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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.

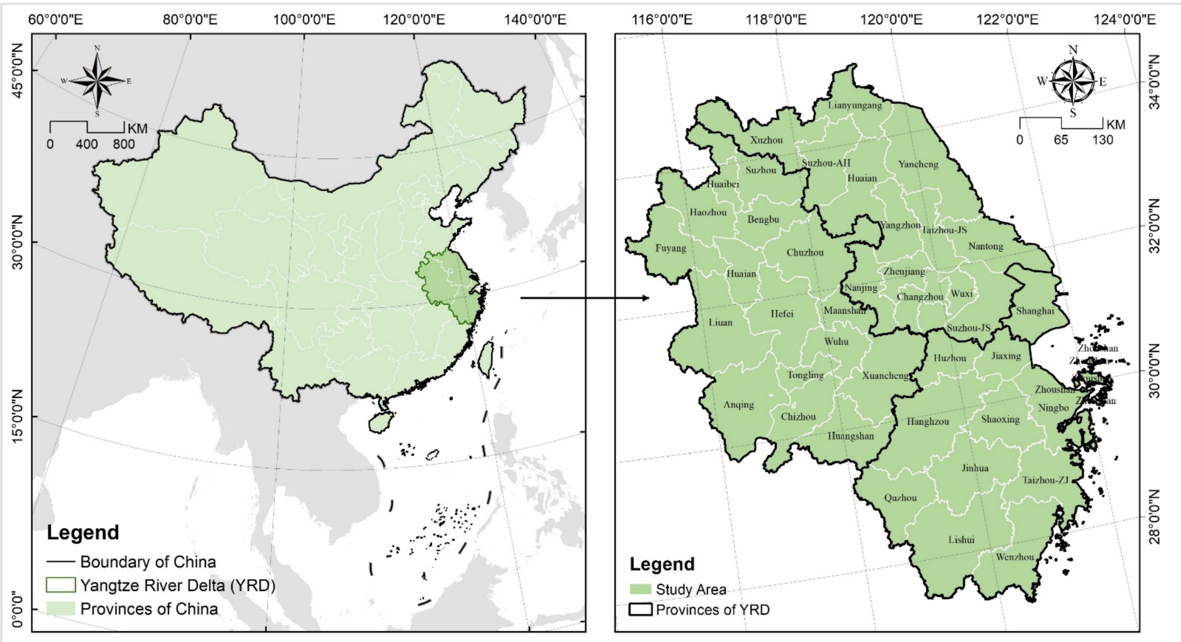

Figure 1. Study area.

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).

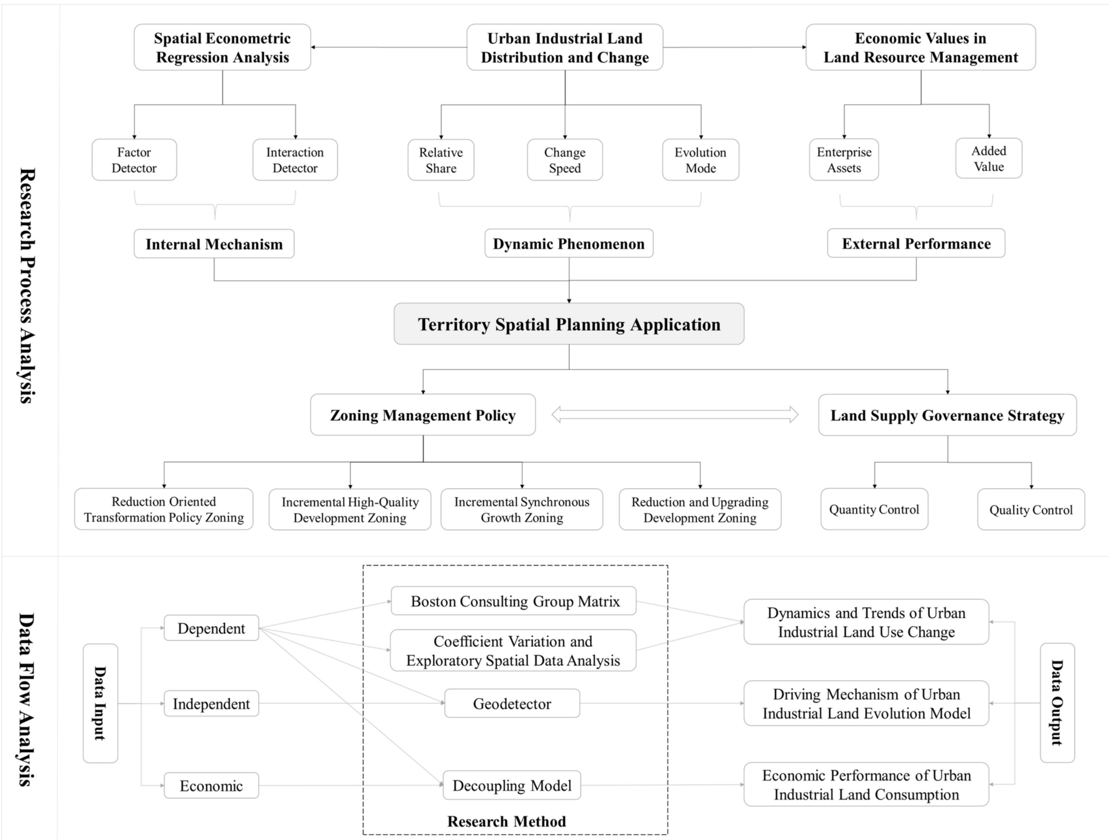

Figure 2. Research steps and technical route.

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]:

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

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

Table 2. Decoupling type and decoupling indicator range.

State	*RS*	*CS*	Characteristic	Future Alternative Strategies
Star-cities	$\frac{\geq}{RS}$	$\frac{\geq}{CS}$	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	$\frac{\geq}{RS}$	$\frac{<}{CS}$	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	$\frac{<}{RS}$	$\frac{\geq}{CS}$	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	$\frac{<}{RS}$	$\frac{<}{CS}$	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]:

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

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].

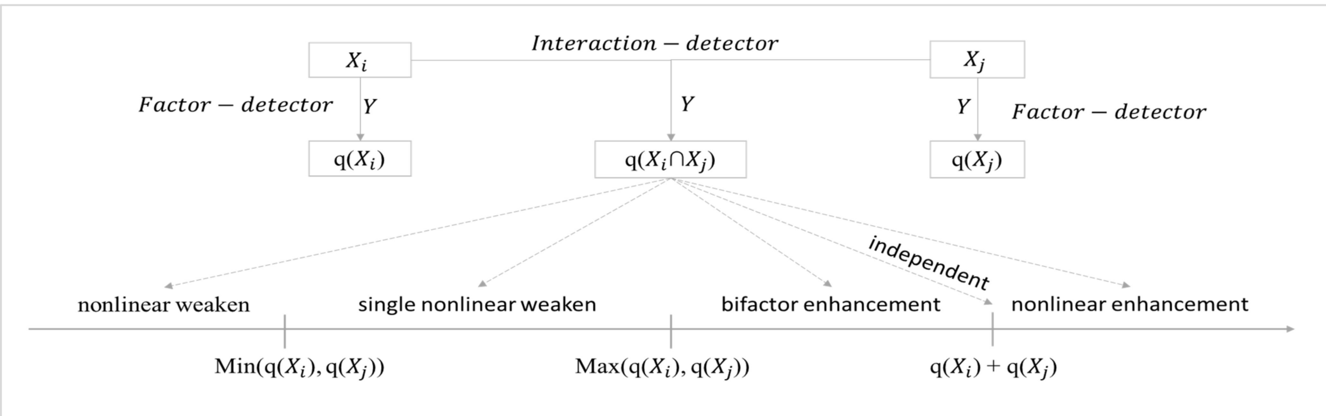

Figure 3. Analysis on the interaction between factors.

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, +∞)	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, +∞)	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.

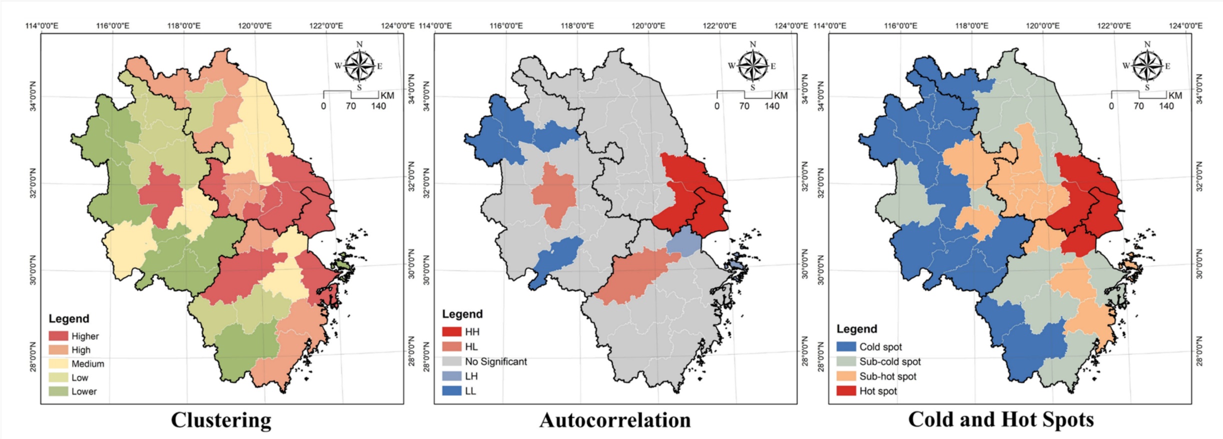

Figure 4. Spatial analysis of the relative share in 2010–2014.

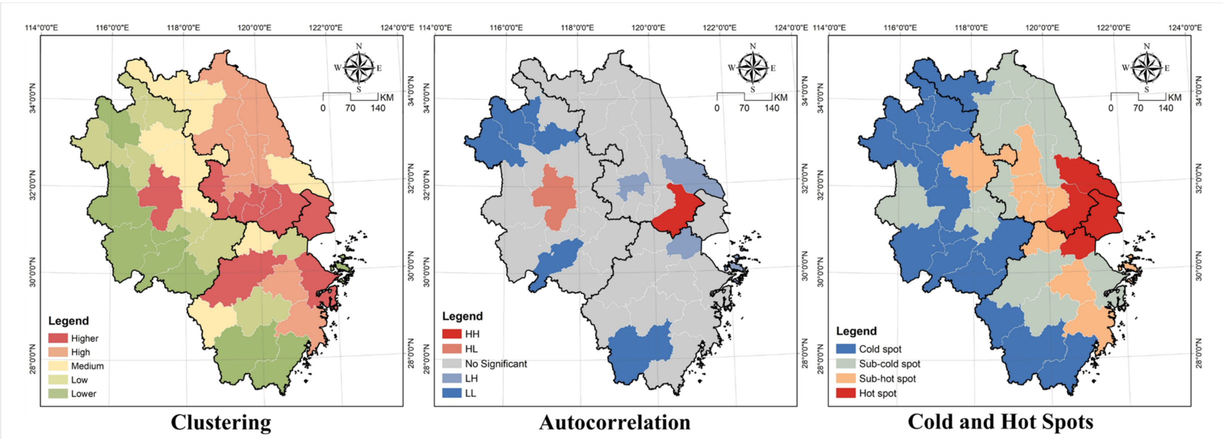

Figure 5. Spatial analysis of the relative share in 2015–2019.

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.

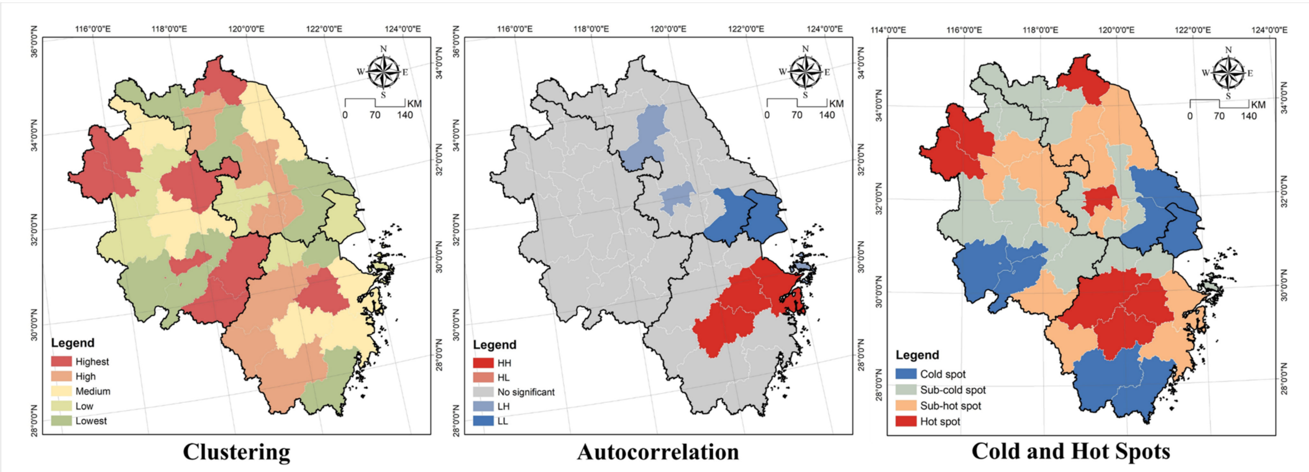

Figure 6. Spatial analysis of the change speed in 2010–2014.

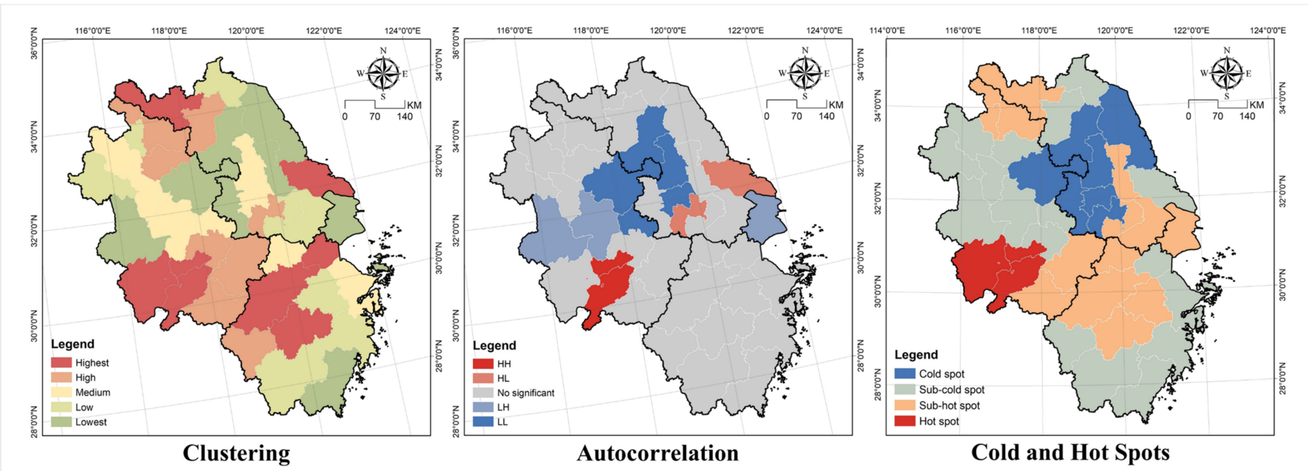

Figure 7. Spatial analysis of the change speed in 2015–2019.

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).

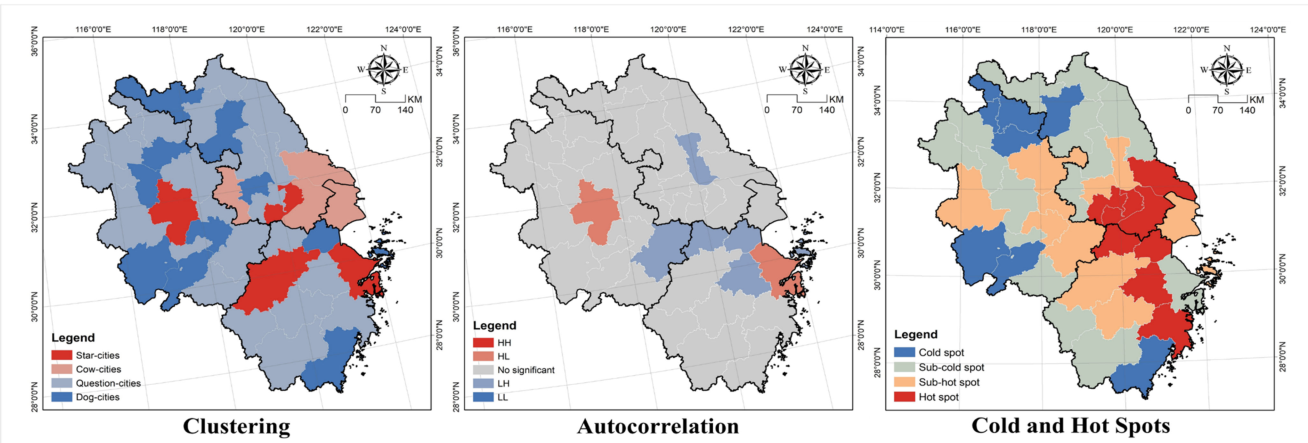

Figure 8. Spatial analysis of the evolution mode in 2010–2014.

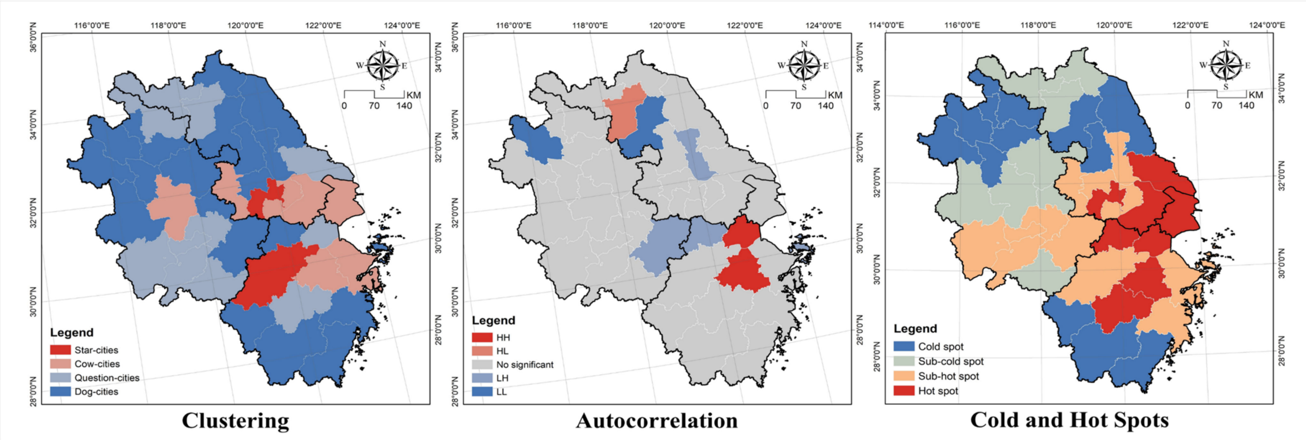

Figure 9. Spatial analysis of the evolution mode in 2015–2019.

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	0.74	0.53	0.71	0.44								
X_5	0.38	0.38	0.41	0.47	0.09							
X_6	0.49	0.47	0.74	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	0.75	0.54	0.46	0.50	0.38	0.65	0.56	0.58	0.35			
X_{10}	0.74	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	0.82	0.60										
X_3	0.73	0.81	0.57									
X_4	0.57	0.81	0.74	0.55								
X_5	0.64	0.81	0.73	0.63	0.31							
X_6	0.64	0.80	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	**0.84**	0.77	0.81	0.83	0.79	0.81	0.75	0.64				
X_9	0.59	0.81	0.78	0.61	0.65	0.65	0.56	**0.84**	0.44			
X_{10}	0.82	0.74	**0.84**	0.81	0.71	0.80	0.78	0.69	**0.84**	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	0.81	0.73	0.56	0.62	0.60	0.61	**0.84**	0.60	0.81	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.

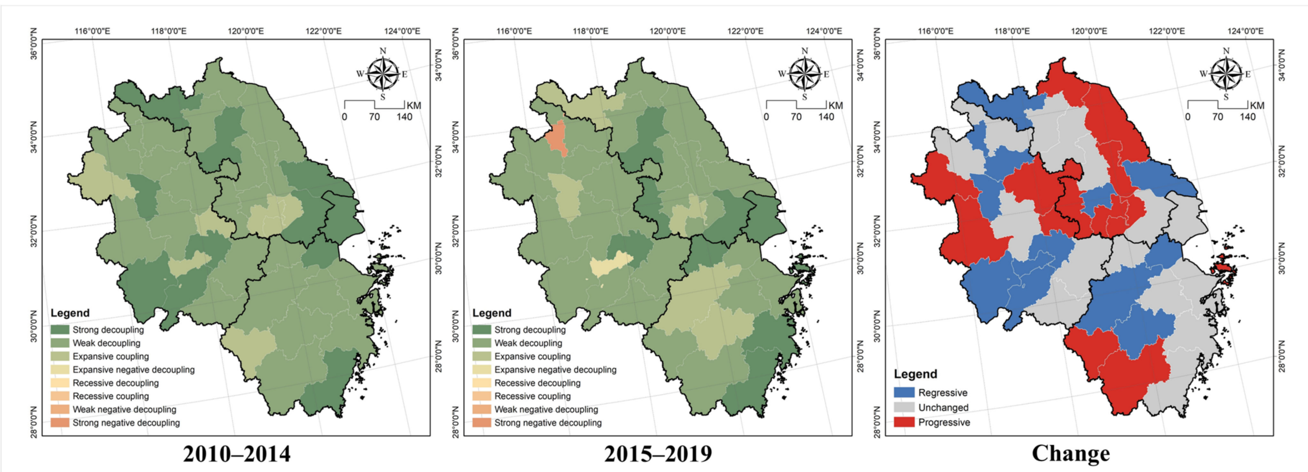

Figure 10. Spatial analysis of the decoupling relationship between urban industrial land and added value in Yangtze River Delta.

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).

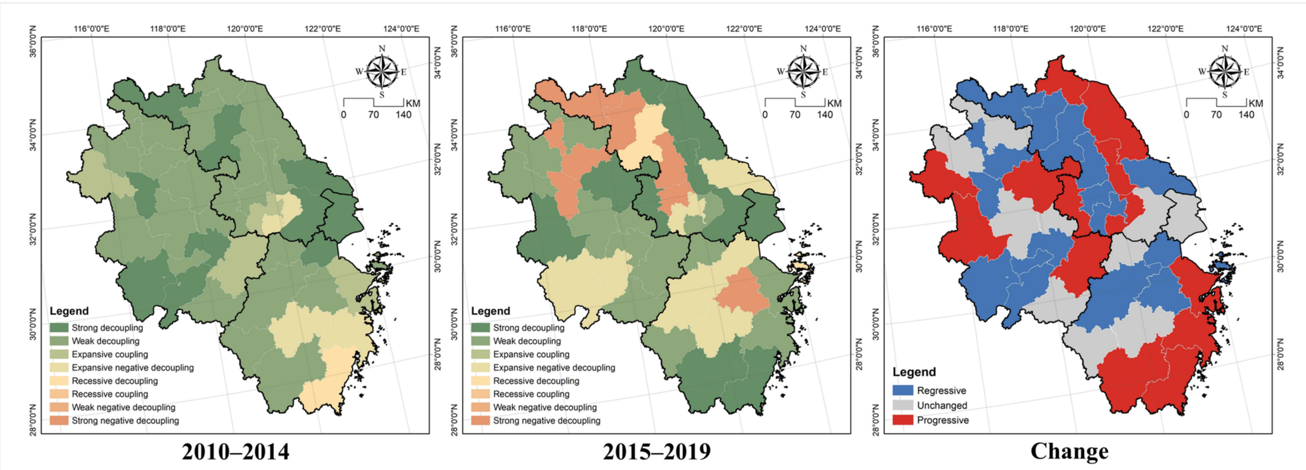

Figure 11. Spatial analysis of the decoupling relationship between urban industrial land and enterprise assets in Yangtze River Delta.

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).

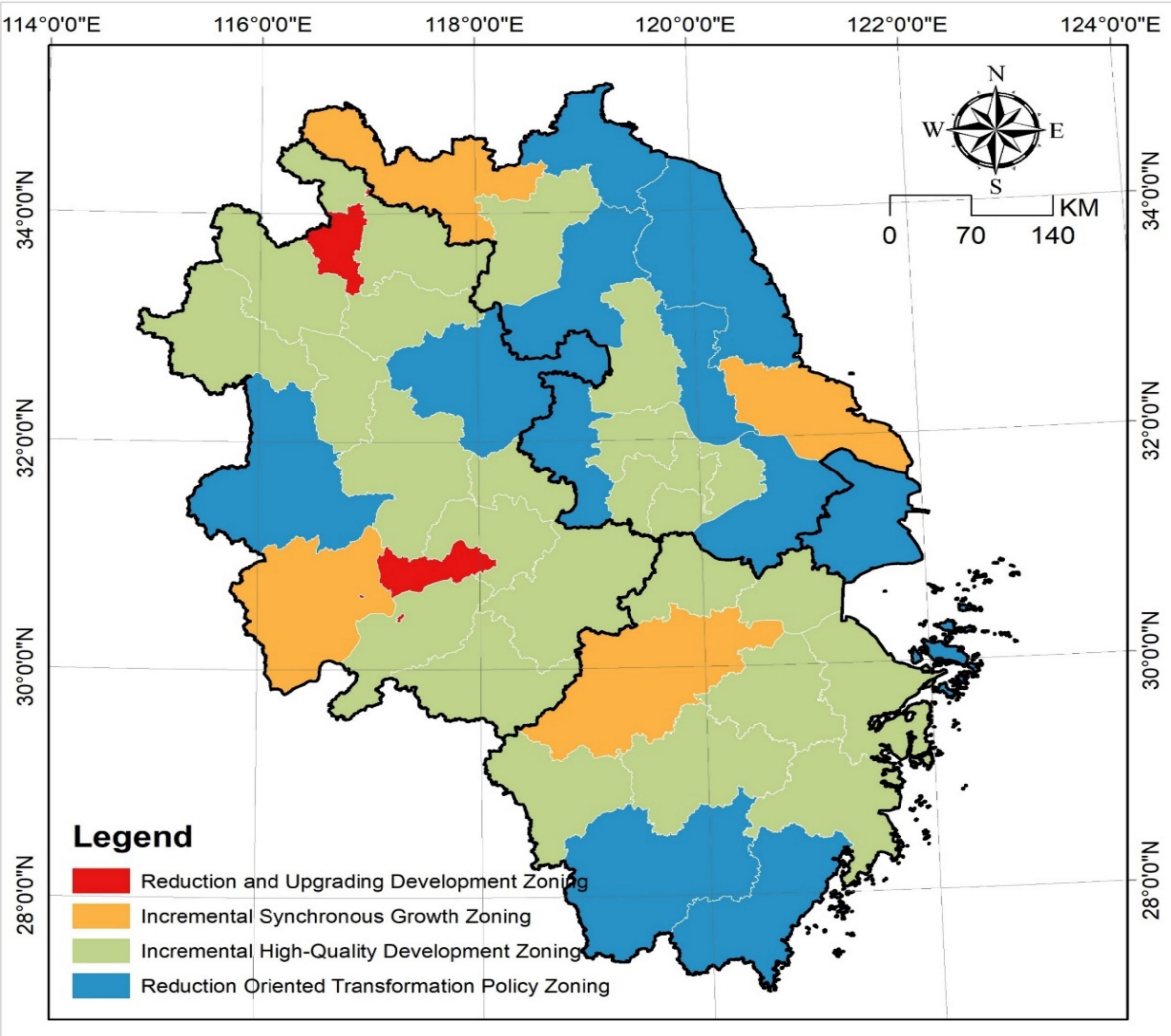

Figure 12. Analysis on the zoning management in Yangtze River Delta.

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

References

1. Louw, E.; Bontekoning, Y. Planning of industrial land in the Netherlands: Its rationales and consequences. *Tijdschr. Voor Econo-Mische En Soc. Geogr.* **2007**, *98*, 121–129. [CrossRef]
2. Roost, F.; Jeckel, E. Post-Fordist Production and Urban Industrial Land Use Patterns. *Urban Plan.* **2021**, *6*, 321–333. [CrossRef]
3. Funderburg, R.G.; Zhou, X.X. Trading industry clusters amid the legacy of industrial land-use planning in southern California. *Environ. Plan. A—Econ. Space* **2014**, *45*, 2752–2770. [CrossRef]
4. Mavrakis, A.; Papavasileiou, C.; Salvati, L. Towards (Un)sustainable urban growth? Industrial development, land-use, soil depletion and climate aridity in a Greek agro-forest area. *J. Arid. Environ.* **2015**, *121*, 1–6. [CrossRef]
5. Huang, Z.J.; He, C.F.; Li, H. Local government intervention, firm-government connection, and industrial land expansion in China. *J. Urban Aff.* **2019**, *41*, 206–222. [CrossRef]
6. Tu, F.; Yu, X.F.; Ruan, J.Q. Industrial land use efficiency under government intervention: Evidence from Hangzhou, China. *Habitat Int.* **2014**, *43*, 1–10. [CrossRef]
7. Zhou, L.; Tian, L.; Gao, Y.; Ling, Y.K.; Fan, C.J.; Hou, D.Y.; Shen, T.Y.; Zhou, W.T. How did industrial land supply respond to transitions in state strategy? An analysis of prefecture-level cities in China from 2007 to 2016. *Land Use Policy* **2019**, *87*, 104009. [CrossRef]
8. Song, M.L.; Wang, S.H.; Wu, K.Y. Environment-biased technological progress and industrial land-use efficiency in China’s new normal. *Ann. Oper. Res.* **2018**, *268*, 425–440. [CrossRef]
9. Busscher, N.; Parra, C.; Vanclay, F. Environmental justice implications of land grabbing for industrial agriculture and forestry in Argentina. *J. Environ. Plan. Manag.* **2019**, *63*, 500–522. [CrossRef]
10. Abel, T.D.; White, J.; Clauson, S. Risky Business: Sustainability and Industrial Land Use across Seattle’s Gentrifying Riskscape. *Sustainability* **2015**, *7*, 15718–15753. [CrossRef]
11. Egidi, G.; Cividino, S.; Quaranta, G.; Alhuseen, A.; Salvati, L. Land mismatches, urban growth and spatial planning: A contribution to metropolitan sustainability. *Environ. Impact Assess. Rev.* **2020**, *84*, 106439. [CrossRef]
12. Wang, Z.S.; Zhao, J.; Lin, S.J.; Liu, Y. Identification of Industrial Land Parcels and Its Implications for Environmental Risk Management in the Beijing-Tianjin-Hebei Urban Agglomeration. *Sustainability* **2020**, *12*, 174. [CrossRef]
13. Kapungwe, E.M. Industrial land use and heavy metal contaminated wastewater used for irrigation in periurban Zambia. *Singap. J. Trop. Geogr.* **2011**, *32*, 71–84. [CrossRef]

14. Tang, B.; Winky, K. Land-use planning and market adjustment under de-industrialization: Restructuring of industrial space in Hong Kong. *Land Use Policy* **2015**, *43*, 28–36. [CrossRef]
15. Zhou, L.; Tian, L.; Cao, Y.D.; Yang, L.C. Industrial land supply at different technological intensities and its contribution to economic growth in China: A case study of the Beijing-Tianjin-Hebei region. *Land Use Policy* **2021**, *101*, 105087. [CrossRef]
16. Gao, J.B.; Qiao, W.F.; Ji, Q.Q.; Yu, C.; Sun, J.W.; Ma, Z.F. Intensive-use-oriented identification and optimization of industrial land readjustment during transformation and development: A case study of Huai'an, China. *Habitat Int.* **2021**, *118*, 102451. [CrossRef]
17. Zambon, I.; Cerda, A.; Gambella, F.; Egidi, G.; Salvati, L. Industrial Sprawl and Residential Housing: Exploring the Interplay between Local Development and Land-Use Change in the Valencian Community, Spain. *Land* **2019**, *8*, 143. [CrossRef]
18. Debela, D.D.; Stellmacher, T.; Azadi, H.; Kelboro, G.; Lebailly, P.; Ghorbani, M. The Impact of Industrial Investments on Land Use and Smallholder Farmers' Livelihoods in Ethiopia. *Land Use Policy* **2021**, *99*, 105091. [CrossRef]
19. Xiong, C.; Lu, J.Y.; Niu, F.Q. Urban Industrial Land Expansion and Its Influencing Factors in Shunde: 1995–2017. *Complexity* **2020**, *2020*, 6769176. [CrossRef]
20. Park, J.I.; Leigh, N.G. Urban Industrial Land Loss and Foreign Direct Investment-Related Manufacturing Job Sprawl: An Atlanta, Georgia MSA Case Study. *J. Urban Technol.* **2017**, *24*, 95–113. [CrossRef]
21. Zhang, L.L.; Yue, W.Z.; Liu, Y.; Fan, P.L.; Wei, Y.H.D. Suburban industrial land development in transitional China: Spatial restructuring and determinants. *Cities* **2018**, *78*, 96–107. [CrossRef]
22. Ustaoglu, E.; Lavalle, C. Examining lag effects between industrial land development and regional economic changes: The Netherlands experience. *PLoS ONE* **2017**, *12*, e0183285. [CrossRef]
23. Villarroya, A.; Puig, J. Urban and Industrial Land-Use Changes Alongside Motorways within the Pyrenean Area of Navarre, Spain. *Environ. Eng. Manag. J.* **2012**, *11*, 1213–1220.
24. Pugh, G.; Fairburn, J. Evaluating the effects of the M6 toll road on industrial land development and employment. *Reg. Stud.* **2008**, *42*, 977–990. [CrossRef]
25. Tonin, S.; Turvani, M. Redeveloping industrial land: Are contamination and remediation schemes affecting the price of industrial real estate properties? *J. Environ. Plan. Manag.* **2014**, *57*, 1043–1065. [CrossRef]
26. Chen, W.; Shen, Y.; Wang, Y.A. Does industrial land price lead to industrial diffusion in China? An empirical study from a spatial perspective. *Sustain. Cities Soc.* **2018**, *40*, 307–316. [CrossRef]
27. Chen, W.; Shen, Y.; Wang, Y.A.; Wu, Q. How do industrial land price variations affect industrial diffusion? Evidence from a spatial analysis of China. *Land Use Policy* **2018**, *71*, 384–394. [CrossRef]
28. Lin, Y.T.; Qin, Y.; Yang, Y.; Zhu, H.J. Can price regulation increase land-use intensity? Evidence from China's industrial land market. *Reg. Sci. Urban Econ.* **2020**, *81*, 103501. [CrossRef]
29. Wu, Y.; Zhang, X.; Skitmore, M.; Song, Y.; Hui, E. Industrial land price and its impact on urban growth: A Chinese case study. *Land Use Policy* **2014**, *36*, 199–209. [CrossRef]
30. Yang, S.F.; Hu, S.G.; Li, W.D.; Zhang, C.R.; Song, D.D. Spatio-Temporal Nonstationary Effects of Impact Factors on Industrial Land Price in Industrializing Cities of China. *Sustainability* **2020**, *12*, 2792. [CrossRef]
31. Li, C.X.; Wu, K.N. An input-output analysis of transportation equipment manufacturing industrial transfer: Evidence from Beijing-Tianjin-Hebei region, China. *Growth Change* **2022**, *53*, 91–111. [CrossRef]
32. Kumpula, T.; Pajunen, A.; Kaarlejarvi, E.; Forbes, B.C.; Stammler, F. Land use and land cover change in Arctic Russia: Ecological and social implications of industrial development. *Glob. Environ. Chang.—Hum. Policy Dimens.* **2011**, *21*, 550–562. [CrossRef]
33. Zhang, J.F.; Zhang, D.X.; Huang, L.Y.; Wen, H.Z.; Zhao, G.C.; Zhan, D.S. Spatial distribution and influential factors of industrial land productivity in China's rapid urbanization. *J. Clean. Prod.* **2019**, *234*, 1287–1295. [CrossRef]
34. Lee, J.; Jung, S. Industrial land use planning and the growth of knowledge industry: Location pattern of knowledge-intensive services and their determinants in the Seoul metropolitan area. *Land Use Policy* **2020**, *95*, 104632. [CrossRef]
35. Aktas, E.; Tahta, B.T. Investigation of suitable land use potential for industrial sites: The case of Kemalpaa. *Environ. Monit. Assess.* **2018**, *190*, 654. [CrossRef] [PubMed]
36. Cheng, H.; Lai, Y.N.; Tong, D. Decoding the decision-making in the new wave of urban redevelopment in China: A case study of a bottom-up industrial land redevelopment in Shenzhen. *Land Use Policy* **2021**, *111*, 105774. [CrossRef]
37. Danilo, V.D. The evolution process of Chicago's industrial land-use policy. *Urban Res. Pract.* **2018**, *11*, 478–491. [CrossRef]
38. Salari, M.; Shariat, S.M.; Rahimi, R.; Dashti, S. Land capability evaluation for identifying industrial zones: Combination multi-criteria decision-making method with geographic information system. *Int. J. Environ. Sci. Technol.* **2019**, *16*, 5501–5512. [CrossRef]
39. Silva, F.B.E.; Koomen, E.; Diogo, V.; Lavalle, C. Estimating Demand for Industrial and Commercial Land Use Given Economic Forecasts. *PLoS ONE* **2014**, *9*, e91991. [CrossRef]
40. Ustaoglu, E.; Silva, F.B.E.; Lavalle, C. Quantifying and modelling industrial and commercial land-use demand in France. *Environ. Dev. Sustain.* **2020**, *22*, 519–549. [CrossRef]
41. Sun, Y.F.; Ma, A.B.; Su, H.R.; Su, S.L.; Chen, F.; Wang, W.; Weng, M. Does the establishment of development zones really improve industrial land use efficiency? Implications for China's high-quality development policy. *Land Use Policy* **2020**, *90*, 104265. [CrossRef]
42. Galarza, M.E.; Gonzalez, I.A.; Enjuto, M.C.T. Industrial Land Policies in Alava. *Bol. De La Asoc. De Geogr. Esp.* **2012**, *58*, 459–462. [CrossRef]

43. Kuang, W.H.; Liu, J.Y.; Dong, J.W.; Chi, W.F.; Zhang, C. The rapid and massive urban and industrial land expansions in China between 1990 and 2010: A CLUD-based analysis of their trajectories, patterns, and drivers. *Landsc. Urban Plan.* **2016**, *145*, 21–33. [CrossRef]
44. Li, L.; Pan, C.Z.; Ling, S.; Li, M.Q. Ecological Efficiency of Urban Industrial Land in Metropolitan Areas: Evidence from China. *Land* **2022**, *11*, 104. [CrossRef]
45. Li, X.; Yu, X.; Wu, K.N.; Feng, Z.; Liu, Y.N.; Li, X.L. Land-use zoning management to protecting the Regional Key Ecosystem Services: A case study in the city belt along the Chaobai River, China. *Sci. Total Environ.* **2021**, *762*, 143167. [CrossRef]
46. Zhang, J.; Zhang, A. Theoretical Explanation and Policy System Construction of Differentiated Land Management. *Chin. J. Agric. Resour. Reg. Plan.* **2018**, *39*, 10–16. [CrossRef]
47. Zirlewagen, D.; von Wilpert, K. Upscaling of Environmental Information: Support of Land-Use Management Decisions by Spatio-Temporal Regionalization Approaches. *Environ. Manag.* **2010**, *46*, 878–893. [CrossRef]
48. Jiang, G.; Ma, W.; Qu, Y.; Zhang, R.; Zhou, D. How does sprawl differ across urban built-up land types in China? A spatial-temporal analysis of the Beijing metropolitan area using granted land parcel data. *Cities.* **2016**, *58*, 1–9. [CrossRef]
49. Dai, P.C.; Sheng, R.X.; Miao, Z.Z.; Chen, Z.X.; Zhou, Y. Analysis of Spatial-Temporal Characteristics of Industrial Land Supply Scale in Relation to Industrial Structure in China. *Land* **2021**, *10*, 1272. [CrossRef]
50. Zeng, C.; Zhao, Z.; Wen, C.; Yang, J.; Lv, T. Effect of complex road networks on intensive land use in China's Beijing-Tianjin-Hebei urban agglomeration. *Land.* **2020**, *9*, 532. [CrossRef]
51. Li, W.; Weng, L.; Zhao, K.; Zhao, S.; Zhang, P. Research on the Evaluation of Real Estate Inventory Management in China. *Land* **2021**, *10*, 1283. [CrossRef]
52. Liu, S.C.; Lin, Y.B.; Ye, Y.M.; Xiao, W. Spatial-temporal characteristics of industrial land use efficiency in provincial China based on a stochastic frontier production function approach. *J. Clean. Prod.* **2021**, *295*, 126432. [CrossRef]
53. Zhang, L.X.; Bi, X.; Huang, Z.J. Urban industrial land use efficiency under the background of economic transformation in the Yangtze River Economic Belt. *Resour. Sci.* **2020**, *42*, 1728–1738. [CrossRef]
54. Huang, Z.J.; Zhu, S.J.; Shi, T. Industrial Land Transfer, Technological Relatedness and Industrial Entry Dynamics. *Econ. Geogr.* **2022**, *42*, 144–155. [CrossRef]
55. Huang, Z.H.; Du, X.J. Strategic interaction in local governments' industrial land supply: Evidence from China. *Urban Stud.* **2017**, *54*, 1328–1346. [CrossRef]
56. Rahman, A.H.; Gandhi, D.K.; Smith, J.B. Industrial Land-Value and Asset Size—Theory and Evidence. *Revue Canadienne des Sciences de l'Administration/Can. J. Adm. Sci.* **1994**, *11*, 177–180. [CrossRef]
57. Lou, J.; Zhao, X.; Wang, L.; Zhu, F.; Jin, P. Industrial Land Provision Based on Enterprise Life Cycle: A Case Study of Jiangsu. *Mod. Urban Res.* **2017**, *10*, 18–24. [CrossRef]
58. Mai, P.T.Q.; Kyoung-Hoon, C.; Gyei-Kark, P. Efficiency Analysis for Major Ports in Korea and China using Boston Consulting Group and Data Envelopment Analysis Model. *J. Navig. Port Res.* **2018**, *42*, 107–116. [CrossRef]
59. Myllyla, Y.; Kaivo-oja, J. Integrating Delphi methodology to some classical concepts of the Boston consulting group framework: Arctic maritime technology BCG Delphi foresight-a pilot study from Finland. *Eur. J. Futures Res.* **2015**, *3*, 2. [CrossRef]
60. Li, W.; Yang, Y.; Zhao, S. Analyses on the Pattern of Chinese FDI Utilization and Strategic Choice Based on the Competition State. *Econ. Geogr.* **2012**, *32*, 23–29. [CrossRef]
61. Zhao, S.; Zhang, P.; Li, W. A Study on Evaluation of Influencing Factors for Sustainable Development of Smart Construction En-terprises: Case Study from China. *Buildings* **2021**, *11*, 221. [CrossRef]
62. Guan, X.Y.; Wang, S.L.; Gao, Z.Y.; Lv, Y.; Fu, X.J. Spatio-temporal variability of soil salinity and its relationship with the depth to groundwater in salinization irrigation district. *Acta Ecol. Sin.* **2012**, *32*, 198–206.
63. Salvati, L.; Venanzoni, G.; Serra, P.; Carlucci, M. Scattered or polycentric? Untangling urban growth in three southern European metropolitan regions through exploratory spatial data analysis. *Ann. Reg. Sci.* **2016**, *57*, 1–29. [CrossRef]
64. Anselin, L. *Spatial Econometrics: Methods and Models*, 1st ed.; Springer: Dordrecht, The Netherlands, 1988; pp. 119–136.
65. Zhang, P.; Li, W.; Zhao, K.; Zhao, S. Spatial Pattern and Driving Mechanism of Urban–Rural Income Gap in Gansu Province of China. *Land* **2021**, *10*, 1002. [CrossRef]
66. Shrestha, A.; Luo, W. Analysis of Groundwater Nitrate Contamination in the Central Valley: Comparison of the Geodetector Method, Principal Component Analysis and Geographically Weighted Regression. *ISPRS Int. J. Geo-Inf.* **2017**, *6*, 297. [CrossRef]
67. Polykretis, C.; Grillakis, M.G.; Argyriou, A.V.; Papadopoulos, N.; Alexakis, D.D. Integrating Multivariate (GeoDetector) and Bivariate (IV) Statistics for Hybrid Landslide Susceptibility Modeling: A Case of the Vicinity of Pinios Artificial Lake, Ilia, Greece. *Land* **2021**, *10*, 973. [CrossRef]
68. Wang, J.F.; Li, X.H.; Christakos, G.; Liao, Y.L.; Zhang, T.; Gu, X.; Zheng, X.Y. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 107–127. [CrossRef]
69. Wang, J.F.; Xu, C.D. Geodetector: Principle and prospective. *Acta Geogr. Sin.* **2017**, *72*, 116–134.
70. Zhao, S.; Yan, Y.; Han, J. Industrial Land Change in Chinese Silk Road Cities and Its Influence on Environments. *Land* **2021**, *10*, 806. [CrossRef]
71. Ma, Y.; Zhang, P.; Zhao, K.; Zhou, Y.; Zhao, S. A Dynamic Performance and Differentiation Management Policy for Urban Construction Land Use Change in Gansu, China. *Land* **2022**, *11*, 942. [CrossRef]

72. Zhao, S.; Zhang, C.; Qi, J. The Key Factors Driving the Development of New Towns by Mother Cities and Regions: Evidence from China. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 223. [CrossRef]
73. Tapio, P. Towards a theory of decoupling: Degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transp. Policy* **2005**, *12*, 137–151. [CrossRef]
74. Li, M.; Shi, Y.Y.; Duan, W.K.; Chen, A.Q.; Wang, N.; Hao, J.M. Spatiotemporal Decoupling of Population, Economy and Construction Land Changes in Hebei Province. *Sustainability* **2019**, *11*, 6794. [CrossRef]
75. Zhou, M.; Hu, B.X. Decoupling of carbon emissions from agricultural land utilisation from economic growth in China. *Agric. Econ.-Zemed. Ekon.* **2020**, *66*, 510–518. [CrossRef]
76. Zhang, P.; Hu, J.; Zhao, K.; Chen, H.; Zhao, S.; Li, W. Dynamics and Decoupling Analysis of Carbon Emissions from Construction Industry in China. *Buildings* **2022**, *12*, 257. [CrossRef]
77. Casadio Tarabusi, E.; Guarini, G. An axiomatic approach to decoupling indicators for green growth. *Ecol. Indic.* **2018**, *84*, 515–524. [CrossRef]
78. Gupta, S. Decoupling: A step toward sustainable development with reference to OECD countries. *Int. J. Sustain. Dev. World Ecol.* **2015**, *22*, 510–519. [CrossRef]
79. Zhao, S.; Zhao, K.; Yan, Y.; Zhu, K.; Guan, C. Spatio-Temporal Evolution Characteristics and Influencing Factors of Urban Service-Industry Land in China. *Land* **2022**, *11*, 13. [CrossRef]
80. Longhofer, W.; Jorgenson, A. Decoupling reconsidered: Does world society integration influence the relationship between the environment and economic development? *Soc. Sci. Res.* **2017**, *65*, 17–29. [CrossRef]
81. Louw, E.; van der Krabben, E.; van Amsterdam, H. The Spatial Productivity of Industrial Land. *Reg. Studies* **2012**, *46*, 137–147. [CrossRef]
82. Wang, Y.; Gu, H.; Zhou, L.; Shen, T. Spatial Patterns and Evolving Characteristics of Industrial Land Conveyance in China from 2007 to 2016. *Areal Res. Dev.* **2018**, *37*, 148–154. [CrossRef]
83. Cui, X.; Meng, X.; Wang, D. Regional Differences and Convergence Characteristics of Industrial Land Marketization in Urban Agglomerations of China from the Spatial Perspective. *China Land Sci.* **2020**, *34*, 34–43. [CrossRef]
84. Zhu, Z.; He, Q.; Qu, X. Evolution Characteristics of Industrial Land of Urban Agglomerations in the Middle Reaches of the Yangtze River. *Econ. Geogr.* **2021**, *41*, 106–114. [CrossRef]
85. Xu, J.; He, Q.; Zhu, Z. The Evolution Characteristics of the Industrial Lands of the Changsha-Zhuzhou-Xiangtan Urban Agglomeration. *Econ. Geogr.* **2018**, *38*, 89–97. [CrossRef]
86. He, H.; Yang, Q.; Bi, G.; Liang, W. Spatio-temporal Characteristics of Industrial Land Supply in Chongqing from 2009 to 2018. *Resour. Environ. Yangtze Basin* **2021**, *30*, 808–817. [CrossRef]
87. Dong, Z.Y.Z.; Li, Y.C.; Balland, P.A.; Zheng, S.Q. Industrial land policy and economic complexity of Chinese Cities. *Ind. Innov.* **2021**, *29*, 367–395. [CrossRef]
88. Qi, J.; Hu, M.; Han, B.; Zheng, J.; Wang, H. Decoupling Relationship between Industrial Land Expansion and Economic Development in China. *Land* **2022**, *11*, 1209. [CrossRef]
89. Mei, L.; Wei, X. Industrial Land Allocation, Spatial Heterogeneity and Industrial Efficiency. *Res. Econ. Manag.* **2022**, *43*, 78–96. [CrossRef]
90. Peng, S.; Wang, Y.; Chen, C.; Wang, J.; Lei, G.; Wu, X. Rationality evaluation and driving force of industrial land expansion in Shandong Province. *Resour. Sci.* **2016**, *38*, 228–238. [CrossRef]
91. Del Pozo, P.B. Promotion and evaluation of industrial land in Asturias. *Bol. De La Asoc. De Geogr. Esp.* **2006**, *42*, 99–119.
92. Zhao, X.F.; Zhang, L.; Huang, X.J.; Zhao, Y.T.; Zhang, Y.P. Evolution of the Spatiotemporal Pattern of Urban Industrial Land Use Efficiency in China. *Sustainability.* **2018**, *10*, 2174. [CrossRef]
93. Qian, L.; Ma, X.; Shi, X.; Zou, X.; Lan, J. Does the supply of industrial land affect industial energy carbon emissions? *China Popul. Resour. Environ.* **2019**, *29*, 57–67. [CrossRef]
94. Xie, W.; Qu, W. Influencing Factors of Enterprises' Land Use Preferences in the Reform of Flexible Leasing of Industrial Land in Chengdu City. *China Land Sci.* **2021**, *35*, 39–46. [CrossRef]
95. Lai, Y.N.; Peng, Y.; Li, B.; Lin, Y.L. Industrial land development in urban villages in China: A property rights perspective. *Habitat Int.* **2014**, *41*, 185–194. [CrossRef]
96. Zeng, P.; Li, J. Spatiotemporal Responses Between Urban Regeneration and Policy Change of Stock Industrial Land: A Case Study of Tianjin Downtown Area. *City Plan. Rev.* **2020**, *29*, 36–46. [CrossRef]
97. Powter, C.; Chymko, N.; Dinwoodie, G.; Howat, D.; Janz, A.; Puhlmann, R.; Richens, T.; Watson, D.; Sinton, H.; Ball, K. Regulatory history of Alberta's industrial land conservation and reclamation program. *Can. J. Soil Sci.* **2012**, *92*, 39–51. [CrossRef]
98. Needham, B.; Louw, E.; Metzemakers, P. An economic theory for industrial land policy. *Land Use Policy* **2013**, *33*, 227–234. [CrossRef]