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The Evolution and Performance Response of Industrial Land Use Development in China's Development Zone: The Case of Suzhou Industrial Park

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Abstract: Development zones are crucial spatial carriers driving economic growth and industrial upgrading, playing a key role in China's development. After years of expansion, these zones face significant challenges in industrial land development and performance enhancement. This paper takes Suzhou Industrial Park (SIP) as a case, which is a model of Sino–Singaporean government cooperation. Using Landsat 4–5 TM data, socioeconomic data, and industrial land use data, spatial analysis and statistical modeling were employed to examine the evolution and phased patterns of industrial land use in SIP from 1994 to 2022. A performance evaluation system encompassing economic benefits, innovation-driven growth, development intensity, green development, and social security was developed to assess land use performance and its responses to spatial transformations. The results reveal that industrial land in SIP experienced a significant change in the intensity of land expansion from 1.031 to 0.352 during 1994–2022, and the peak circle density expanded from 3 km to 15 km. The mean value of the comprehensive performance score during 2017–2022 was 42.18, with the highest economic efficiency (40.54) and a lower innovation capacity (16.98). The development of industrial land in SIP presents the stage characteristics of monocentric polarization, polycentricity, and spatial diffusion toward a generalized development zone, showing significant path dependence, and the difference in the land use performance of different industrial types is obvious. In the future, the optimization and redevelopment of the stock of land should be strengthened to promote the optimization of the spatial layout of technology-intensive industries and the technological upgrading of labor-intensive industries, as well as achieving sustainable economic growth through innovation-driven, green development and enclave economy collaboration. This study provides a reference for the industrial layout and high-quality sustainable development of development zones.

Keywords: development zone; Suzhou Industrial Park (SIP); industrial land; spatial evolution

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1. Introduction

Development zones serve as critical spatial carriers for global economic growth and industrial upgrading, playing a significant role in optimizing land resource utilization efficiency and promoting regional coordinated development. International practices in industrial parks across Europe, North America, and Asia offer valuable references for enhancing industrial land's performance and optimizing its spatial layout. For instance, Denmark's

Kalundborg Industrial Park achieves resource-sharing and high efficiency through a circular economy model [1], while Silicon Valley in the United States fosters the agglomeration of high-value-added industries through intensive land use and spatial optimization [2]. In Asia, Japan and South Korea have effectively improved the land use efficiency and reduced environmental pressures through compact urban design and technological innovation [3,4]. These international experiences underscore that optimizing industrial land's performance and spatial layout is key to achieving high-quality development in industrial parks.

China's development zones have made remarkable achievements in driving economic growth and industrial transformation. However, with increasing land resource scarcity [5] and growing environmental protection demands [6], challenges persist in improving industrial land development and performance [7,8]. Addressing these issues requires urgent solutions to optimize industrial land allocation and enhance spatial land use efficiency. SIP, a flagship development zone co-established by the Chinese and Singaporean governments, has rapidly industrialized since its inception in 1994. By attracting foreign investment and fostering high-tech industrial clusters, SIP provides valuable lessons for improving land resource utilization and performance in development zones [9].

In recent years, scholars have made significant progress in understanding the driving mechanisms of land use in development zones [10], evaluating intensive land use [11], and analyzing industrial agglomeration characteristics [12,13]. Research based on industrial location theory and bid-rent models has revealed the complex relationships between land prices, industrial location, and spatial distribution [14,15]. Moreover, advances in remote sensing and spatial analysis technologies have enabled the quantitative study of land use efficiency, effectively revealing the dynamic characteristics of spatial layouts in development zones [16]. Existing studies have further explored the connections between development zone performance and land use allocation [17,18], covering evaluation indicator systems, methodological designs, and case applications [19].

Despite these advances, the current research on SIP primarily focuses on evaluating its overall economic performance. There is a lack of studies examining the spatial heterogeneity of the land use within this development zone and the impact on its comprehensive performance. Additionally, systematic research is needed to dynamically reveal the relationship between the spatial configurations and land use performance at different development stages, particularly using high-spatiotemporal-resolution data and spatial analysis techniques. For SIP, as a representative development zone influenced by multiple factors [20,21], the interaction mechanisms between the spatial configurations and land performance across its development phases require deeper analysis. Such studies can provide theoretical foundations for optimizing land resource allocation and achieving sustainable development in development zones.

This paper takes SIP as a case study, utilizing Landsat 4–5 TM remote sensing imagery, socioeconomic data, and industrial land data from 1994 to 2022. By constructing a comprehensive performance evaluation system and employing spatial analysis and statistical modeling, this research explores the spatiotemporal evolution of industrial land use in SIP and its response mechanisms to comprehensive performance. This study aims to uncover the complex relationships between internal spatial configurations and land use performance, proposing optimization strategies to provide scientific guidance for the industrial layout and sustainable high-quality development of other development zones.

2. Materials and Methods

2.1. Study Area

SIP is located in Suzhou, Jiangsu Province, China (120°38′6″–120°51′37″ E, 31°14′1″–31°26′10″ N), which covers the Taihu Plain of the Yangtze River Delta (Figure 1). SIP was the first transnational industrial park established by China and Singapore jointly and is also the largest Sino–foreign cooperative development zone in China. SIP has ranked highest seven times consecutively in comprehensive evaluations of Chinese national-level

development zones and has become a significant window of China's reform and opening up and a successful example of international cooperation.

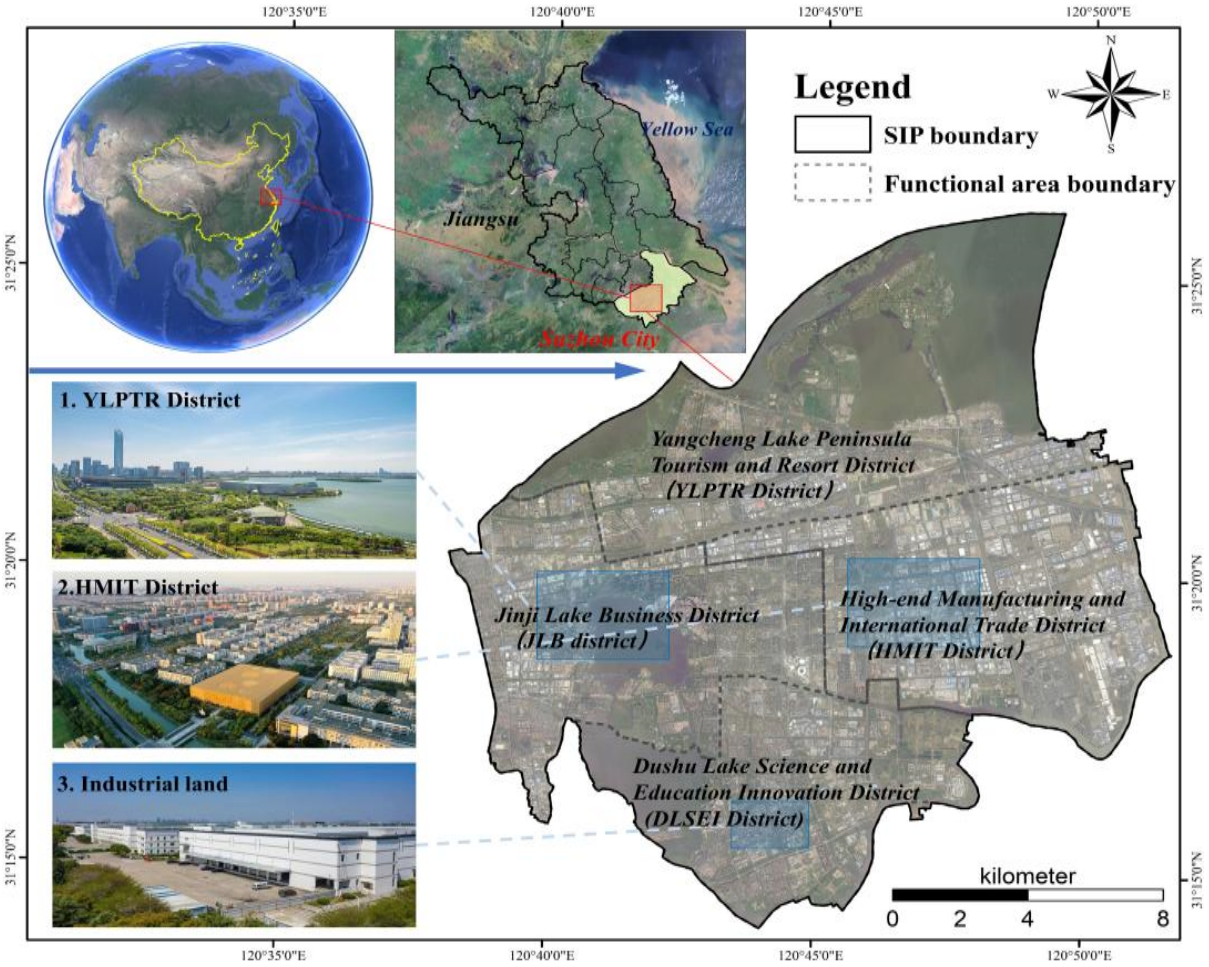

Figure 1. Study area location diagram.

In 2022, the administrative area of SIP covered 278 km^2, with an area of 80 km^2 designated for Sino–Singaporean cooperation. The total industrial output above its designated size reached 685.02 billion CNY, with more than 9000 manufacturing enterprises operating in the zone, encompassing 33 major industrial categories, 161 subcategories, and 443 minor categories. SIP is divided into four functional areas, including the Jinji Lake Business District (JLB), the High-End Manufacturing and International Trade Zone (HMIT), the Yangcheng Lake Peninsula Tourism Resort (YLPTR), and the Dushu Lake Science and Education Innovation Zone (DLSEI). Currently, the developed industrial land amounts to 51.3 km^2, with only 2.85 km^2 of land available for development, highlighting a pronounced contradiction between land supply and demand.

2.2. Data Sources and Processing

The data used included remote sensing imagery, industrial land data, and socioeconomic data: (1) Landsat 4–5 TM satellite remote sensing imagery (https://www.gscloud.cn/search, accessed on 10 October 2023) was selected at six-year intervals, specifically for the years 1994, 2000, 2006, 2012, 2018, and 2022, according to the period of the park's planning. (2) Industrial land survey data for SIP from 2017 to 2022 encompassed information on land area, industry type, floor area ratio, building density, output per unit of land, tax revenue per unit of land, and the number of employees per unit of land and were sourced from the SIP Management Committee. (3) Socioeconomic data were obtained from

the Suzhou Industrial Park Statistical Yearbook (https://www.sipac.gov.cn/, accessed on 12 October 2023), including statistics on gross regional product, industrial added value, industrial output, and actual foreign investment.

In terms of the data processing, the remote sensing imagery was cropped and initially interpreted through the supervised classification feature in ENVI (5.3, ITT, Colorado Springs, CO, USA). Then, spatial registration and visual interpretation were performed using ArcGIS (10.8, ESRI, Redlands, CA, USA) for enhanced visualization. Based on the "National Economic Industry Classification and Codes (GB/T 4754-2017)" [22], the "National High-tech Industries (Manufacturing) Classification (2017)" [23], and the "Statistics of High-tech Industries in Development Zones" [23] released by SIP, the industry types were divided into six major categories (Table 1), reflecting the characteristics of the development zone industry.

Table 1. Industry classification and description.

Industry Classification	Industry Definition
Light Industry, Textile, and Food Industry	Refers to industries producing light industrial products and other daily consumer goods
Raw Material Processing Industry	Refers to industries that process raw materials into intermediate products or semi-finished goods that meet production needs
Traditional Manufacturing Industry	Refers to industries that use traditional production technologies to manufacture basic materials and component products
High-End Equipment Manufacturing	Refers to industries that produce high-value-added and high-tech products
Other Manufacturing Industry	Refers to manufacturing sectors that do not fall under traditional or high-end equipment manufacturing
Industrial Supporting and Service Industries	Refers to industries that provide support security and services for industrial production and daily life

2.3. Analyses and Evaluation Methods

2.3.1. Analysis of the Evolution of Industrial Land Development Scale Characteristics

A statistical analysis of the industrial land scale in SIP from 1994 to 2022 was conducted, and the phases of changes in expansion intensity were delineated based on the downward trend of the aggregation coefficient line. The calculation formula is as follows:

$$U_v = \left(\sqrt[t]{A_t / A_0} - 1\right) \times 100\% \quad (1)$$

$$U_s = [(A_t - A_0)/(t \times S_0)] \times 100 \quad (2)$$

In this formula, U_v represents the expansion speed; U_s denotes the expansion intensity; A_t indicates the land area at the end of the study period; A_0 refers to the land area at the beginning of the study period; the time span of the study is t; and each unit area is S_0.

The Relationship Between the Perimeter and Area of the Industrial Land

The morphological characteristics of industrial land development are characterized by the fractal dimension, the regularity index, and the compactness index. ArcGIS was used to extract the attribute values of the industrial land's patch area (A) and perimeter (P). The calculations for each index are as follows:

$$ln\ A = \frac{2}{D} ln\ P + C \quad (3)$$

$$SK = |1.5 - D| \quad (4)$$

$$BCI = 2\sqrt{\pi A}/P \quad (5)$$

In these formulas, D represents the fractal dimension of the industrial land parcels; SK denotes the patch regularity index; BCI is a patch's compactness; A is the area of industrial land; P is the total perimeter of the patches; and C is a constant (intercept). The complexity of a patch's shape and the regularity of the boundary are inversely proportional to the value of D. The range of D is [1,2], and when D = 1.5, the patch is described using random Brownian motion; the closer the value is to this point, the lower the stability of the patch. The theoretical range for SK is 0 to 0.5; a larger SK value indicates that the shape of the industrial land is more regular, and vice versa. A larger BCI value signifies the higher compactness of an industrial land patch.

Spatial Autocorrelation

This study employed a spatial autocorrelation analysis to evaluate the correlation of variable values at different locations, illustrating the patterns of the spatial expansion of the industrial land. The Getis-Ord Gi* index was utilized to detect the aggregation of the regional attributes, and ArcGIS was used to grid the industrial land in the park into 500 m × 500 m cells, which effectively reflected the size of the industrial land parcels.

$$G_i^* = \frac{\sum_{j=1}^{n}(w_{ij}x_j) - \overline{x}\sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \overline{x}^2}\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \quad (6)$$

In this formula, G_i^* represents the hotspot index; x_j denotes the attribute of the spatial grid j; w_{ij} is the weight between the spatial grids i and j; n is the total number of the spatial grids; and $\overline{x}$ represents the mean attribute value.

LISA's Temporal Path

LISA's temporal path was employed to reveal the local dynamics of land expansion. Here, the length of time for LISA represents the dynamic characteristics of the industrial land's evolution, while the direction of movement indicates integrative changes in local industrial land. LISA's temporal path is calculated using expansion intensity as the variable, with the formula as follows:

$$\Gamma_i = \frac{N\sum_{t=1}^{T-1}\gamma(L_{i,t}, L_{i,t+1})}{\sum_{i=1}^{N}\sum_{t=1}^{T-1}\gamma(L_{i,t}, L_{i,t+1})} \quad (7)$$

$$\theta_i = arctan\frac{\sum_j sin\theta_j}{\sum_j cos\theta_j} \quad (8)$$

In this formula, Γ_i and θ_i represent the path length and the direction of movement for the spatial grid, respectively; N denotes the number of spatial grids, which in this study was set at 570; this research spanned various time intervals, denoted as T; $L_{i,t}$ refers to the position coordinates of the spatial grid i within the LISA scatter plot at time t; and $\gamma(L_{i,t}, L_{i,t+1})$ indicates the displacement of the spatial grid i from time t to t + 1. θ_i indicates the average direction of movement, where values from 0° to 90° signify positive coordinated growth, demonstrating integrative spatial dynamics, with both the grid and its neighborhood exhibiting a trend of high positive growth in expansion intensity; values from 90° to 180° indicate low growth in the expansion intensity of the spatial grid, while the neighborhood shows high growth; values from 180° to 270° represent negative coordinated growth, again demonstrating integrative spatial dynamics, with both the grid and its neighborhood displaying a trend of low growth; and values from 270° to 360° indicate high growth within the spatial grid, while the neighborhood experiences low growth in its expansion intensity.

Circle Density

The circle analysis method was utilized to examine the evolution of urban functional land in a "center–periphery" model. After comparing multiple buffer ranges, including 100 m, 300 m, 500 m, and 1000 m, this study determined that a radius of 500 m was most suitable for the scale of the study area. Therefore, a buffer with a 500 m radius was created, and ArcGIS was used for spatial statistical analysis of the evolution of the industrial land's circle density in the study area from 1994 to 2022. The formula is as follows:

$$P_i = \frac{A_i}{M_i} \times 100\% \tag{9}$$

In this formula, P_i represents the land density of circle i; A_i represents the industrial land area; and M_i denotes the area of the i-th circle. These variables are used to evaluate the intensity and distribution characteristics of land use within each concentric circle.

The Industry Specialization Index

The location quotient (LQ) was employed to reflect the level of industrial specialization, illustrating the specialization level among different industries and regions. The calculation formula is as follows:

$$Q_{ij} = \frac{e_{ij}/e_i}{E_{nj}/E_n} \tag{10}$$

In this formula, Q_{ij} denotes the location quotient; e_{ij} represents the output of industry j in circle i; e_i denotes the total output of circle i; E_{nj} represents the output of industry j within the park; and E_n denotes the total output of the park. When $Q_{ij} > 1$, this suggests that an industry has a comparative advantage within the same circle; when $Q_{ij} \leq 1$, there is no comparative advantage. An increase in the location quotient indicates a growing comparative advantage, whereas a decrease suggests a reduction.

The Krugman specialization index was utilized to measure the degree of industrial specialization among the regions. The calculation formula is as follows:

$$K_{ij} = \sum_{k=1}^{n} \left| S_{ik} - S_{jk} \right| \ (0 \leq K_{ij} \leq 2) \tag{11}$$

In this formula, K_{ij} is the Krugman specialization index for circle i compared to circle j; S_{ik} and S_{jk} represent the proportions of the output of industry k within the total output of industries i and j, respectively; and n is the number of industries within the park.

2.3.2. Performance Analysis of Industrial Land Use

The Performance Evaluation Indicator System

This analysis focused on industrial land use from 2017 to 2022, utilizing land parcels as the evaluation units. The selection of the indicators and the establishment of weights were made with reference to the relevant literature [24]. A performance evaluation system for industrial land use was developed, encompassing five-dimensional goals: economic efficiency, innovation-driven development, development intensity, green development, and social security. This system included 10 sub-goals and 24 evaluation indicators (Table 2). The average performance scores from 2017 to 2022 were visually represented using a spatial grid of 500 m × 500 m, facilitating a comprehensive assessment of the land use performance across the period specified (Figure S1).

Table 2. Performance evaluation indicator system for industrial land use.

Goal	Weight	Sub-Goal	Weight	Indicator	Weight	Unit	Nature
Economic efficiency	0.3	Enterprise economic scale	0.5	Total output	0.3	10,000 CNY	Positive
				Taxes and fees paid	0.3	10,000 CNY	Positive
				Existence of above-scale enterprises	0.4	—	Positive
		Land input–output	0.5	Fixed asset investment intensity per hectare	0.3	10,000 CNY/hm^2	Positive
				Output per hectare	0.3	10,000 CNY/hm^2	Positive
				Taxes and fees paid per hectare	0.4	10,000 CNY/hm^2	Positive
Innovation driven	0.2	Enterprise innovation support	0.2	Infrastructure support level	0.3	—	Positive
				Enterprise land tenure	0.7	Years	Negative
		Enterprise technological development level	0.8	Existence of strategic emerging enterprises	0.5	—	Positive
				Existence of high-tech enterprises	0.5	—	Positive
Development intensity	0.15	Spatial location conditions	0.3	Distance to highway entrances	0.3	km	Negative
				Distance to railway freight stations	0.4	km	Negative
				Distance to inland river freight ports	0.3	km	Negative
		Land use intensity	0.7	Floor area ratio	0.5	—	Positive
				Building density	0.5	%	Positive
Green development	0.15	Green production	0.5	Electricity consumption per unit output	0.5	Kwh/CNY	Negative
				Water consumption per unit output	0.5	Tons/10,000 CNY	Negative
		Ecological protection	0.5	Distance to major lakes and water areas	0.4	km	Positive
				Ecological protection red line and control	0.6	km	Positive
Social security	0.2	Employment supply	0.5	Number of employment positions	0.5	Positions	Positive
				Employment population density	0.5	People/hm^2	Positive
		Housing suitability	0.5	Distance to city center	0.1	km	Positive
				Distance to residential areas	0.1	km	Positive
				Accessibility to transportation hubs	0.8	km	Negative

The Performance Response Index

Drawing on the elasticity formula from economics, the performance response index for industrial land use was introduced, indicating how changes in land use performance respond to variations in land use. The calculation formula is as follows:

$$I = \frac{d_{IK}}{d_{IS}} \times \frac{IS}{IK} \tag{12}$$

In this formula, I is the performance response index for changes in the land use development scale, and $\frac{d_{IK}}{d_{IS}}$ represents the derivative of land use performance with respect to the land use evolution scale in the fitted function. It reflects the sensitivity of performance improvements to changes in the land use scale; IS and IK represent the land use scale and land use performance, respectively. When I is positive, this indicates a positive response relationship between the land use performance and the scale of land development. When I is negative, this signifies a negative response relationship. When I is zero, this suggests that theoretically the scale of land development has no impact on the land use performance.

3. Results

3.1. The Evolution and Phases of Industrial Land Development

3.1.1. Changes in the Scale Characteristics of the Industrial Land

The evolution of the industrial land scale in SIP from 1994 to 2022 can be divided into three expansion periods, characterized by an initial increase in expansion intensity, followed by a subsequent decline (Figure 2a). Based on the clustering results of the expansion intensity (Table S1), it is observed that when the number of clusters exceeds three, the decline in the silhouette score of the clustering coefficient stabilizes (Figure 2b). Consequently, the expansion periods are delineated as 1994–2006, 2007–2012, and 2013–2022.

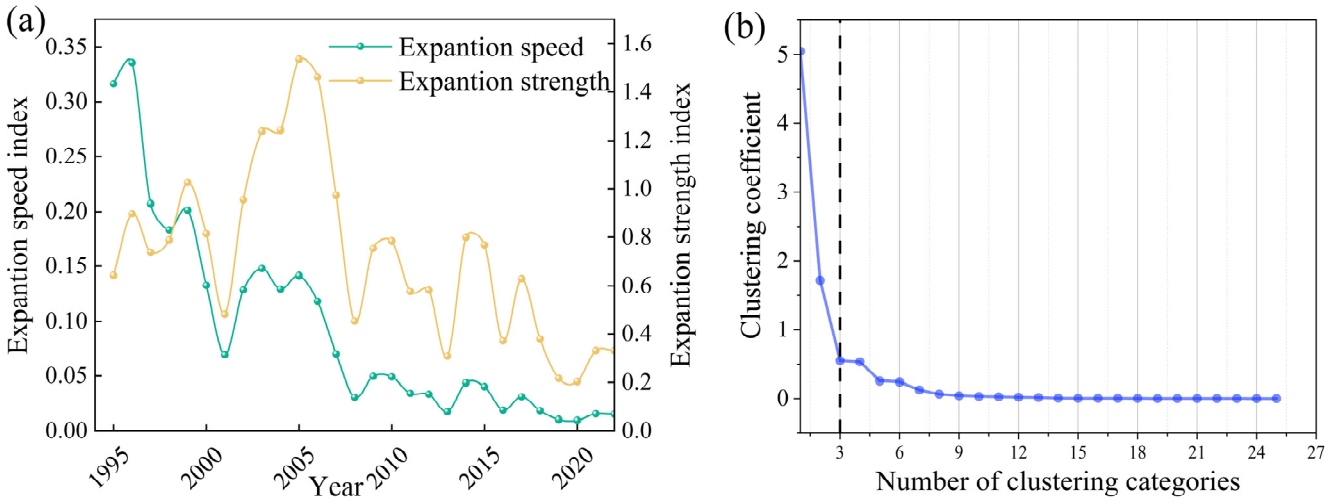

Figure 2. Changes in industrial land scale and basis for stage division. (**a**) Expansion speed and intensity land during 1994~2022; (**b**) clustering coefficient curve graph plot.

During the period from 1994 to 2006, the expansion intensity of the industrial land remained relatively high, with an average of 1.031 across most years, despite a decline to 0.482 in 2001. The dominant clustering types during this phase were types 1 and 3 (Figure 2b). In the subsequent period from 2007 to 2015, the average expansion intensity decreased to 0.667, yet all years except for 2013 maintained expansion intensities above 0.4, with type 1 being the predominant clustering type. From 2016 to 2022, the average expansion intensity further declined to 0.352, with only 2017 witnessing a peak of 0.629; all the other years did not exceed an expansion intensity of 0.4, with type 2 being the dominant clustering type.

3.1.2. Changes in the Morphological Characteristics of the Industrial Land

The patch mosaic structure of the industrial land exhibits a relatively regular pattern, with a minor fluctuation observed overall. The expansion mode alternates between sprawl and infill development (Table 3 and Figure 3).

Table 3. Fractal dimension, regularity index, and compactness index of industrial land.

Year	P−A Relationship Model	R^2	Fractal Dimension (D)	Patch Regularity Index (SK)	Patch Compactness Index (BCI)
1994	lnA = 1.9723lnP − 2.6803	0.9918	1.014	0.486	1.724
2000	lnA = 1.7639lnP − 1.2557	0.9675	1.134	0.366	1.686
2006	lnA = 1.8664llnP − 1.9751	0.9655	1.072	0.428	1.681
2012	lnA = 1.8065lnP − 1.6194	0.9523	1.107	0.393	1.695
2018	lnA = 1.9303lnP − 2.4328	0.9671	1.036	0.464	1.743
2022	lnA = 1.8676lnP − 1.1726	0.8565	1.071	0.429	1.706

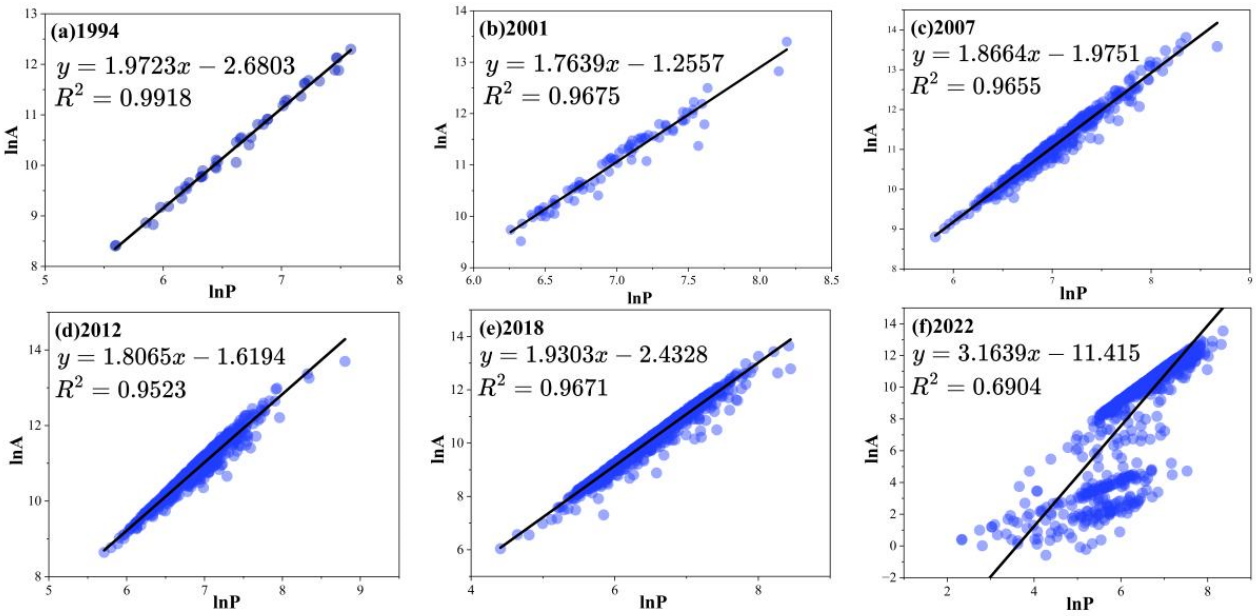

Figure 3. The circumference–area (P-A) relationship of the industrial land.

Analyzing the data by period, from 1994 to 2000, the fractal dimension (D) increased while the patch regularity index (SK) decreased (Table 3). This indicates that the mosaic pattern of the industrial land was complex and unstable, primarily characterized by sprawl. From 2001 to 2005, D decreased, suggesting that the patches of industrial land became more stable and regular, primarily driven by infill development.

Between 2006 and 2011, D increased again, with sprawl remaining the predominant mode of expansion. During the period from 2012 to 2017, D decreased, reflecting an increase in the regularity of the patch mosaic structure, with infill development as the main focus. This period also indicated a concentration on the integration of the stock land.

From 2017 to 2022, D increased while SK decreased, signaling a return to a certain degree of sprawl in industrial land. Overall, from 1994 to 2022, the compactness index of the patches experienced three distinct phases: from 1994 to 2005, the index declined, indicating loose expansion primarily reliant on annexing the surrounding land and sprawl; from 2006 to 2017, the index showed an overall increase, with industrial land characterized by scale integration and cluster development; and from 2018 to 2022, the index slightly decreased again, reflecting insufficient internal integration, loose expansion, and dominance of sprawl, coupled with a lag in the adjustment of stock land.

3.2. Changes in the Spatial Pattern of Industrial Land Development

3.2.1. Circle Changes in Spatial Development

The spatial development of the industrial land in SIP from 1994 to 2022 exhibits distinct stages and circle characteristics (Figure 4). The peak density of land use progressed from 3 km at its origin in 1994 to 10 km in 2012 and subsequently to 15 km by 2022, culminating

in three notable density peaks at 3 km, 10 km, and 15 km. From 1994 to 2000, the industrial land was primarily concentrated in the central zone, clearly reflecting a "center–periphery" model. In 2006, density peaks of industrial land emerged at distances of 6 km and 10 km from the center, indicating an expansion into the second tier of the spatial structure, thereby reinforcing the "center–periphery" dynamic. By 2018, the density peaks shifted to 12 km and 15 km, signaling the establishment of a new center within the third tier of the spatial hierarchy, which resulted in the formation of multiple land use centers.

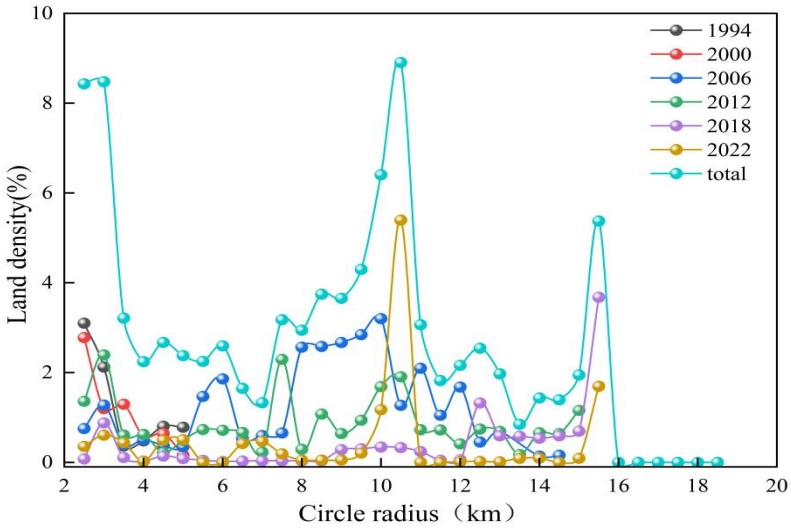

Figure 4. Circle density of industrial land use in the study area, 1994 to 2022.

The circle distribution of industrial sectors within the park reveals notable differences in terms of industrial agglomeration, specialization levels, and land use efficiency (Table 4). Specifically, the location entropy of high-end equipment manufacturing decreases from the inner to the outer circle, indicating that the inner circle exhibits a higher degree of industrial agglomeration and specialization. In contrast, traditional manufacturing demonstrates a distinct advantage in the agglomeration effects at the outer circle. Additionally, the location entropy of the raw material processing industry exhibits a clear circular distribution characteristic.

Table 4. Industry location entropy and Krugman specialization index for 2022.

	Circles	Inner	Middle	Outer
Industry location quotient	Light industry, textile, food	0.651	0.688	2.922
	Raw material processing	0.947	1.198	2.175
	Traditional manufacturing	0.5	1.563	1.304
	Advanced equipment manufacturing	1.11	0.929	0.64
	Other process manufacturing	0.654	0.619	0.594
	Industriy supporting production and living services	0.59	1.293	2.267
	Circle relationship	Inner–middle	Middle–outer	Inner–outer
	Krugman specialization index	0.265	0.475	0.688

There is a clear mismatch in the spatial distribution of the number of enterprises and their output value (Figure 5). As of 2022, the spatial aggregation of enterprises across different industries did not align with their corresponding output values. For instance, the output value hotspot for high-end equipment manufacturing is concentrated in the northern region of the HMIT (Figure 5j), whereas the majority of enterprises are primarily located in the southern areas of the DLSEI and JLB (Figure 5d), reflecting a spatial misalignment in the agglomeration distribution.

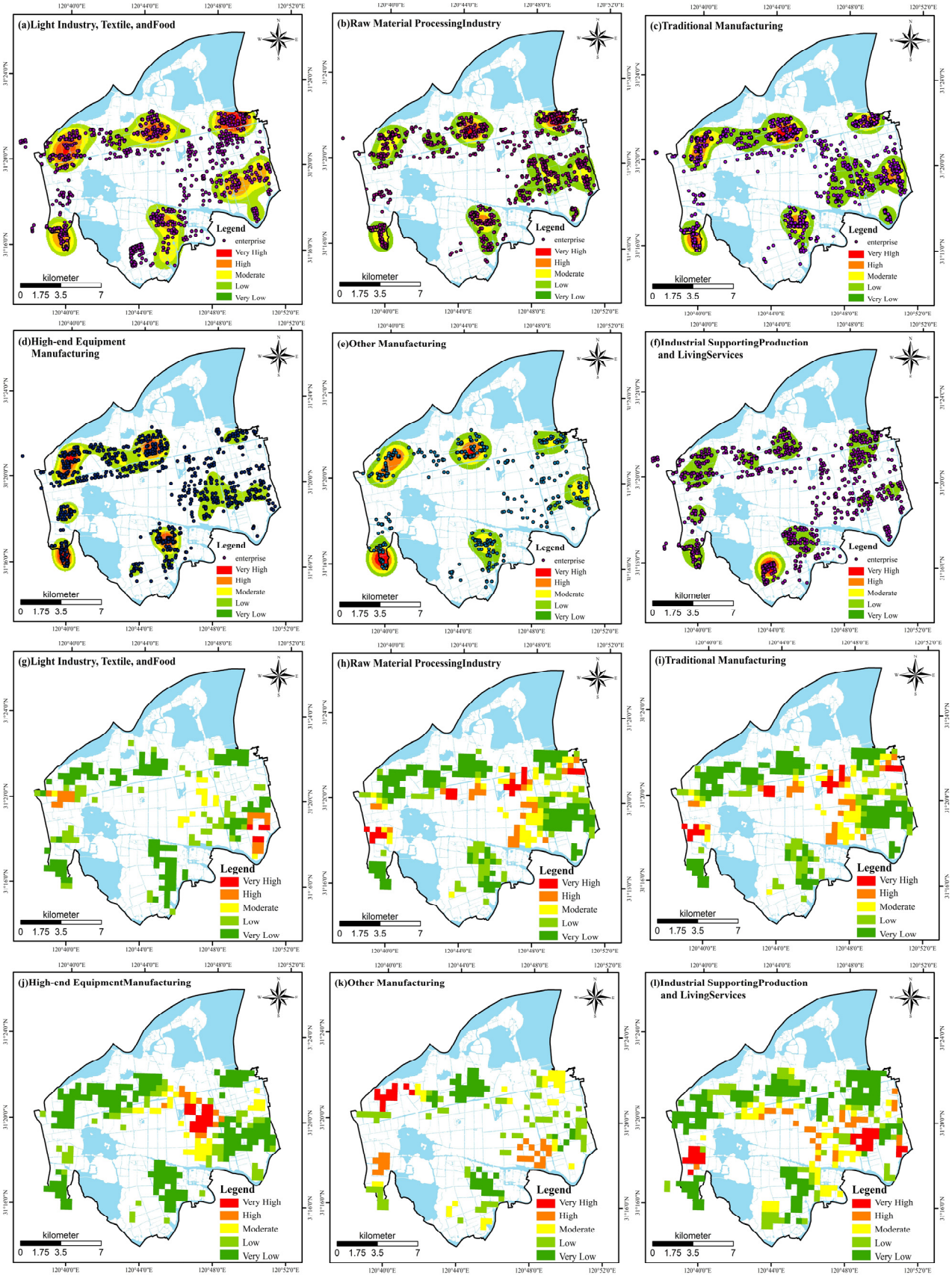

Figure 5. Comparison of enterprise quantity and output value hotspots by industry in 2022. (**a**–**f**) represent the distribution and density of industry enterprises, while (**g**–**l**) represent the spatial distribution of industry output value.

3.2.2. Polarization and Diffusion in Spatial Development

From 1994 to 2022, the spatial development of industrial land in SIP demonstrated a clear trend of agglomeration (Table 5), evolving from polarization to diffusion (Figure 6). During the period from 1994 to 2000, the overall Moran's *I* statistic, indicative of the overall spatial autocorrelation, exhibited low values alongside significantly low Z-values, suggesting a weak polarization effect in land expansion. In the subsequent period from 2001 to 2005, there was an increase in Moran's *I*, indicating strengthening of the central polarization effect in spatial development. Between 2005 and 2011, the polarization effect of industrial land use became notably positive. However, from 2012 to 2022, Moran's *I* decreased, reflecting a reduction in polarization and an enhancement of the diffusion effect. Overall, the tendency for spatial agglomeration in industrial land development from 2001 to 2022 was for it to initially intensify and subsequently diminish.

Table 5. Moran's *I* of industrial land expansion intensity during 1994~2022.

Period	Moran's *I*	Z Value	*p* Value	Variance
1994~2000	0.175	1.317	0.188	0.029
2001~2005	0.258	2.059	0.039	0.020
2006~2011	0.435	7.771	0.000	0.003
2012~2017	0.331	9.320	0.000	0.001
2018~2022	0.221	10.847	0.000	0.000

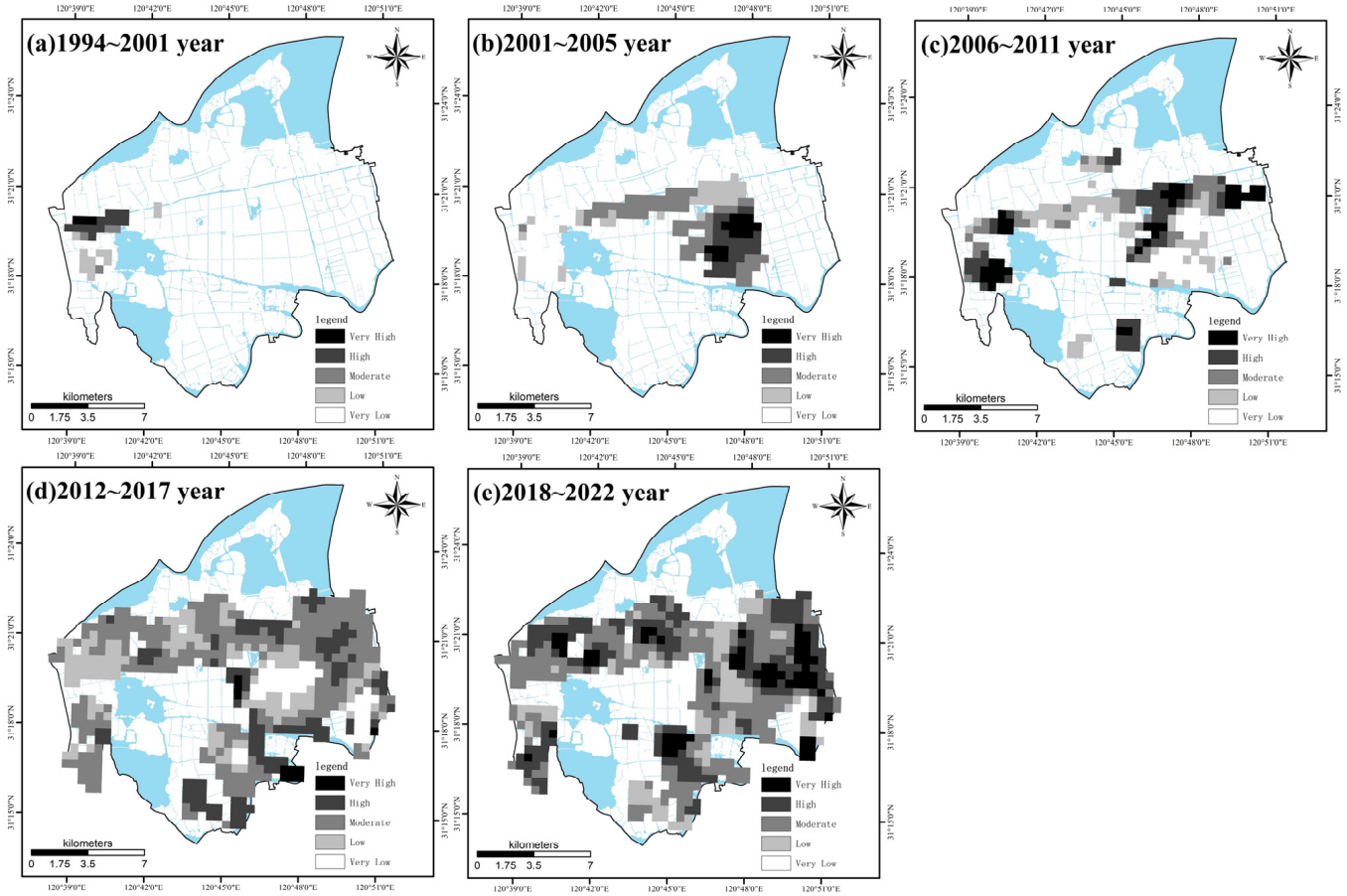

Figure 6. Distribution of industrial land spatial expansion hotspots.

3.2.3. Sprawl and Clustering in Spatial Development

The evolution of the industrial land in SIP exhibits a distinct local spatial structure characterized by path dependency and clustering effects. Areas with relatively high values

in terms of the time path length of LISA are predominantly located in the central region of the industrial park (Figure 7), indicating a dynamic spatial structure. In contrast, the low-value areas are relatively stable, reflecting a development pattern characterized by internal activity and external stability. The primary directions of spatial movement for the industrial land are concentrated between 0°–90° and 180°–270°. The trends in the intensity of expansion within grids and neighboring areas show a similar pattern, demonstrating integrated spatial dynamism. Numerous plots exhibit a synergistic effect among grids, indicating that the evolution of the spatial pattern of industrial land expansion presents the characteristic of spatial clustering. Conversely, fewer plots move in the directions of 90°–180° and 270°–360°, where the intensity of the expansion within grids and neighboring areas diverges, with these plots generally located at the periphery of the integrated moving areas. This suggests a more cohesive core of development, surrounded by less dynamically evolving outer zones.

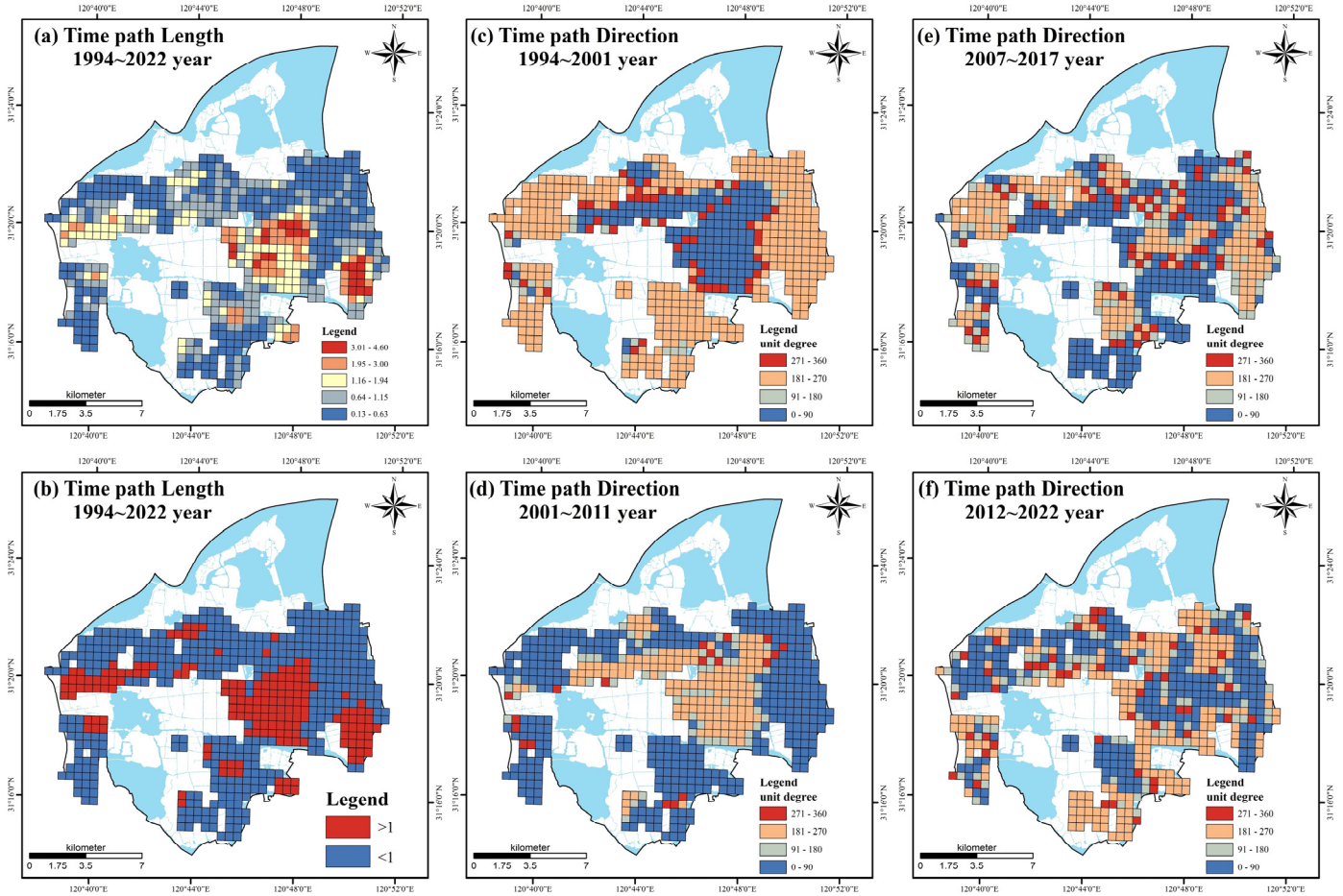

Figure 7. LISA time paths of industrial land evolution.

3.3. Variation in the Performance of the Industrial Land and Its Response to Land Use Evolution

3.3.1. Changes in Industrial Land Performance

An analysis of the performance of the industrial land in SIP from 2017 to 2022 reveals average scores for the economic benefit, innovation capacity, green development, social security, and overall performance indicators of 40.54, 16.98, 18.64, 49.13, and 42.18, respectively. The spatial distribution exhibits a pattern where the inner zones outperform the outer zones (Figure 8). While the economic benefit of the industrial land shows a high potential ceiling, indicating the presence of several enterprises with a high output efficiency, there remains a significant number of enterprises with low productivity, leading to pronounced polarization of the economic benefit.

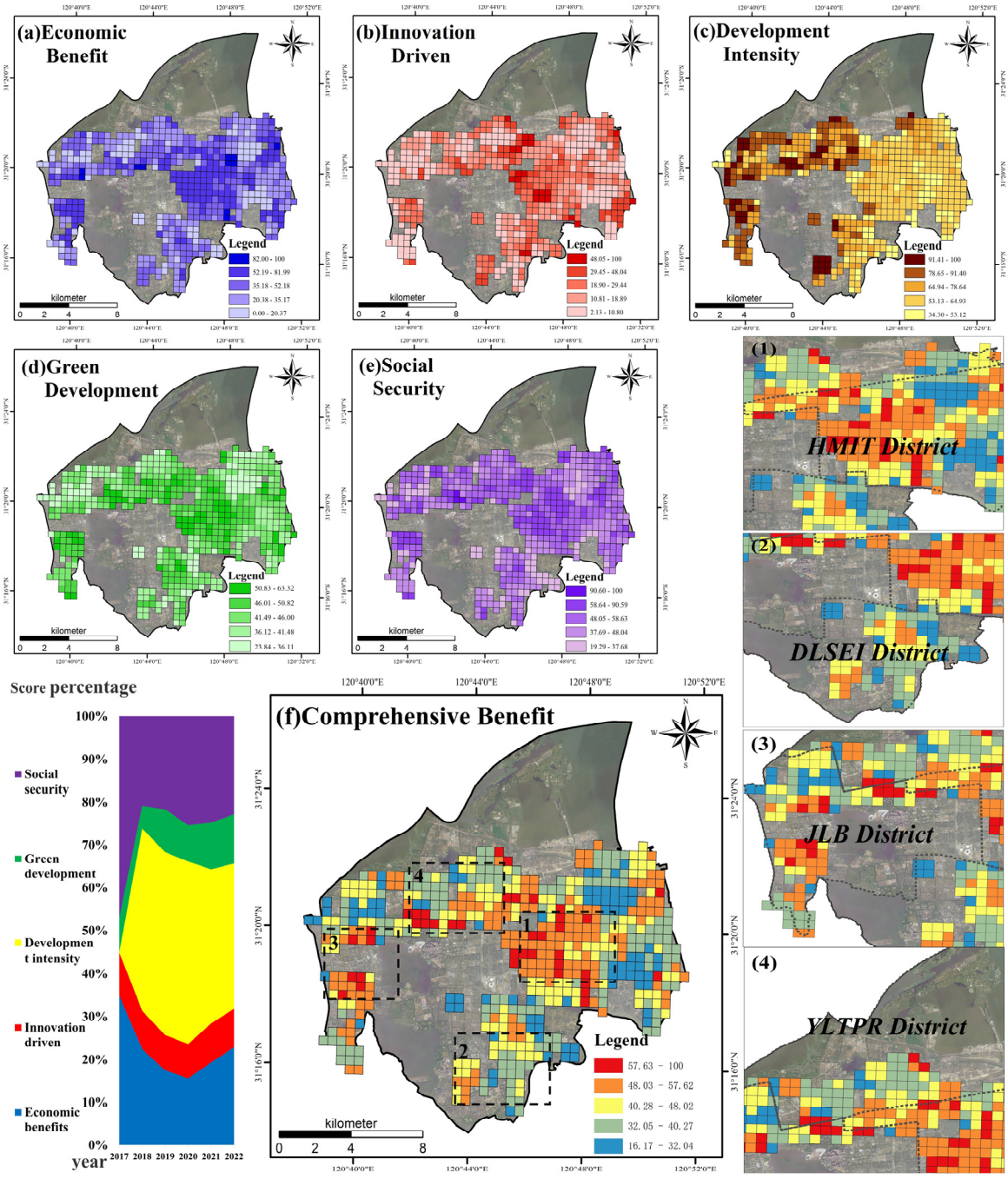

Figure 8. Spatial distribution of industrial land performance scores.

The proportion of industrial land with a high innovation capacity is notably low, with nearly 74% of the industrial land falling within a range characterized by a weak innovative performance. Furthermore, some areas and industries demonstrate excessive energy consumption. Spatially, the performance of the industrial land reflects marked disparities, with significant characteristics of concentration of the higher economic benefit into the inner region and a lower benefit in the periphery. The scale distribution indicates that the higher-scoring parcels are predominantly located in the HMIT, comprising nearly 30% of both the number and area of parcels. Conversely, the parcels with medium scores are primarily situated in the outskirts of the HMIT, similarly accounting for approximately 30% in terms of both number and area. The lower-scoring parcels tend to be smaller and more dispersed and exhibit considerable variability in their scores, also approximating 30%

in number and area, and are primarily located in the outer zone, particularly east of the DLSEI and HMIT.

3.3.2. Response of Industrial Land Performance to Land Scale Evolution

The fitting results between land scale and economic benefit (Figure 9c), the innovation-driven factor (Figure 9d), green development (Figure 9f), and comprehensive benefit (Figure 9h), respectively, all passed the significance test (*F*-test), indicating a close correlation between these factors and land scale. However, the fitting result between land scale and social security (Figure 9g) did not pass the significance test.

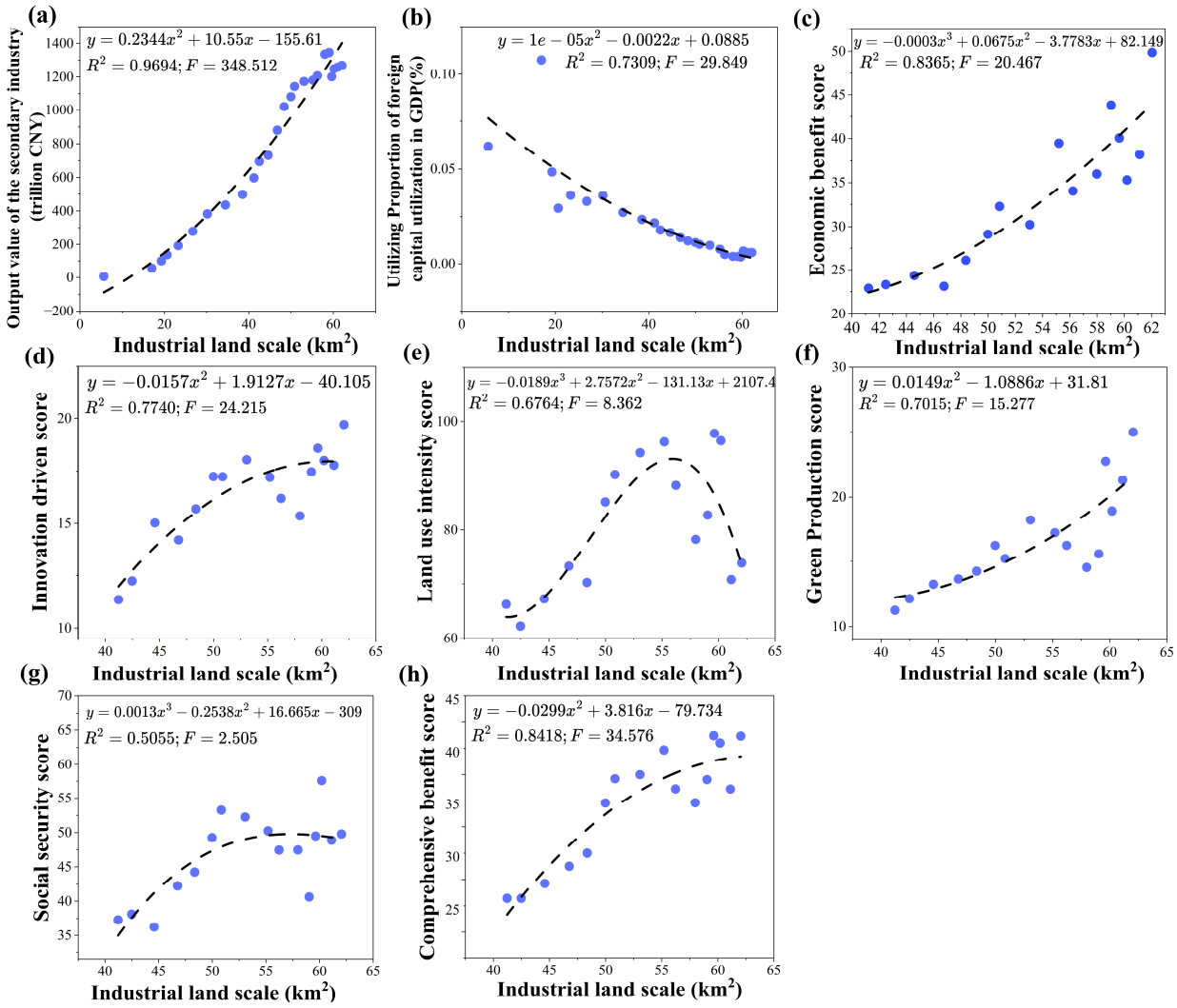

Figure 9. Fitting curve between industrial land scale and various types of industrial land performance. (**a**) fitting of output value of the secondary industry and land scale. (**b**) fitting of utilizing of foreign capital in GDP and land scale. (**c**) fitting of economic efficiency and land scale. (**d**) fitting of innovation driven score and land scale. (**e**) fitting of land use intensity score and land scale. (**f**) fitting of green production score and land scale. (**g**) fitting of social security score and land scale. (**h**) fitting of comprehensive benefit score and land scale.

The performance response index of the secondary industry's output value to land scale (Figure 10a) shows a trend of rapid decline, followed by stabilization. Between 1994 and 2004, the index I decreased sharply to 2, suggesting that as the land scale expanded rapidly, the output performance declined quickly. Although the absolute value I remained relatively high, the performance output was still significant during this period of an increase in land

scale. From 2004 to 2022, the index I fluctuated slightly around 2, indicating that as the land scale increased, the output performance stabilized at a positive value I, suggesting that the increase in land scale continues to have a positive impact on the output performance and that land scale expansion can still enhance the output benefit while approaching a fixed level.

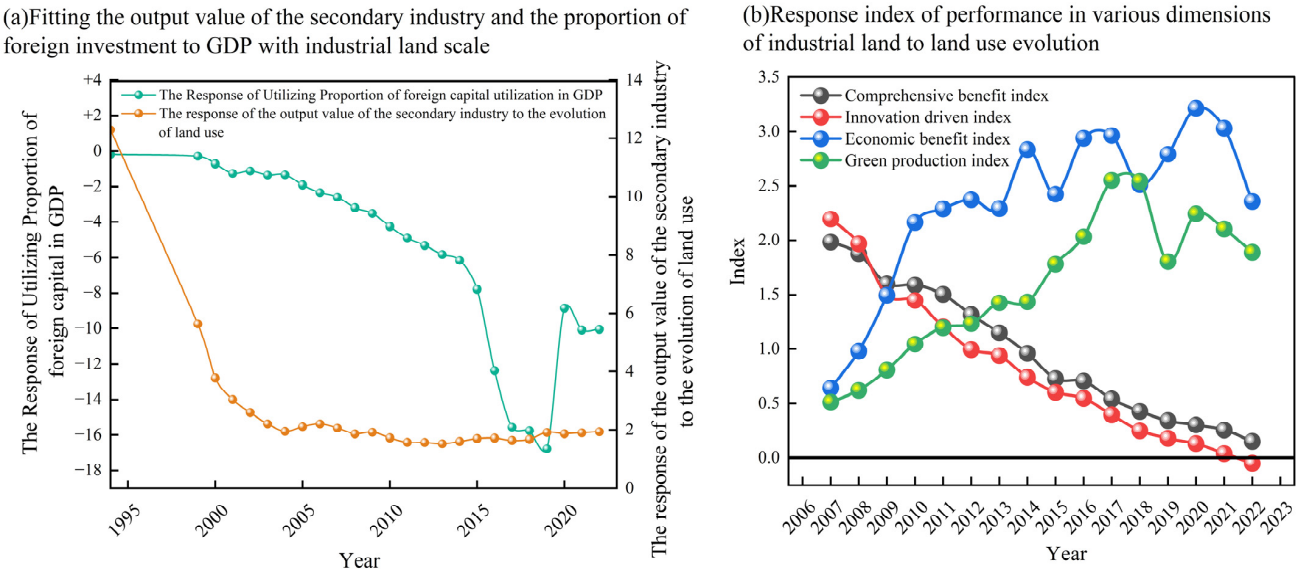

Figure 10. Response of various performance dimensions of industrial land to land scale.

From 1994 to 2022, the response index of the foreign investment as a proportion of GDP in SIP to land scale was negative and gradually declined (Figure 10a). This indicates that as the supply of industrial land in the park continued to increase, the region gradually reduced its reliance on foreign investment, resulting in a weakened driving effect of foreign capital on the economy. During this period, land expansion did not significantly enhance the overall economic performance (Figure 10b); the actual economic demands and development objectives of the park could not be achieved by merely increasing the land supply. From 2017 to 2022, the increase in industrial land scale had a certain positive effect in terms of its economic benefit, suggesting that during this phase, land expansion indeed contributed to economic growth. However, the response index for the innovation-driven factor and comprehensive performance exhibited a downward trend during the same period, with the index for the innovation-driven factor even reaching a negative value in some years.

4. Discussion

4.1. Path Dependence of Industrial Land Development in Development Zones and Solutions

The evolution of the industrial land in SIP exhibits significant phased characteristics and path dependence. From 1994 to 2005, the expansion of industrial land centered around single-polarization development, primarily concentrated in the JLB. The core area which received support from high-standard infrastructure and policy rapidly attracted numerous high-value-added industries and foreign investment [25], forming a competitive growth pole [26], which aligns with classic "growth pole theory". However, this single-centered aggregation model gradually revealed the issue of path dependence in subsequent stages. In the early phases of development, there was a tendency to focus on the performance indicators based on rapid land expansion and the financial return, neglecting the slower but significantly beneficial effects of the industrial agglomeration [7]. Because they lacked the corresponding resources and policy support, the peripheral areas failed to develop synchronously [20], reflecting significant disparities in the spatial development momentum [27]. Similar phenomena have been observed in regions such as Shenzhen (e.g., Futian,

Luohu) and Tianjin Binhai New Area. Therefore, it is crucial for policy formulation to involve zoning management and the assessment of spatial zoning strategy.

The period from 2006 to 2011 marked a transition to a decentralized development model that broke the industrial limitations of the JLB core area, creating new industrial agglomeration points in secondary centers like the DLSEI. This layout alleviated the spatial pressure in the core area, optimized the functional zoning, enhanced the overall land use efficiency, diversified the industries, and reduced the local energy consumption and carbon emissions [28]. From the perspective of geographic spatial diffusion theory, this multi-centered development aligns with the "diffusion wave" model. SIP has introduced high-value-added industries such as nanotechnology parks to facilitate a shift in manufacturing being labor-intensive to capital-intensive and a significant decrease in the proportion of foreign investment to the GDP (Figure 10a). This release of endogenous industrial momentum achieved spatial redistribution of the industries. However, despite the continuous expansion of the secondary centers and the clear characteristics of cluster development, the tiered disparity remained. Such challenges are also evident in technology parks in Bangalore, India, and the San Francisco Bay Area (e.g., Mountain View and San Jose) [29,30], where the peripheral areas have struggled to overcome the core area's dominance in terms of innovation resources and the industrial chains, hindering the formation of a balanced, multi-centered, collaborative effect. At this phase, the development zone should enhance the collaborative innovation and industrial synergy between the core and the peripheral areas, leveraging upstream and downstream cooperation in the industrial chains, technological diffusion, and industry integration to establish a regional competitive advantage.

From 2012 to 2022, the industrial land demonstrated a pattern of spatial diffusion and generalized development zone expansion, leading to a clear trend of spread. This phase exhibited the characteristics of "suburbanization" and "re-agglomeration", which facilitated the optimization of the internal spatial structure of the park [31]. As the industrial land use in SIP approached saturation, the park adopted an enclave model to foster cross-regional economic cooperation with other cities, such as the north–south collaboration of Suzhou–Suqian Industrial Park [32]. This approach alleviated the development pressure on the core area while enabling the transfer of medium- and low-value-added industries to the peripheral regions, which allowed the core area to focus on high-end manufacturing and innovative industries, reflecting the essence of "industrial gradient transfer theory". This generalized development strategy enhances SIP's resource allocation efficiency in a broader region, providing a viable expansion model for other development zones. This development aligns with industrial gradient transfer theory, as transferring the medium- and low-value-added industries to the peripheral areas allows parks to concentrate on high-end manufacturing and innovative industry development. Development zones with limited land resources must focus on optimizing the spatial and industrial structures both within and outside parks, which enhances the coupling degree and agglomeration efficiency of regional industrial networks and strengthens the interconnectivity and synergy among various industrial clusters to improve overall economic competitiveness [33].

4.2. Diminishing Marginal Returns of Land Use Expansion and the Corresponding Strategy

The spatial agglomeration of the development zones reinforces a "core–periphery" structure, creating economic highlands [34]. However, the response of the industrial land's performance to changes in land scale indicates that as the industrial land expanded during the phases of spatial diffusion and generalized development zone expansion, the growth in land scale not only could not generate economic benefits but also brought diminishing marginal returns on land use apparently. This suggests that mere reliance on land scale expansion is insufficient to enhance regional economic performance sustainably. To deal with this challenge, SIP issued a revised master plan in 2012, expanding the park's spatial scope and outlining new objectives such as industrial transformation, spatial optimization, and ecological improvement, which signaled a transition toward green development.

The Green Production Response Index from 2020 to 2022 indicates that the impact of land expansion in SIP on green production gradually weakened (Figure 10b). This may be attributed to the economic uncertainties caused by the COVID-19 pandemic, with policies placing greater emphasis on economic growth and industrial productivity, while relatively less attention was given to green incentives and stringent environmental regulations. Targeted policies for green production enterprises, such as tax reductions, low-interest loans, and direct subsidies, should be introduced to encourage enterprises to refocus on green transformation. Introducing clean technologies and green buildings is crucial for achieving a balance between economic growth and environmental protection [9]. Furthermore, the innovation-driven response index showed a declining trend during this phase, with negative values emerging, which indicates that the physical spatial expansion has a limited effect on enhancing the innovative capacity. This proves that development zones should strengthen their innovation capabilities and the green production performance of the peripheral areas while promoting spatial diffusion to ensure their long-term competitiveness and sustainable development.

To address the challenges of limited land resources and diminishing marginal returns, SIP has facilitated the digital transformation of its traditional industries by integrating technologies such as the Internet of Things, cloud computing, and artificial intelligence to shift from dependence on physical spatial expansion to the development and utilization of virtual spaces gradually. This transformation not only enhances economic output and spatial competitiveness on limited land [35] but also strengthens the economic resilience of parks in response to external shocks, generating significant spatial spillover effects [36]. These phenomena indicate that development zones should focus further on innovation-driven strategies and emphasize the integration of virtual land [37], particularly in the deep integration of the digital economy and information technology. This will facilitate a transition of the regional economy from physical expansion to smart and efficient development, which will lay the foundation for sustainable development of high quality in the future.

4.3. Strategies for Land Use and Spatial Optimization Expansion

The spatial evolution characteristics of land use in SIP are dynamically coupled with industrial development, showing an overall trend towards a spatial distribution pattern of zonal differentiation. With spatial diffusion and polarization in the development process of SIP, the spatial layout of different industries is continuously optimized and adjusted, exhibiting a certain degree of spatial self-organization. As land is the core resource for the spatial organization of development zones, utilization efficiency and optimization strategies are critical to the sustainable development of the region [38]. Based on the results of the comprehensive evaluation of industry (Figure S2), SIP's industries exhibit significant differences in scores. These differences are influenced not only by the industry type but also by factors such as technological intensity, output level, and their dependence on land resources. The high-end equipment manufacturing industry, as a technology-intensive sector, is able to achieve a higher land use efficiency due to its dominant position in the industrial chain. These enterprises play a positive role in promoting the overall technological innovation in the park and increasing its output value, thus improving land unit output and spatial utilization efficiency. In contrast (Table S2), labor-intensive industries such as raw material processing, due to their low technological level, low added value, and small scale, usually result in lower land use efficiency and economic benefits. Capital-intensive industries, such as the chemical raw material and product manufacturing industry and the metal product industry, show larger differences in scores. Although these industries require substantial capital input in the production process, differences in technology levels and production modes lead to significant variations in their land use performance.

However, as SIP's multi-polarized pattern gradually improved, a lack of internal integration of industrial land and a loosely spread diffusion state again dominated (Table 5). In the diffusion phase, nearing the spatial growth limit (2018–2022), the BCI slightly

declined again, reflecting the need for enhanced management of stock land adjustments and redevelopment during the diffusion process [39]. Therefore, SIP has focused on dynamic land renewal strategies [40], such as improving land's spatial potential through three-dimensional space developments and high-rise industrial buildings [41]. Through cross-regional "enclave" economy expansion [42], SIP has achieved efficient use of its land resources [43].

To promote the efficient allocation of land resources and balanced development in the development zone, SIP has established a land performance evaluation mechanism to monitor its land use efficiency in real time. It adjusts its policies and spatial planning to promote balanced development within the zone [44]. Analysis of the spatial agglomeration of the number of enterprises and output value indicates the existence of spatial mismatches in certain areas, where the production space allocation does not fully match the level of industry agglomeration, weakening the economic efficiency of the development zone [45]. This mismatch mainly arises from misalignment between the enterprise lifecycles and land lease terms, leading to inefficient enterprises being unable to exit the market in a timely manner. SIP should strengthen lifecycle management of its enterprises and adopt flexible land-leasing policies.

4.4. Implications, Limitations, and Perspectives

The land use model of SIP provides a valuable reference for other development zones. Firstly, SIP's rapid development has experienced a typical evolution from being single-center to multi-center and then to a generalized development zone, emphasizing the importance of flexibly adjusting the spatial layout of development zones according to changes in economic and social demands. Secondly, the spatial zoning structure of the industrial layout and its dynamic adjustment with the spatial development of the development zone indicate that attention should be paid to the dynamic adjustment and optimization of the industrial configuration and the spatial distribution in the development process, prioritizing support for technology-intensive industries (such as high-end equipment manufacturing) with a higher land use efficiency and gradually promoting the technological upgrading of traditional industries. Finally, SIP has effectively overcome its spatial resource constraints through an enclave economy model, which suggests that when facing spatial growth limits, the enclave model can guide further development in the later stages of a development zone's growth through regional collaboration.

This study mainly focused on macro-level spatial changes and did not explore the micro-level responses and evolution mechanisms at the enterprise level in depth. Future research should involve cross-zone and cross-country comparative analyses, particularly between developed and developing countries, to reveal more universal industrial land development models. With the promotion of sustainable development goals, research on green transformation and the low-carbon economy in development zones will become increasingly important. Future research should also focus on the potential of virtual space and digital technologies to optimize land use, providing new theoretical support for the sustainable development of global development zones.

5. Conclusions

This paper analyzed the evolution of the industrial land in SIP and its response in terms of its comprehensive performance and revealed the spatial characteristics, overall benefits, and dynamic relationships at different development stages. The main conclusions are as follows: (1) The development of industrial land in SIP has undergone three distinct phases: single-centered polarization, multi-centered development, spatial diffusion toward a generalized development zone, demonstrating the clear characteristics of the phases and path dependence. (2) Industrialization significantly promoted rapid economic growth; however, the marginal benefits of spatial expansion decreased noticeably. Furthermore, there were significant differences in the land use performance across different industry types. During the diffusion stage of development zones, attention should be given to the

adjustment and redevelopment of stock land, optimizing the spatial layout of technology-intensive industries and enterprises, and driving the technological upgrading and industrial agglomeration of labor-intensive industries. (3) Once development reaches a certain stage, it is insufficient for sustainable economic growth to rely solely on physical expansion of the land. Therefore, it is crucial to strengthen collaboration with enclave economies and actively implement innovation-driven strategies and green development initiatives.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/land13122182/s1. Table S1: Systematic clustering of industrial land expansion intensity; Table S2: Manufacturing industry situation in SIP; Figure S1: Industrial land change from 1994 to 2022; Figure S2: Performance score chart of industries landuse.

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