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Spatial and Temporal Distribution Characteristics and Influential Mechanisms of China's Industrial Landscape Based on Geodetector

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Abstract: The industrial landscape constitutes a crucial aspect of a region's historical and cultural identity, serving as a valuable asset in the development of industrial tourism. Exploring the industrial landscape supports initiatives in industrial tourism, acts as a catalyst for community revitalization, and contributes to sustainable urban progress. The primary objective of this research was to investigate the spatial distribution characteristics and underlying determinants of China's industrial landscape (CIL) to inform urban planning, cultural heritage preservation, and sustainable development initiatives. This study utilized analytical tools, such as the nearest neighbor index, geographic concentration index, and hot spot analysis, to comprehensively examine the spatial distribution of CIL. Additionally, Geodetector was employed to explore the correlating factors behind this distribution. The findings reveal the following: (1) CIL exhibited a pronounced agglomerative spatial pattern characterized by a high degree of concentration, significant disparities, and substantial spatial autocorrelation. (2) Over time, the agglomeration of CIL varied, intensifying initially and then diminishing, with the center of gravity of its distribution shifting eastward before subsequently moving westward in a directional trend resembling "northeast–southwest". (3) There was a diverse array of industrial landscape types within China, with notable disparities in the prevalence of different categories. The manufacturing and transportation sectors boasted the highest number of heritage sites. (4) The distribution pattern of CIL was shaped by factors such as the level of economic development, socio-demographic conditions, transportation infrastructure, and cultural milieu. The interplay between these factors had a substantial impact on this distribution pattern.

Keywords: industrial landscape; influence mechanism; Geodetector; heritage protection; spatial–temporal patterns



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1. Introduction

The industrial landscape constitutes a significant facet of the urban landscape, encapsulating the technological advancements and industrial evolution that have profoundly shaped human history, particularly during the epochal Industrial Revolution [1,2]. In the context of post-industrial societies, the preservation and transmission of this landscape have become a global issue [3]. Especially within the realm of sustainable urban development, the preservation and reuse of the industrial landscape have emerged as pivotal mechanisms for facilitating urban revitalization [4] and fostering economic growth [5]. The industrial landscape encompasses the tangible remains of technological and industrial history, including manufacturing and mining sites, as well as power and transportation infrastructure. It records the social and material cultural activities of people in the construction of infrastructure, the collection of raw materials, the production of objects, and the distribution of energy [6]. Recently, the practice of preserving and reutilizing the industrial

landscape has undergone substantial expansion through the support of relevant policies, with countries and cities actively exploring different approaches and models [7–9]. However, regional differences in the conservation of the industrial landscape are evident due to various constraints, such as economic, cultural, and policy factors. Simultaneously, there remains an overall insufficiency of knowledge about the industrial landscape [10], resulting in the phenomena of “scattering” and “isolation” [11]. These challenges have emerged as pivotal obstacles to the sustainable development of the industrial landscape, constituting urgent issues that demand resolution through both historical and cultural heritage preservation and the promotion of a sustainable industrial landscape. Therefore, scientifically identifying and analyzing the spatial distribution characteristics of the industrial landscape, as well as elucidating the underlying influential mechanisms, will facilitate more efficient integration and utilization of industrial landscape resources. Moreover, these practices will provide robust guidance for formulating strategies pertaining to the development of industrial tourism.

Industrial archaeology, which aims to preserve and document the remains of the Industrial Revolution, began exploring industrial landscape conservation in the mid-to-late 19th century [12]. When the International Consortium for the Conservation of Industrial Heritage (TICCIH) was founded in 1978, a milestone was reached in the early development of industrial landscape conservation [13]. Initially, the primary focus was on the physical remnants of industrial activity, encompassing structures and machinery. However, crystallizing the concept of industrial landscape was not achieved until the adoption of the Nizhny Tagil Charter for the Industrial Heritage by TICCIH [6] in 2003 and The Dublin Principles [14] by the International Council on Monuments and Sites (ICOMOS) in 2011. These charters established definitions and values that provide a comprehensive framework for the field [15]. Subsequently, there has been a growing academic interest in industrial landscapes, broadening the research scope to include heritage significance evaluation [16–19], adaptive reuse strategies [20–22], community engagement [23–25], and the exploration of the tourism potential of industrial landscapes [26,27]. This broader focus represents a holistic approach to understanding and preserving the complex nature of industrial landscapes. Research on industrial landscapes, which are critical to urban and regional development, has spanned conservation design, public perception, and cultural values. With the reduction in industrial activities, the preservation and assessment of industrial landscapes have emerged as pivotal research areas [28,29]. Innovative research into the role of social media in enhancing public engagement and awareness about conservation underscores the significant potential of digital platforms for the preservation of industrial landscapes [30]. Moreover, public perceptions and preferences concerning post-industrial landscapes critically influence landscape planning and management [31]. Advanced methodologies, such as deep learning techniques and multiple regression models, are employed to analyze public perceptions of restoration in post-industrial parks, elucidating the distinct contributions of natural and man-made elements in boosting public satisfaction and restorative experiences [32]. The transformation of industrial landscapes involves not only physical changes but also significant shifts in social and cultural dimensions. For instance, an ethnographic examination of the transition of industrial landscapes across six European countries investigated the interplay between industry, industrial landscapes, and class identities, unveiling the extensive impact of industrial landscapes on social memory and identity [33]. Nonetheless, investigations into the spatial distribution and correlating factors of industrial landscape resources are relatively recent, having attracted scholarly attention only in recent years. Recent studies revealed that industrial landscapes predominantly cluster in regions characterized by abundant natural resources and high population density [34]. These studies further investigated the spatial distribution features of the industrial landscape [35], considering factors such as the geographical distribution [36,37], industry type [38], structural typology [39], and economic systems [40], and presented comprehensive models for industrial landscape preservation.

While the aforementioned studies provided comparative analyses of the spatial distribution of the industrial landscape and its determining factors, they exhibited certain limitations. First, the majority of these investigations focused on exploring the industrial landscape of specific cities or industry types, such as the military industrial landscape [41], petroleum industrial landscape [42], and rural industrial landscape [43]. This limited scope may restrict the breadth and representativeness of the samples, thereby posing challenges in generalizing findings across a wider spectrum of the industrial landscape. Consequently, it becomes difficult to provide a comprehensive portrayal of its overall characteristics. Second, the research methodology employed was primarily rooted in traditional qualitative analysis methods when examining the influential mechanisms of the spatial distribution. These qualitative approaches may fall short of capturing the intricate interdependencies, particularly the geographical relationships. Furthermore, in terms of research content, the selection and measurement of relevant factors have predominantly remained within the purview of qualitative analyses, with quantitative analytical methods not yet widely employed to augment the explanatory capacity of these influential factors. A more balanced integration of qualitative and quantitative methodologies has the potential to provide a more nuanced and comprehensive understanding of the spatial dynamics associated with the industrial landscape.

Geodetector, which is a powerful analytical tool, has been widely utilized for the comprehensive exploration of a broad range of geographic phenomena and their influencing factors. This tool has been applied across critical fields, such as environmental science [44,45], public health [46,47], resource management [48], and ecological risk assessment [49]. For instance, Geodetector facilitated assessments of nitrate contamination in the groundwater in California's Central Valley, identifying the principal factors contributing to this issue [50]. Furthermore, Geodetector was instrumental in evaluating the groundwater recharge potential of the Upper Blue Nile Basin in Ethiopia through integration with the WetSpa-M model [51]. Scholars also adeptly employed Geodetector to analyze from a global perspective the spatial and temporal clustering characteristics of the COVID-19 outbreak and its related factors [52]. Despite these diverse applications, deploying Geodetector to examine the spatial distribution of heritage, particularly within industrial landscapes, remains notably limited.

In view of this, this study utilized data from the National List of Industrial Heritage (NIHL) and the China Industrial Heritage Protection List (CIHPL) as representative datasets for China's industrial landscape (CIL). It employed a combination of analytical techniques, including the geographic concentration index, hot spot analysis, and kernel density analysis, to comprehensively illustrate the spatial heterogeneity traits of CIL. Moreover, Geodetector analysis was employed in this study to investigate the factors that influenced the spatial distribution of CIL. The integration of these methodologies was designed to provide a comprehensive depiction of the spatial dynamics and determinants of CIL. The findings will provide strategic recommendations for urban planning, heritage conservation, and sustainable development, and promote industrial tourism and urban revitalization.

2. Materials and Methods

2.1. Data Sources

The data utilized in this research were obtained from two primary sources: the CAST database, which includes a total of 197 sites published by the MIIT in five separate batches, and the CIHPL, which consists of three batches comprising 300 sites published by CAST. After removing duplicate entries, our dataset comprised 484 unique sites. We obtained geographic coordinates using the geographic coordinate picker in Google Maps. We partitioned the industrial heritage elements characterized by linear features, such as railroad heritage sites, into nodes based on provincial administrative boundaries and selected representative coordinates to capture their geographical extent. For instance, the Jinpu Railway, originating from Tianjin, which is a centrally governed municipality, traverses four provinces (Hebei, Shandong, Anhui, and Jiangsu), as well as the municipality of

Tianjin, before concluding in Nanjing within the province of Jiangsu. Consequently, we selected coordinates from five key stations along its route: Tianjin North Railway Station, Qingxian Railway Station in Hebei Province, Zaozhuang Railway Station in Shandong Province, Bengbu East Railway Station in Anhui Province, and Nanjing Pukou Railway Station in Jiangsu Province. These geographic coordinates were then imported into ArcGIS 10.2 software to generate a comprehensive map illustrating the spatial distribution of CIL sites (Figure 1).

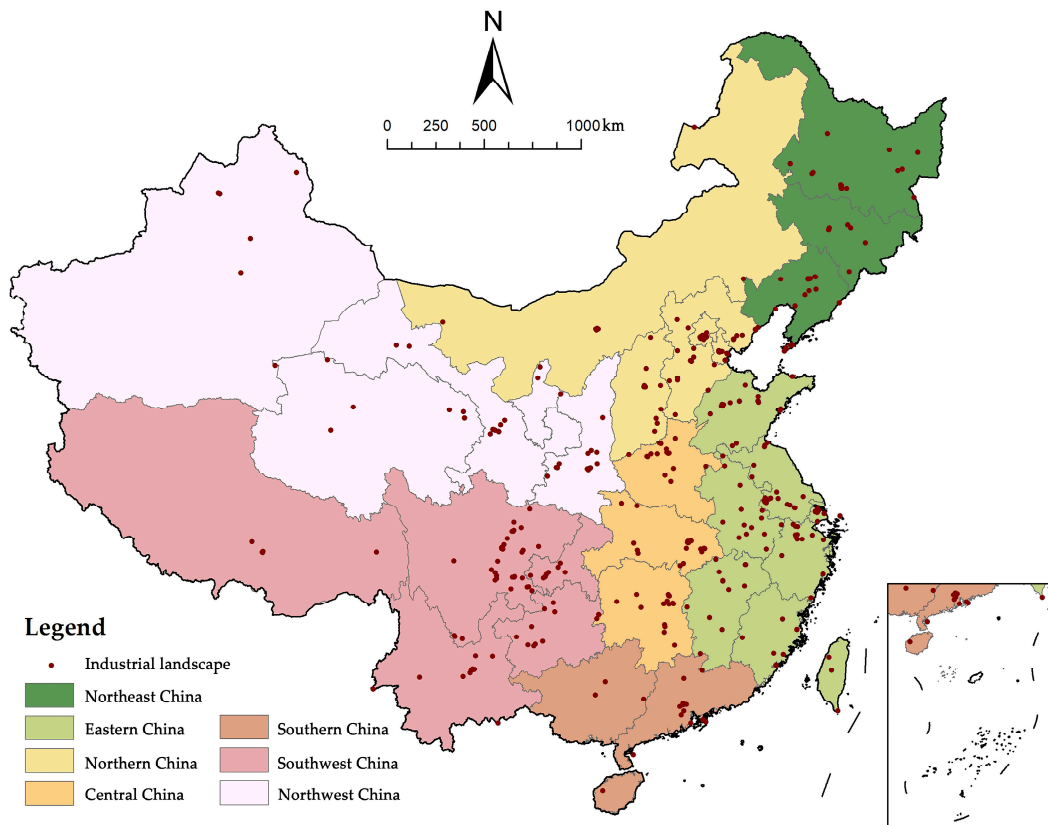


Figure 1. Spatial distribution of CIL sites.

Map vector information was sourced from the Resource Environment and Data Center of the Chinese Academy of Sciences (<http://www.resdc.cn/> (accessed on 5 January 2024)). Our humanistic data, which encompassed various factors that affect the industrial landscape distribution, were collected from authoritative sources, including the 2020 China Statistical Yearbook, China Cultural Relics, and Tourism Statistical Yearbook, and the 2020 National Economic and Social Development Statistical Bulletin for each respective region.

2.2. Research Methodology

To conduct a comprehensive assessment of the spatial characteristics and the determinants that affected CIL, this investigation incorporated a selection of widely recognized indices and models within the field of geospatial research (Figure 2). Utilization of the nearest neighbor index, for instance, facilitated the categorization of the spatial patterning of CIL sites, enabling the distinction between tendencies toward clustering, dispersion, and randomness. Subsequently, the imbalance index was employed to quantify the extent of variability in the spatial distribution of CIL sites, thereby highlighting potential regions of imbalance or concentration. Hot spot analysis served to identify clusters of high or low values within CIL, providing insights into the spatial correlations and patterns of concentration. Complementing this analysis, the standard deviation ellipse tool tracked the temporal shifts and evolution of these clusters over time. Finally, Geodetector analysis

quantitatively evaluated the impact of humanistic factors on the spatial distribution of CIL, affording us a nuanced comprehension of the intricate interplay between human activities and the environment in shaping the distinctive characteristics of industrial landscape sites.

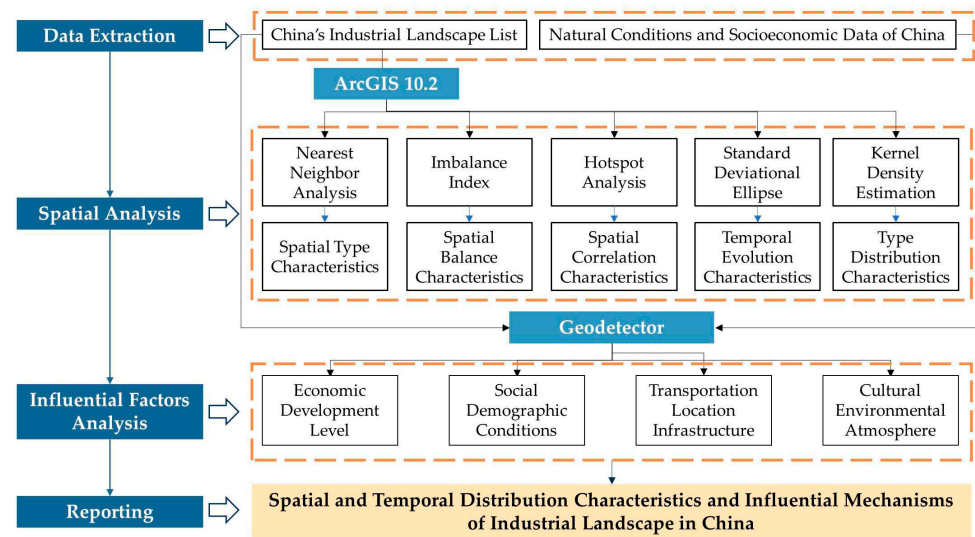


Figure 2. Research framework diagram.

2.2.1. Nearest Neighbor Index

The nearest neighbor index (NNI) acts as a spatial measure of the closeness of point elements in a geographic setting. It is calculated as the ratio of the observed mean distance of the nearest neighbor to the expected mean distance under complete spatial randomness [53]. In this research, the NNI was utilized to characterize the spatial pattern of CIL. The formula is as follows [54]:

$$NNI = \frac{\bar{r}_1}{\bar{r}_e} = \frac{\bar{r}_1}{\frac{1}{2}\sqrt{\frac{n}{A}}} \quad (1)$$

where NNI represents the nearest neighbor index, \bar{r}_1 represents the average value of the Euclidean distance r_1 between the nearest neighbors, \bar{r}_e represents the theoretical nearest neighbor distance, n represents the number of industrial heritage sites, and A represents the study area. If $NNI > 1$, CIL sites tended to be evenly distributed; if $NNI = 1$, the sites were randomly distributed; and if $NNI < 1$, there tended to be an agglomerative distribution [54].

2.2.2. Geographic Concentration Index

The geographic concentration index reflects the distribution of point elements in geographic space [55]. In this study, the geographic concentration index was applied to measure the degree of spatial balance in CIL at the national scale; the formula is

$$G = \sqrt{\sum_{i=1}^n (X_i / H)^2} \quad (2)$$

where G represents the geographic concentration index, X_i denotes the distribution number of CIL sites in the i th provincial administrative region, and H denotes the total number of CIL sites. The larger the value of G , the more centralized the distribution of CIL sites was, and the smaller the value of G , the more discrete the distribution of CIL sites was. If $G > G_0$, this indicates that CIL sites were characterized by a centralized distribution, where G_0 represents the geographic concentration index when CIL sites were distributed on average.

2.2.3. Hot Spot Analysis

Hot spot analysis is used to analyze where the spatial clustering of high-value elements or low-value elements occurs in a region [56]. In this study, hot spot analysis was used to

analyze the differences in the degrees of similarity of CIL spatially distributed phenomena in spatially neighboring regions. The hot spot analysis tool based on the Getis–Ord G_i^* statistical index was used in GIS 10.2 to reflect the clustering of spatial high-value areas (hot spot areas) and low-value areas (cold spot areas) by calculating the Z-values and p-values between the elements, as follows [57]:

$$G_i^* = \frac{\sum_{j=1}^n w_{i,j} x_j - \bar{X} \sum_{j=1}^n w_{i,j}}{S \sqrt{\frac{n \sum_{j=1}^n w_{i,j}^2 - \left(\sum_{j=1}^n w_{i,j}\right)^2}{n-1}}} \quad (3)$$

where i represents the central element, j denotes all elements in the domain, x_j signifies the attribute value of element j , $w_{i,j}$ indicates the spatial weight between elements i and j , and n represents the total number of elements. A higher G_i^* score implies a more compact clustering of CIL, while a lower score suggests otherwise.

2.2.4. Kernel Density Analysis

Kernel density analysis represents a technique for assessing the density of points by considering the effect of distance attenuation, thereby vividly illustrating the concentration level of point features [58,59]. In this research, the method of kernel density analysis was applied to examine the density characteristics of different CIL types using the following formula [60]:

$$ff(x) = \frac{1}{nh} \sum_{i=1}^n k\left(\frac{x - x_i}{h}\right) \quad (4)$$

where k is the spatial weight function, where if the industrial landscape was closer to the center point, the greater the weight, and vice versa; h ($h > 0$) is the bandwidth; $(x - x_i)$ is the value of the distance from the estimated value point x to the industrial landscape x_i ; and n is the number of CIL sites.

2.2.5. Geodetector

Geodetector serves as an effective tool for detecting spatial heterogeneity and elucidating the underlying driving forces [61]. Factor detection in Geodetector enables the identification of the individual influences that explain the target variable to a certain extent, while interaction detection can determine whether the combined effect of these influences enhances or diminishes the explanatory power of the target variable. This study analyzed the influence of humanistic factors on the spatial differentiation of CIL sites with the help of the factor detection and interaction detection tools in Geodetector [62].

$$q = \left(N\sigma^2 - \sum_{h=1}^L N_h \sigma_h^2 \right) / N\sigma^2 \quad (5)$$

In this formula, L represents the number of strata of the influence factor X ; N_h and N denote the counts of industrial landscape sites within stratum h and the entire region, respectively; and σ_h^2 and σ^2 represent the variance in density of industrial landscape sites within stratum h and across the entire region, respectively. The parameter q ($0 \leq q \leq 1$) represents the measurement of the effect that an influencing factor has on the spatial distribution of CIL sites. A greater q value reflects a more pronounced effect of the influencing factor on spatial patterns, whereas a smaller q value indicates a less significant impact [63].

3. Results

3.1. Spatial Distribution Characteristics

3.1.1. Spatial Typology Characteristics: Agglomerative Distribution

CIL predominantly exhibited the characteristics of a clustered distribution. This distribution pattern was quantitatively assessed using the NNI within ArcGIS 10.2, resulting in a calculated NNI for CIL of 0.406. This value, which is significantly less than 1, indicates a

high level of spatial clustering. Conventionally, an NNI value of ≤ 0.5 typically indicates an aggregated distribution, while $0.5 < \text{NNI} \leq 0.8$ corresponds to an aggregated–random distribution. A value of $0.8 < \text{NNI} < 1.2$ is interpreted as a random distribution; $1.2 \leq \text{NNI} < 1.5$ suggests a random–discrete distribution; whereas $\text{NNI} \geq 1.5$ is indicative of a uniform distribution across space [64]. This pronounced clustering not only reflects the spatial dynamics of CIL but also highlights the significant potential for promoting industrial tourism within China.

An analysis of the spatial distribution of the industrial landscape across China’s geographical divisions revealed a significant regional disparity. The majority of these sites were concentrated in Eastern China, which, together with Northern China, accounted for approximately 50% of the country’s total industrial landscape sites. Conversely, Southern China contained the smallest proportion of these sites. By employing NNI to evaluate the clustering within each geographical division, it became evident that a distinct pattern of agglomeration characterized all regions. Northeast and Central China were particularly notable for their pronounced clustering, which was indicative of a robust agglomeration distribution. In contrast, Southern China displayed the lowest level of clustering, aligning more closely with a random distribution. The remaining regions were characterized by an agglomeration–random distribution pattern (Table 1). This uneven distribution accentuated the regional particularities in the preservation and presentation of industrial heritage, which could inform targeted approaches to industrial landscape management and tourism development strategies.

Table 1. Nearest neighbor index and spatial type of industrial landscape in seven geographic regions of China.

Geographic Region	Number of Industrial Landscape Sites	Proportion (%)	Cumulative Percentage (%)	NNI	Z-Value	p-Value	Type of Spatial Distribution
Eastern China	142	29.34	29.34	0.593	−0.9181	0.000	Aggregated–random
Northern China	85	17.56	46.90	0.512	−8.615	0.000	Aggregated–random
Southwest China	76	15.70	62.6	0.525	−7.923	0.000	Aggregated–random
Northeast China	58	11.98	74.58	0.406	−8.427	0.000	Aggregated
Central China	57	11.78	86.36	0.492	−7.274	0.000	Aggregated
Northwest China	44	9.09	95.45	0.541	−5.821	0.000	Aggregated–random
Southern China	22	4.55	100	0.967	−0.284	0.000	Random

3.1.2. Spatial Distribution Characteristics: Uneven Distribution

The spatial distribution of CIL sites was quantitatively evaluated using the geographic concentration index and the imbalance index to evaluate the distributional equity. The findings indicate a pronounced disequilibrium in the distribution across the country. Specifically, the geographic concentration index for CIL registered at 20.53. In the hypothetical scenario of an equitable distribution, where 484 industrial landscape sites were uniformly dispersed across China’s 34 provincial regions, the anticipated average would be approximately 14 sites per region, resulting in a geographic concentration index (G_0) of 17.15 for a uniform distribution. The observed index (G) surpassed G_0 ($G > G_0$), which substantiated the fact that the provincial-level distribution of CIL sites exhibited a higher level of concentration than what would be anticipated in a scenario of uniform distribution.

The degree of distributional equity of CIL sites across provincial regions was assessed using the imbalance index. As calculated by Equation (2), it was evident that the imbalance index $S = 0.38$ ($0 < S < 1$) indicated an unbalanced spatial distribution of CIL sites. This finding of disequilibrium was supported by the convex shape exhibited in the Lorenz curve (Figure 3), which provided further empirical evidence of the spatial disproportionality of CIL sites across the provincial regions.

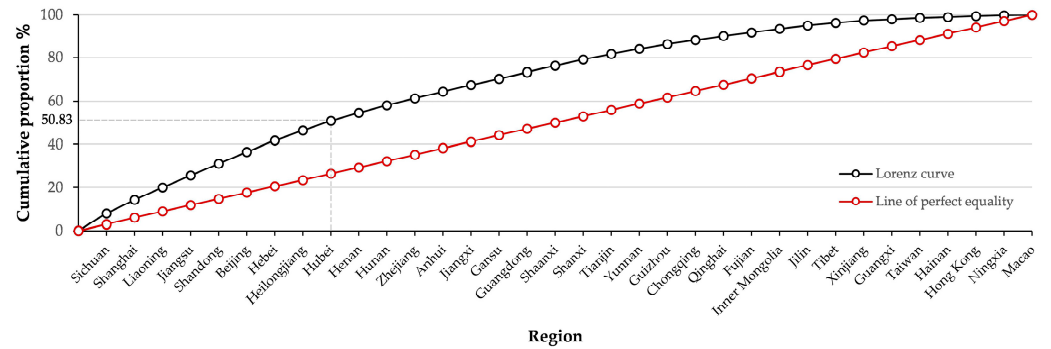


Figure 3. The Lorenz curve of the spatial distribution of CIL sites.

3.1.3. Spatial Association Characteristics: Significant Spatial Autocorrelation

Using the 34 provincial-level administrative divisions of China as the fundamental spatial units, this research employed the Getis–Ord G_i^* index to analyze statistically significant spatial clustering within each province. The results were classified into four distinct categories: hot spot, sub-hot spot, sub-cold spot, and cold spot (Figure 4). The hot spot and sub-hot spot areas accounted for 73.35%, and the cold spot and sub-cold spot areas accounted for 26.65% (Table 2).

Table 2. List of cold and hot zones of CIL.

Hot Spot Classification	Provincial Administrative Regions	Number Of Industrial Landscape Sites	Proportion (%)
Hot spot areas	Anhui, Beijing, Chongqing, Hebei, Henan, Jiangsu, Shandong, Shanghai, Tianjin, Zhejiang	206	42.56
Sub-hot spot areas	Guizhou, Hubei, Inner Mongolia, Jiangxi, Qinghai, Shaanxi, Shanxi, Sichuan, Tibet, Yunnan	149	30.79
Sub-cold spot areas	Fujian, Gansu, Guangxi, Heilongjiang, Hunan, Jilin, Liaoning	100	20.66
Cold spot areas	Guangdong, Hainan, Hong Kong, Macao, Ningxia, Taiwan, Xinjiang	29	5.99

This analysis revealed that the spatial distribution of CIL sites was predominantly characterized by the presence of hot spots, with a comparatively lesser incidence of cold spots and sub-cold spots, indicating a generally dynamic pattern. Typically, the hot spots were concentrated in the eastern coastal regions, forming extensive clusters, while the cold spots exhibited more scattered distributions resembling peripheral points in the western and southern regions of China. The presence of distinct transitional zones between the hot and cold spots further indicates that CIL exhibited significant spatial autocorrelation.

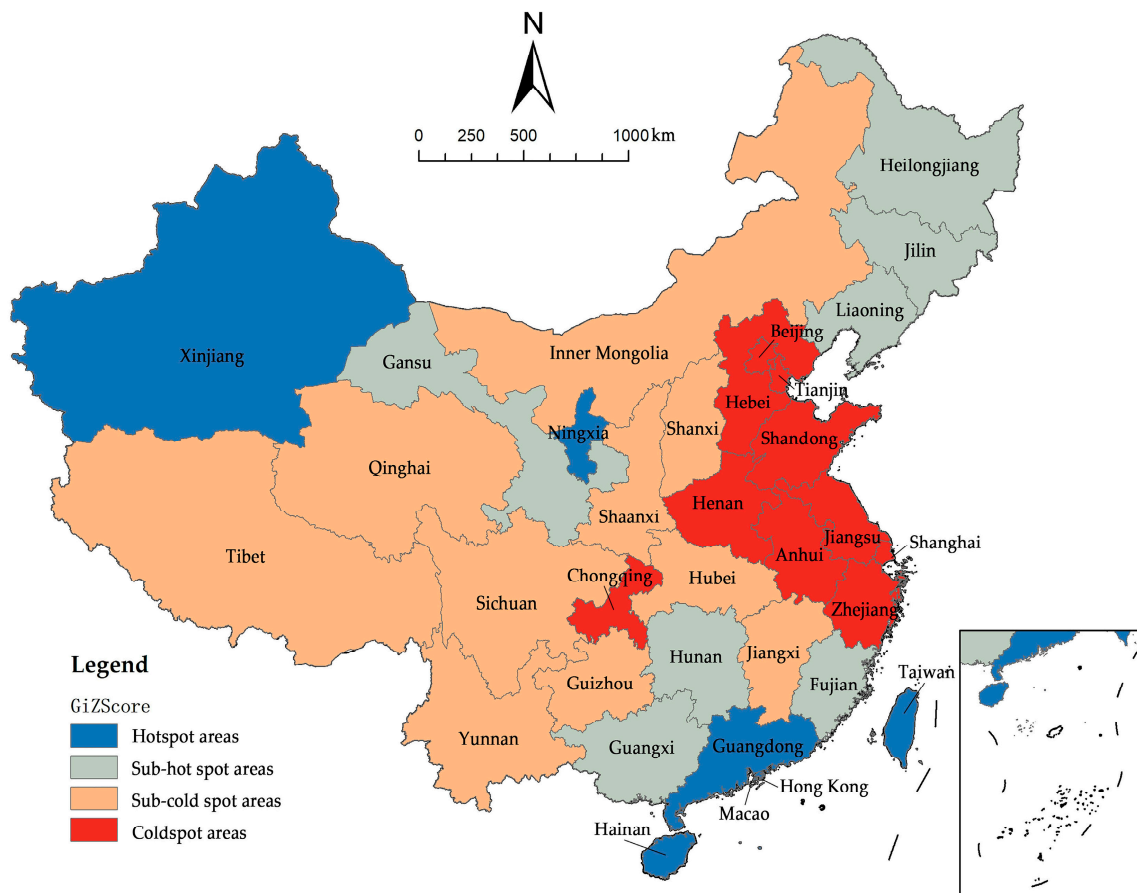


Figure 4. Cold and hot spot analysis of CIL.

3.2. The Characteristics of Time and Type Distribution

3.2.1. Temporal Evolution Characteristics: East First, Then West

Revisiting previous research [34,39] and considering the distinctive characteristics of CIL, this study tracked its progression through six successive developmental stages: the traditional handicrafts phase (before 1839); the emergence of modern industry (1840–1894); the expansion of modern industry (1895–1917); the zenith of modern industrial development (1918–1936); the decline of modern industry (1937–1949); and finally, the revival of modern industry (starting from 1950). By utilizing standard deviation ellipse analysis and center of gravity analysis, we revealed a distinct “northeast–southwest” orientation in the spatial distribution of CIL sites, with minor temporal shifts in directionality (Figure 5). The centroid of the standard deviation ellipse was positioned within the range of $111^{\circ}21'36''$ E to $118^{\circ}42'36''$ E and $31^{\circ}42'36''$ N to $34^{\circ}7'48''$ N, indicating a skew toward the southeast of China’s geometric center and signifying a higher concentration of industrial landscape sites in the eastern and southern regions. The trajectory of the centroid exhibited a distinct eastward and then westward movement pattern. The azimuthal shift demonstrated an initial increase, followed by a subsequent decrease, indicating that the spatial distribution of CIL sites transitioned from “northwest–southeast” to “north–south”, and eventually returned to “northwest–southeast”. Moreover, the standard deviations along the X- and Y-axes consistently increased, indicating a clear trend toward dispersion, which suggests that the level of CIL site agglomeration gradually diminished over time (Table 3).

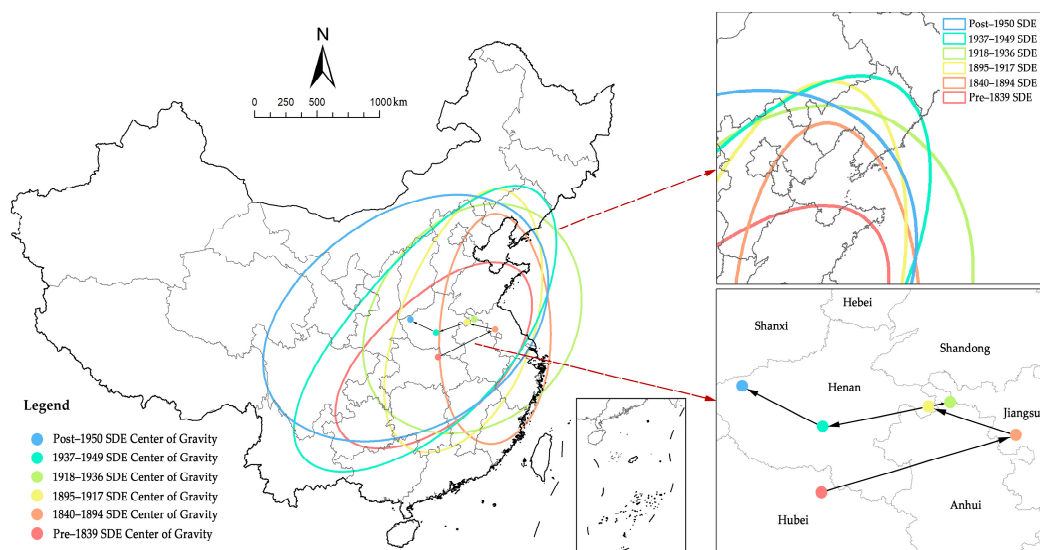


Figure 5. Standard deviation elliptic distribution of CIL sites in different periods.

Table 3. Parameters related to the standard deviation ellipse of CIL.

Period	Standard Deviation along the X-axis	Standard Deviation along the Y-axis	Turning Angle	Coordinates
The traditional handicrafts phase (before 1839)	4.622	9.777	60.65	113°31'48" E, 31°42'36" N
The emergence of modern industry (1840–1894)	4.812	8.235	13.59	118°42'36" E, 33°13'48" N
The expansion of modern industry (1895–1917)	5.591	10.385	35.81	116°22'12" E, 34°0'36" N
The zenith of modern industry (1918–1936)	7.478	10.262	67.24	116°59'24" E, 34°7'48" N
The decline of modern industry (1937–1949)	6.047	14.304	54.65	113°32'24" E, 33°27'36" N
The revival of modern industry (starting from 1950)	7.853	13.298	71.60	111°21'36" E, 34°32'24" N

3.2.2. Characteristics of Type Distribution: Predominantly Manufacturing

Utilizing the established framework for industrial landscape classification [34,62] and adapting it to reflect the distinctive industrial features of China, this study categorized CIL into 12 primary categories and 38 sub-categories. The distribution of industrial landscape sites across these categories demonstrated significant disparity. Manufacturing and transportation sites were the most abundant, amounting to 152 and 143 sites, respectively, which together comprised 60% of the total number of industrial landscape sites. The industrial landscape associated with the energy and mineral sectors was also noteworthy, with more than four sites in each sub-category, collectively accounting for 18% of the total. In stark contrast, the housing and paper industrial landscape categories were the least represented, featuring only three sites each, demonstrating the uneven distribution of industrial landscape types (Figure 6).

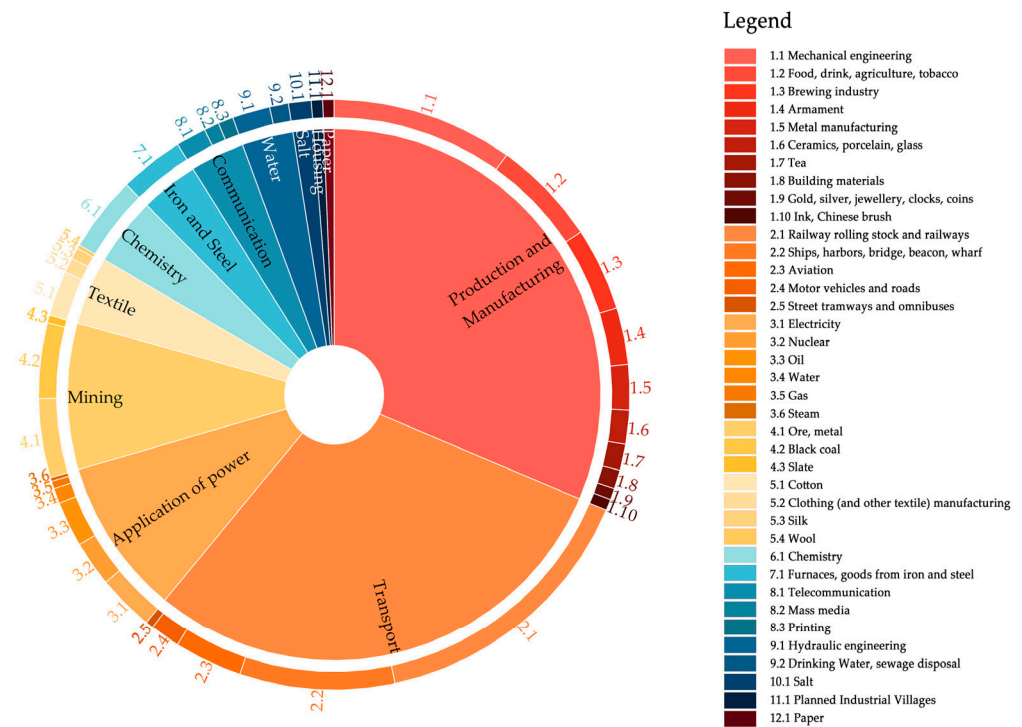


Figure 6. Classification of types of Chinese industrial heritage.

The spatial distribution of CIL sites exemplified the heterogeneity that arose from divergent geographical features, resource allocation complexity, and varied historical development trajectories. Specifically, the production and manufacturing industrial heritage formed two principal high-density zones situated in the Beijing–Tianjin–Hebei region and the Yangtze River Delta. This distribution extended inland following the courses of the Yellow and Yangtze Rivers and was complemented by secondary density zones in Sichuan Province in the southwest and the three northeastern provinces, and collectively formed a spatial pattern of “four cores and two belts” (Figure 7a). The spatial distribution pattern depicted herein delineated the historical trajectory of China’s industrial development, where the Beijing–Tianjin–Hebei and Yangtze River Delta regions emerged as pioneering hubs. Following its foundation, the People’s Republic of China played a crucial role in promoting the expansion of its manufacturing sector. The manufacturing industrial heritage concentrated in Sichuan and the northeastern provinces reflects two significant industrial epochs—the relocation of industry inward during wartime and the establishment of the northeastern industrial base. In contrast, the transportation industrial heritage, which was primarily situated in the coastal areas of Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta, reflected the early modernization of China with the opening of ports and the pioneering of modern transportation networks to establish vital transportation hubs (Figure 7b).

The energy industrial landscape, which was closely linked to resource reserves and geographic attributes, formed two high-density clusters centered on Gansu and Sichuan, and extended along the Yellow and Yangtze Rivers, regions which were home to a majority of China’s hydroelectric power stations. The northeast and northwest, which served as key energy extraction bases, exhibited a spatial pattern of “two cores and multiple points” (Figure 7c). The mineral industrial landscape was a significant indicator of mineral resource distribution, with two prominent high-density core areas emerging: one characterized by abundant coal resources in North China and the other by rich metal resources in Central China. Additionally, a sub-density core area associated with metal mines existed in Yunnan. Notably, the northeast region was characterized by a concentration of iron ore and coal mines (Figure 7d). On the other hand, the textile industrial landscape dominated in the

Jiangsu and Zhejiang regions, and created a high-density core area. The excavation of silk fabrics at the Liangzhu Site traces back China's traditional silk-weaving industry to ancient times. However, the industrial landscape of modern textile technology, which was introduced during the Industrial Revolution, was dispersed throughout Central China (Figure 7e).

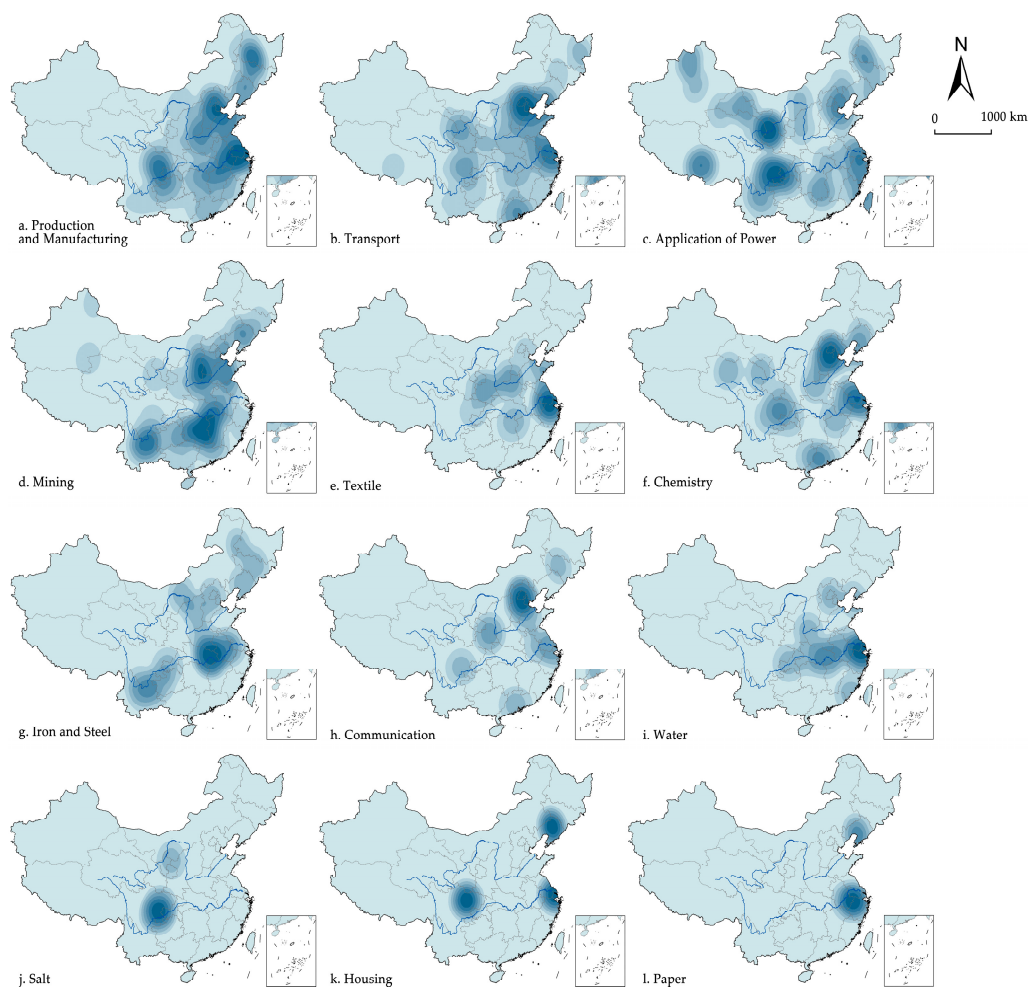


Figure 7. Classification of types of Chinese industrial landscape.

The chemical industrial landscape featured two core areas in Beijing–Tianjin–Hebei and the Yangtze River Delta, which were influenced by the region's abundant sea salt resources, and exhibited additional distributions in Central China and the Pearl River Delta (Figure 7f). The iron and steel industrial landscape, which was predominantly located in the central region and linked to iron ore resources, was also present in scattered distributions in the northeast, southwest, and north, creating a “one nucleus and three patches” pattern (Figure 7g). The communication industrial landscape was densely clustered in Beijing, which reflected its historical significance as a political center and a hub for modern communication (Figure 7h). The water industrial landscape was primarily located along the Yangtze River, where the Yangtze Delta acted as its focal point, and it was influenced by the history of hydrological project construction (Figure 7i). The salt industrial landscape formed a notable core in Sichuan (Figure 7j), which is renowned for China's well-known salt production base in Zigong. The number of housing and paper industrial landscape projects was limited, displaying a dispersed distribution pattern that resembled scattered points (Figure 7k,l).

4. Correlating Factors of the Spatial Distribution of CIL

4.1. Selection of Correlating Factors

The industrial landscape plays a pivotal role as a spatial repository of urban culture, holding significant historical importance for city development and the process of industrialization. The emergence and geographical distribution of the industrial landscape are influenced by a combination of economic, social, and cultural factors. Given the predominant location of the industrial landscape within urban areas, the influence of natural environmental variables, such as topography, elevation, and climate, on its spatial distribution appears to be relatively limited. As a result, this study did not take into account the effects of natural factors on the industrial landscape distribution. Instead, it integrated existing research findings by considering the inherent attributes of the industrial landscape and its contemporary developmental context while incorporating insights from the spatial distribution of traditional villages [65,66], cultural heritage sites [67], and intangible cultural heritage sites [64]. With meticulous consideration of data availability, 12 specific indicators were carefully selected from the dimensions of the economic development level, social demographic conditions, transportation infrastructure, and cultural environment (Table 4). These indicators were used to analyze the multifaceted determinants that shaped the spatial patterns of CIL.

Table 4. The results of the univariate detection of correlating factors in the spatial distribution of CIL sites.

Influencing Factors	Specific Indicators	q-Value	p-Value	q-Value
Economic development level	GDP (X_1)	0.639	0.000	0.435
	Per capita disposable income of urban residents (X_2)	0.259	0.207	
	The number of large-scale industrial enterprises (X_3)	0.406	0.077	
Social demographic conditions	Urbanization rate (X_4)	0.638	0.005	0.671
	Population density (X_5)	0.611	0.009	
	The number of students in higher education institutions (X_6)	0.764	0.000	
Transportation infrastructure	Road network density (X_7)	0.592	0.006	0.372
	Railroad network density (X_8)	0.416	0.066	
	Freight volume (X_9)	0.255	0.184	
Cultural environment	Budget for cultural heritage conservation (X_{10})	0.521	0.003	0.443
	The number of national key cultural heritage conservation units (X_{11})	0.279	0.239	
	Museum visitation statistics (X_{12})	0.528	0.003	

4.2. Univariate Analysis

There was considerable variation in the relative influence of various factors on the spatial differentiation of CIL. This study utilized Geodetector analysis to quantify the impacts of these factors on the spatial distribution of CIL sites. According to the findings, these factors were ranked accordingly based on their influence: $X_6 > X_1 > X_4 > X_5 > X_7 > X_{12} > X_{10} > X_8 > X_3 > X_{11} > X_9$ (Table 4).

4.2.1. Economic Development Level

The economic status exerted a considerable impact on the spatial distribution of CIL sites. Both the GDP and the number of large-scale industrial enterprises reflect the

intensity of urban economic activity [68], with the industrial landscape typically more prevalent in areas where urban economic activity is more intense. For example, provincial administrative regions with high GDPs, including Sichuan Province, Shanghai Municipality, Shandong Province, and Jiangsu Province, were characterized by a rich distribution of industrial landscapes.

This distribution pattern can be attributed to various factors. The primary one is the need for considerable financial resources for the sustainable management of the industrial landscape, including preservation and modification to meet contemporary needs [69]. Therefore, regions characterized by higher GDPs, which serve as indicators of vigorous economic activities and investments, are more inclined to endorse preserving and reusing the industrial landscape [70]. Additionally, economically prosperous regions typically invest in enhancing the quality of life and cultural facilities for their citizens, including the maintenance of historical and industrial sites, thereby creating a conducive milieu for landscape preservation. Furthermore, regions characterized by a higher number of industrial enterprises typically indicate a more advanced level of industrialization, and consequently, a more substantial industrial landscape. For instance, cities such as Shanghai, Tianjin, and Ningbo in Jiangsu Province, which emerged as commercial ports in the 1840s following the Opium Wars, attracted foreign investments and factory establishments that solidified their industrial base. The rapid industrialization that followed has led to a rich repository of industrial landscape in these regions.

In addition, there is a direct correlation between urban residents' per capita disposable incomes and their cultural landscape consumption patterns. With the improvement in economic conditions, there is an increasing demand for cultural landscape experiences [71], which, in turn, influenced the spatial distribution of CIL sites due to the disposable income of urban residents.

4.2.2. Social Demographic Conditions

Social demographic conditions were fundamental in shaping the spatial distribution of CIL sites. Urbanization drives the transformation of the industrial structure, often leading to the displacement or obsolescence of industrial facilities, thereby potentially expanding the inventory of industrial landscape sites [72]. Concurrently, urbanization catalyzes economic growth, attracting investments and fostering conditions conducive to the restoration and reinvigoration of the industrial landscape, thereby generating a beneficial cycle. Furthermore, urban population density has an important impact on CIL distribution. Regions with denser populations tend to be more actively engaged in landscape preservation efforts. Local communities in such areas often show greater initiative and enthusiasm for advocating and participating in the conservation and adaptive reuse of cultural landscapes. This community-driven engagement is crucial to the sustainability of industrial landscape conservation efforts [73].

Regions with higher educational attainment often exhibit a deeper awareness regarding cultural landscape preservation. For example, the Beijing–Zhangjiakou Railway, which is significant in the history of China's industrial development, was designated as a heritage park in 2019 (Figure 8) [74]. Local universities have leveraged their academic specialties and expertise in landscape protection and revitalization by conducting field research, organizing work camps, and developing programs. This active participation accentuates the significant role that academic institutions play in safeguarding the industrial landscape. Such initiatives are vital in perpetuating its legacy, reflecting the public's engagement and concern for landscape conservation, and strengthening the preservation of historical and cultural assets.



Figure 8. Jing-Zhang Railway Heritage Park (The Chinese characters in the picture are “Jingzhang”).

4.2.3. Transportation Infrastructure

The transportation infrastructure foundation is a critical factor in the spatial distribution of the industrial landscape. Well-developed transport systems, including roadways, railways, ports, and airports, are essential in fostering industrial advancement [75]. The establishment of such networks facilitates the efficient transit of raw materials, merchandise, and labor, thereby catalyzing industrial proliferation and engendering a legacy of the rich industrial landscape. Concurrently, transportation infrastructures themselves often constitute a significant category of industrial landscape, with railway sites alone accounting for 15.3% of the total landscape inventory. Furthermore, the accessibility provided by these transportation networks enhances the appeal of sites for investors engaged in adaptive reuse initiatives targeting the industrial landscape. Through these ventures, industrial sites are transformed into museums, cultural hubs, and retail spaces that contribute to industrial landscape conservation and revitalization [76]. This metamorphosis not only safeguards critical historical assets but also creates economic value and repurposes cultural resources.

The China Railway Museum, which is a prime example of the railroad industrial landscape, occupies the historic grounds of the Zhengyangmen Station on the Beijing–Fengtian Railway (Figure 9) [77]. Established in 1903, the station has witnessed over a century of history and was repurposed in 2008 as the China Railway Museum. This institution is dedicated to documenting the inception and evolution of China’s railroads. The museum serves not only as a testament to the Beijing–Fengtian Railway but also symbolizes the broader development of Chinese railroad infrastructure. It highlights the integral role of the railroad in China’s industrial landscape and its enduring cultural significance.



Figure 9. China Railway Museum’s Zhengyangmen Branch (The Chinese characters in the picture are “China Railway Museum”).

4.2.4. Cultural Environment

The spatial distribution of the industrial landscape is significantly influenced by the cultural context, as reflected in the allocation of funds for the protection of cultural relics by local governments. This financial commitment demonstrates the importance attributed to the cultural and historical landscape, and a greater emphasis on this valuation not only

motivates local authorities to actively safeguard and promote industrial heritage but also guarantees that adequate resources are available for its effectiveness. Museums, serving as vital institutions for public engagement with cultural and historical narratives, provide direct metrics of public interest through visitor numbers. High visitation rates play a crucial role in propagating the narratives of the industrial landscape, further supporting its preservation and innovative repurposing.

Moreover, areas with a concentration of national key cultural heritage conservation units often serve as historical repositories, creating a favorable atmosphere for the expansion of creative and cultural industries [78]. It deserves special mention that the spatial distribution of industrial landscapes benefits significantly from a rich cultural heritage given that industrial buildings are highly suitable for transformation into cultural and creative centers, thanks to their spatial characteristics and historical value [79]. These elements have a multifaceted influence on the spatial patterning of the industrial landscape, while simultaneously fostering new pathways for regional economic rejuvenation.

4.3. Factor Interaction Analysis

The determinants of spatial variation in CIL were examined through the Geodetector analysis, which assessed the capacity of different correlating factors to interact and exert composite effects. Building upon the investigation of the 12 individual factors and the subsequent analysis of their interactions, this study’s results demonstrate that the spatial distribution of CIL sites was influenced by interdependent factors characterized by two-factor interactions or nonlinear enhancement (Figure 10). This indicates that the interaction between any two factors played a crucial role in shaping the geographical arrangement of CIL, and the intricate interplay of multiple factors exerted a more profound influence on its spatial distribution.

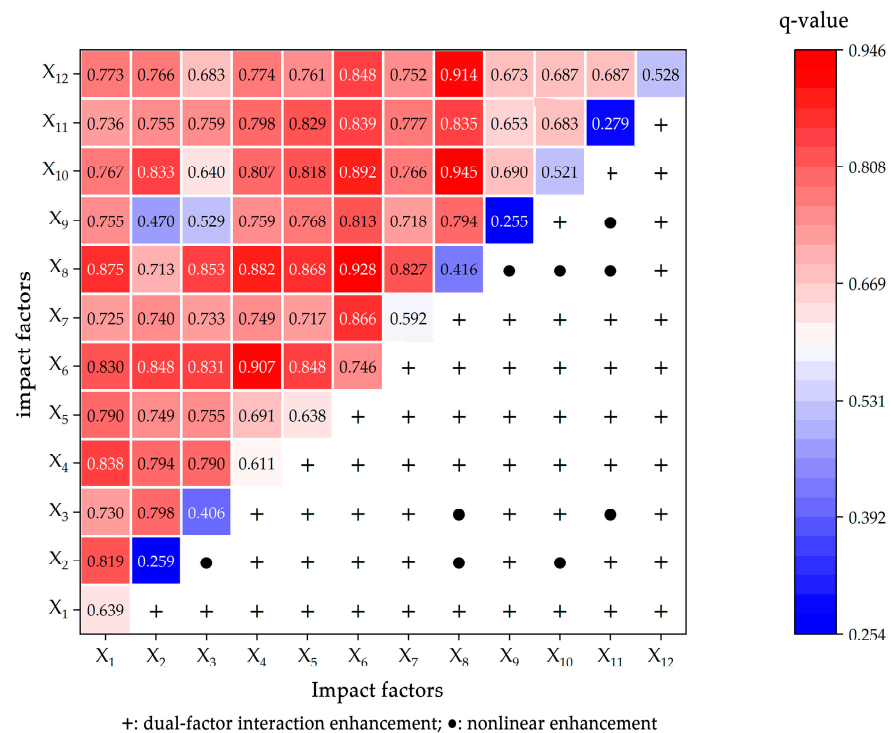


Figure 10. The results of the interaction detection of correlating factors on the spatial distribution of CIL.

Drawing from the analysis of these interactions, the five most notable interaction combinations identified were denoted as $X_8 \cap X_{10}$ (0.945), $X_6 \cap X_8$ (0.928), $X_8 \cap X_{12}$ (0.914), $X_6 \cap X_5$ (0.907), and $X_6 \cap X_{10}$ (0.892). These findings collectively highlight the prominence of interactions that involved the transportation infrastructure as a fundamental factor, especially

when combined with social demographic conditions, indicating a clear and dominant trend. This underscores that the interplay between the transportation infrastructure and social demographic conditions was the primary determinant in shaping the spatial distribution of CIL. Within these interactions, the number of students in higher education institutions and railroad network density emerged as the most influential factors. This phenomenon can be explained by the close relationship between the development of railroad networks and the formation and evolution of the industrial landscape. Furthermore, the number of students in higher education institutions played a crucial role in conserving and spreading the culture of the industrial landscape, ultimately promoting its sustainable development [80].

5. Discussion

So far, several authoritative listings of industrial heritage landscapes have been introduced by national government agencies and academic departments in China. This initiative has not only facilitated the protection and reuse of industrial landscapes in China but has also provided policy guidelines for industrial tourism and urban revitalization. However, the challenges of preserving the unique value of industrial landscapes [10,81], promoting their transformation and development [82,83], and mitigating residual pollution remain urgent issues to be addressed [84,85]. In the digital age, the transformation of industrial landscapes is intricately connected to the growth of industrial tourism. By boosting the economic vitality of cities, industrial tourism attracts new industries and investments [86], which are crucial for the protection and utilization of industrial landscapes [87]. This, in turn, fosters the optimization of urban space and functional enhancement. Therefore, a thorough study of the spatial distribution of industrial landscapes and their influencing factors not only provides crucial insights for the planning and development of industrial tourism routes but also significantly advances the fields of industrial tourism, economic growth, and cultural heritage preservation.

Relevant studies show that the spatial distribution of industrial landscapes in Europe is influenced by multiple factors, such as altitude, topography, socio-economic level, cultural tourism potential, and infrastructure level, with the socio-economic level playing a dominant role [37,62,88]. For the spatial distribution of industrial heritage in China, natural resources, population density and transportation conditions are closely related [34,39]. Through single-factor analysis and interaction analysis, this study identified key factors that affected the spatial distribution of CIL, including the number of students in higher education institutions, GDP, urbanization rate, population density, and road network density. These findings are basically consistent with existing research conclusions. To be specific, it was evident that the spatial layout of CIL exhibited a symbiotic relationship that was primarily involved with “population, culture, economy, and transportation” under the combined influence of several factors (Figure 11). Specifically, socio-demographic conditions emerged as the foundational factors that shaped the spatial distribution of CIL sites. These conditions, which encompassed population size and educational attainment, played a pivotal role in determining the extent of CIL preservation. Regions characterized by larger populations and higher levels of education tended to demonstrate heightened engagement in the preservation of industrial heritage. Moreover, the cultural and environmental contexts were identified as catalysts that impacted the distribution of CIL sites. Cultural context and societal atmosphere significantly contributed to the genesis and safeguarding of the industrial landscape. Regions rooted in diverse cultural traditions and fostering a positive cultural environment tended to prioritize the conservation of the industrial landscape. The level of local economic development served as the foundation for the spatial distribution of industrial landscapes, as relatively prosperous regions tended to possess a greater capacity for preserving and repurposing industrial landscapes. Lastly, the transportation infrastructure was considered a fundamental factor that significantly influenced the spatial distribution of CIL. Enhanced transportation networks were positively correlated with increased industrial activities, leading to a higher concentration of industrial landscape sites in such areas. These findings not only provide crucial insights

into the intricate spatial distribution of China's industrial landscape but also underscore the significance of multifaceted interactions.

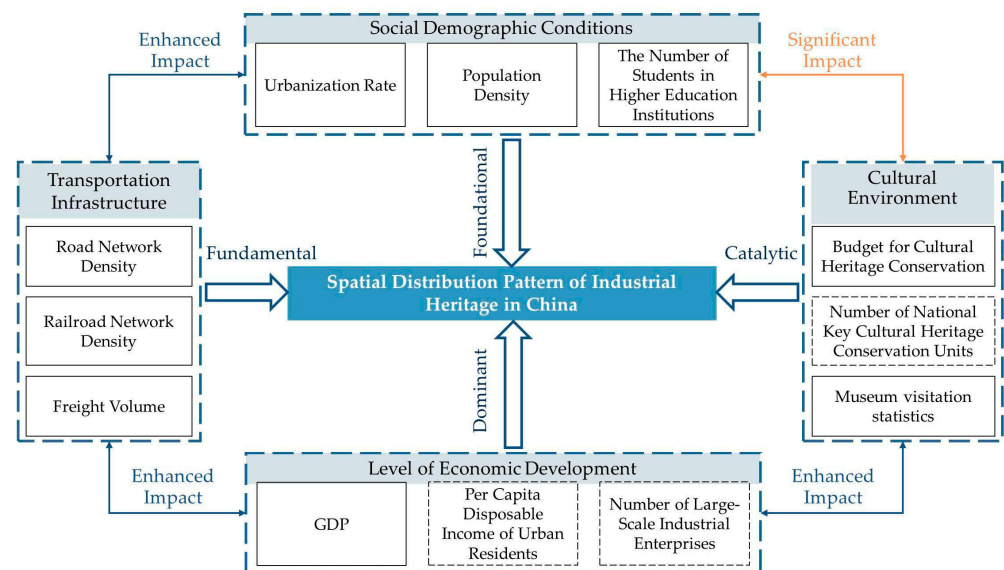


Figure 11. The influential mechanisms of CIL spatial distribution.

However, this study had some shortcomings:

This research primarily focused on the static spatial distribution characteristics of CIL, lacking a dynamic analysis. Considering the ongoing evolution of CIL, it is anticipated that various levels and categories of industrial landscape lists will emerge in the future. Therefore, further research is needed to track the evolutionary development of the CIL spatial layout.

This study encountered challenges in obtaining relevant data and information, as well as quantifying certain correlating factors. Consequently, the exploration of the impacts on the CIL spatial distribution may not be exhaustive. Factors such as historical context and policy orientation remain incompletely identified and analyzed. To address these gaps, future research should employ interdisciplinary methods to enhance the analysis of these factors.

Although the spatial analysis tools employed in this study, such as Geodetector, demonstrated efficacy in analyzing spatial patterns and influencing factors, they possess inherent limitations. To enhance our understanding of CILs, future research will leverage more sophisticated analytical methods or embrace a multidisciplinary approach. Potential advancements may include applying machine learning techniques to spatial analysis or integrating socio-economic data more intricately to elucidate the complex interplay of factors influencing the distribution of CIL sites.

6. Conclusions

This research included a comprehensive examination of CIL by utilizing ArcGIS software and employing quantitative analysis techniques, including the nearest neighbor index, geographic concentration index, and standard deviation ellipse. Additionally, in conjunction with the Geodetector method, this study explored the factors that affected the spatial distribution of CILs. The key findings of this investigation are summarized as follows:

1. The spatial distribution of CIL exhibited a pronounced clustering pattern, with a significantly higher concentration of industrial landscape sites in the eastern region compared with the western region, indicating notable spatial disparities. Notably, hot spot areas dominated the spatial distribution of CIL, while cold spot regions were

relatively scarce. Additionally, there was significant spatial autocorrelation between the cold and hot spot areas.

In terms of the temporal evolution, CIL exhibited a northeast–southwest trajectory, with the epicenter initially shifting toward the east and gradually moving westward, accompanied by a diminishing level of agglomeration. Additionally, China exhibited a diverse array of industrial landscape types that could be classified into 12 primary categories and 38 subcategories. Relevantly, the manufacturing and transportation sectors exhibited dominance in terms of abundance. These diverse industrial landscape types exhibited significant spatial disparities in both density and geographical dispersion.

Multiple factors along cultural and environmental contexts, including economic growth, social and demographic circumstances, and transportation infrastructure, intricately affected the spatial distribution of CIL sites. Among these factors, the number of students in higher education institutions, GDP, urbanization rate, and population density exhibited more pronounced influences and were crucial in determining the pattern of CIL distribution. Furthermore, a detailed analysis of how these elements interacted demonstrated that the combined effect of two factors played a more pivotal role in influencing the geographical spread of CIL than any single factor. Particularly, it is important to emphasize that the dominant factor identified as having a significant impact on the spatial pattern of CIL was the interaction between the transportation location and socio-demographic conditions.

2. In the past two decades, there has been growing recognition and support from both the government and civil society in China for the conservation of the industrial landscape. In response to this growing awareness, comprehensive inventories of the industrial landscape have been compiled, accompanied by the establishment of a framework comprising policies and regulations aimed at preservation, interpretation, and public engagement with these sites. The industrial landscape serves not only as a repository of urban memory and a conduit for cultural transmission but also as a pivotal force in urban economic regeneration. Its conservation is instrumental in advancing sustainable development, refining industrial configurations, and enhancing the share of innovation-driven and creative pursuits. In view of this, the present study provided a comprehensive analysis of the spatial distribution characteristics of CIL and its influencing factors from a macroscopic perspective. The findings of this study can serve as a scientific basis for the protection, management, and tourism development of the industrial landscape, thereby enhancing urban resilience and promoting sustainable development in this field.

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