promote the sustainable and responsible management of REE resources, ensuring a balance between economic growth, environmental stewardship, and social equity. By fostering international collaboration and research, we can collectively navigate the challenges and opportunities presented by these critical elements, shaping a more sustainable and resilient future for all.

5. Conclusions

The econometric analysis conducted in this study has demonstrated the importance of rare earth elements in the agricultural, manufacturing, and service economic sectors in the United States. It has been identified that factors such as the exploitation of rare earth elements, the employment they generate, domestic consumption, imports, and the prices of these elements significantly impact the economy. The concentration of rare earth element production and consumption in China poses challenges regarding dependence on other countries and the security of supply.

Furthermore, it has been highlighted that rare earth elements are essential for manufacturing technological products and have a transversal impact on the economy's primary, secondary, and tertiary sectors. Mining and processing rare earth elements are complex and expensive, underscoring the importance of addressing the sustainability and security of supply issues.

In this sense, it is essential to properly understand and manage the impact of rare earth elements on the economy to promote sustainable and resilient economic development. Special attention is required to diversify supply sources, innovate extraction and processing technologies, and promote sustainable practices using these essential elements. Additionally, it is recommended to analyze the behavior of the price of Terbium since this harms the primary and tertiary sectors.

Although the findings are important for future research, it should be mentioned that they also have limitations. Among the limitations of this study are the data and the potential for biases or missing information related to the temporal dimension.

For future research, the long-term analysis and evaluation of public policies aimed at the exploitation of rare earth elements, and the research and development of products made using these elements should be considered. Likewise, it is recommended to analyze panel data with information from other producing countries and thus take advantage of the temporal nature of the variables.

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Data Availability Statement: The database is available in the Helvia repository of the Universidad de Córdoba at http://hdl.handle.net/10396/27658, accessed on 1 January 2024.

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

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