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Spatial Distribution and Elements of Industrial Agglomeration of Construction and Demolition Waste Disposal Facility: A Case Study of 12 Cities in China

Wenwei Huang [1,2], Xiangmian Zheng [1], Baojun Bai [2] and Liangfu Wu [1,*]

[1] School of Civil Engineering and Transportation, South China University of Technology, Guangzhou 510640, China; hww@scut.edu.cn (W.H.); ctxmzheng@mail.scut.edu.cn (X.Z.)
[2] Postdoctoral Innovation Practice Base of Guangdong Province, South China University of Technology—CSCEC, Guangzhou 510640, China; baibaojun@cscec.com
* Correspondence: wuuuliangfu@sina.com

Abstract: Site selection is the key to carrying out the industrial layout of construction and demolition waste (CDW) resourcing enterprises. The current study needs more data on CDW industry location. The current construction waste resource utilization rate and industrial layout need to be improved. This study uses statistical and visualization methods to analyze key factors affecting the location of CDW recycling enterprises. Additionally, it identifies planning strategies and policy incentives to drive industry development. The study explicitly adopts global and weighted geographic regression (GWR) analysis methods and uses ArcGIS 10.8 to visualize point of interest (POI) data. It was found that (1) the main factors affecting the spatial distribution of the CDW recycling economy, in order of importance, are river network density, financial subsidies, R&D incentives, the number of building material markets, the value added by the secondary industry, the area of industrial land, and the density of the road network. The three main drivers of site selection decisions are government subsidies, market size, land, and transportation resources. (2) Enterprise industry chain and transportation costs are industrial economic decision-making considerations. Enterprises are generally located on flat terrain, around industrial parks, near the center of urban areas, and close to demand and cost reduction. (3) At the city level, there are more resource-based enterprises in cities with high levels of economic development and strong policy support. The spatial distribution of enterprises is consistent with the direction of urban geographic development. There is a positive global correlation between construction waste resourcing enterprises. Ningbo, western Qingdao, and northern Beijing show high aggregation characteristics. Low–low aggregation characteristics exist in regions other than central Chongqing. High–low aggregation characteristics are found in the center of the main city of Chongqing, eastern Shanghai, and central Nanjing. Low–high aggregation is distributed in northeastern Ningbo, northern Guangzhou, and southern Shenzhen. (4) Regarding industrial agglomeration, except for Nanjing, construction waste industrial agglomeration occurs in all 11 pilot cities. Among them, Shanghai, Xiamen, and Hangzhou have industries that are distributed evenly. Xi'an and Chongqing have a centralized distribution of industries. Guangzhou, Shenzhen, Beijing, Ningbo, and Qingdao have multi-center clustering of industries. Nanning's industry has a belt-shaped distribution. This research explores the micro elements of industry chain integration in the CDW industry. It combines incentive policies and urban planning at the macro level. Together, these efforts promote sustainable city construction. This research provides CDW location data and dates for future digital twin and city model algorithms. It supports industrial planning, transportation, spatial optimization, carbon emission analysis, city operations, and management and aims to enhance the city's green and low-carbon operations.

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1. Introduction

The construction industry is important in the economies of various countries. In China's rapid urbanization process, economic activities such as renovating old cities, constructing new houses and infrastructure, and demolishing old buildings generate large quantities of construction waste. China is the world's most populous country and the largest producer of solid waste. Approximately 10 billion tons of new solid waste are generated annually, with historical stockpiles reaching 60–70 billion tons. The intensity of solid waste generation is high, its utilization is inadequate, and the problem of "garbage surrounding the city" is very prominent in some cities. This poses a significant challenge to environmental carrying capacity and resource availability. Depending on its nature, 50% to 90% of construction waste can be recycled [1]. However, the current resource utilization rate of construction waste in China is only 40%, which is far below the level of developed countries. The current disposal methods must be updated, mainly relying on landfills and piles. The management system still needs to meet the needs of sustainable development. This is a waste of resources and puts pressure on the environment.

Research on construction waste contributes to clean production and low-carbon industries. It also enhances urban competitiveness through environmental protection. Construction waste management research is divided into two primary directions: technology-oriented and macro-management. Technology-oriented research focuses on recycled aggregate technology [2], resource utilization process upgrading [3], screening and disposal of virgin waste [4], and other specific technical means. On the other hand, the study of macro-management focuses on analyzing the obstacles to the implementation of resource utilization [5], waste minimization measures [6,7], production forecasts [8,9], material flow analysis [8,10], and performance evaluation [11] among others. The methods involved include qualitative analysis [5,12], system dynamics [13], triangular fuzzy number [3], BIM [7,14], and Life Cycle Assessment [11].

The siting process is the center of research in the spatial planning of construction waste treatment facilities. Currently, most studies focus on mathematical planning models [15], multi-criteria decision-making models [16], and models based on GIS spatial analysis techniques [17,18]. However, the limitations of a single method have gradually emerged, and it is easy to produce significant errors in the site selection problem. In recent studies, scholars have added weighting analysis [19] and deep learning [15] theoretical methods to optimize and improve the site selection model. A few studies also focus on improving established siting models [20]. By establishing the optimization objective, quantitative influencing factors and evaluation indexes are established to find the optimal solution.

As an essential carrier of resource utilization of construction waste, the research value of the resource regeneration industry cluster is becoming increasingly prominent. The research on resource regeneration industrial clusters is mainly divided into two categories. The first category focuses on the analysis of the internal network structure of the cluster [21]. This type of research focuses on the interactions and complex network of relationships among the elements within the cluster. The aim is to reveal the development direction and optimization goals of clusters. The methods involved are mainly quantitative analysis, which is realized by constructing economic or structural equation models. The second category focuses on the connection between clusters and the external environment. It analyzes the influence of the external environment on industrial clusters [22] and the role of cluster development in promoting the regional economy [23]. The benefits generated by clusters are assessed by reflecting on clusters' formation mechanisms and processes and establishing the importance of various elements.

This research centers on three core issues: the driving factors of the construction and demolition waste (CDW) industry, the integration of the industrial chain, and the facilitating role of urban planning. First, this study analyzes the spatial distribution characteristics of CDW resourcing enterprises in depth. This study analyzes the spatial layout characteristics of the construction waste circular economy. For the development prospects of the industry, this paper will analyze the corresponding industry-driving factors and the corresponding incentive policies. Through industry chain analysis, this paper identifies the construction waste resourcing industry clusters and reveals their formation mechanism. Further, this research explores how to promote the formation of a green, low-carbon, energy-saving, and environmentally friendly industrial chain and constructs an indicator system of influencing factors. It applies global regression and weighted geographic regression models to find the key factors affecting enterprises' spatial distribution and heterogeneity. Finally, this paper profoundly analyzes the relationship between the construction waste industry's aggregation mode and urban spatial distribution characteristics. Site selection is the key to carrying out the industrial layout of construction and demolition waste (CDW) resourcing enterprises. The current study needs more statistics on CDW industry location data. This research provides location data of 12 pilot cities in China. By exploring the micro level of industry chain integration elements of the CDW industry, combined with the two macro levels of incentive policies and urban planning, the research jointly promotes the sustainable construction of cities.

2. Literature Review

Research on construction waste (CDW) resource utilization has progressed in several fields. However, existing studies have focused on generated construction waste, which lacks industrial attention and multi-city empirical analysis of solid construction waste treatment. Wang et al. used methods such as standard deviation ellipse modeling and environmental Kuznets curves to analyze the spatial and temporal evolutionary characteristics of the amount of construction waste generated in 30 provinces and regions from 2007 to 2018 and explore the relationship between economic growth and its heterogeneity [24]. Wang et al. investigated the spatial heterogeneity of CDW generation in different provinces affected by a variety of factors through the GWR model [25]. These studies provide valuable inspiration for explaining the CDW generation process. Using spatial analysis, Gao et al. used Beijing as a case study to investigate construction waste's spatial layout agglomeration characteristics and recycling facilities [26]. Wang et al. investigated the Yangtze River Delta region. They used the Spatial Durbin Model (SDM) to explore the development of the construction waste disposal industry in several cities and its spatial distribution characteristics and identified relevant influencing factors [14].

The current study focuses on a single city and region and the application of construction waste generation. It lacks statistical analysis, comparative studies, an experience summary of multiple pilot cities across the country, and a cross-sectional comparison of the resource utilization of the industry. The spatial layout of the construction waste industry and the resource utilization pattern are still unclear, hindering the industry's theoretical guidance. The current digital analysis and decision making of CDW have yet to be studied. This study has promoted the application of City Information Modeling, GIS spatial analysis, policy incentives, industrial planning, transportation economics, spatial optimization decision-making, and green and low-carbon city operations.

2.1. Construction Waste Disposal

Existing studies have analyzed the reasons for the low utilization rate of construction waste resource utilization in China from different perspectives, including the low utilization rate of recycled aggregate technology [27], poor economic efficiency [28], and imperfect policies and regulations [12]. Moreover, there needs to be better recognition of the consumer market [29], low efficiency of waste management systems [12], and single waste disposal facilities [30]. Among them, as an essential node of waste management, the planning layout of CDW directly affects the efficiency of urban construction waste resource management. Unreasonable layout leads to environmental pollution and rising transportation costs [31]. Moreover, it affects the motivation of enterprises to operate. Local governments in China have introduced a series of policies, regulations, and technical standards to promote the classification, recycling, and resource utilization of construction waste. Despite initial attempts in some cities, the CDW industry as a whole is still in the primary stage [32]. Resourceful disposal facilities in some cities cannot meet local demand and need careful consideration in site selection. Therefore, the construction and spatial layout of CDW facilities need to be further optimized.

Construction waste management is integral to the construction production process [33]. It focuses on the reduction in waste generation and the promotion of resource reuse. The sustainable management of construction waste has become a pressing issue globally, involving social, environmental, and economic aspects. Significant reductions in construction waste generation are possible through careful management of the entire process from project design to demolition. An efficient strategy is reducing the waste expected during the design phase [34]. This approach is effective in alleviating the pressure of subsequent waste management. However, most of the facilities that need to be dismantled are currently not considered to be in the design stage, favoring the two main areas of post-operational landfill and recycling.

Landfilling is still the primary way of disposing of construction waste in many parts of the world. Backfilling is a method of using construction waste as fill material. Although it can partially realize the reuse of waste, the scope of application and economic benefits are limited. Most construction waste is transported to the suburbs without treatment and deposited in open piles or landfills. Landfilling consumes many land resources, leading to high land acquisition and transportation costs. Meanwhile, the dust and other pollutants generated during landfilling seriously pollute the surrounding environment. The reality is that illegal dumping is still a severe problem, especially in developing countries [35]. In conclusion, landfills consume many land resources and may bring long-term environmental pollution problems.

Another disposal method is recycling. Recycling involves sorting, crushing, screening, and converting construction waste into building materials such as recycled aggregates and concrete [36]. These recycled materials are widely used in constructing new buildings and repairing and remodeling old buildings. Through systematic classification, treatment, and reuse, construction waste management is optimized, significantly reducing dependence on new resources and effectively reducing environmental pollution [37,38]. The contradiction between high production and inefficient construction waste disposal is becoming increasingly significant globally.

2.2. Drivers of the Construction Waste Industry

Multiple factors, including technological innovation, talent education, market demand, and policy support, drive the development of frontier industries. Scholars have conducted in-depth studies of different industries. Fox and Skitmore [39] identified the critical elements for developing the global construction industry through rooted theory, including industry practices, financial resources, personnel skills, government policies, construction technology research and development, and construction culture. Based on the PPM theory, Dou et al. combined the entropy method and clustering model to analyze the driving factors of the manufacturing industry in the Guangdong–Hong Kong–Macao Greater Bay Area. They found that manufacturing technology development has the spatial distribution characteristics of radiation from the core area. Economic development depends on existing industrial systems, while government policies significantly affect environmental development [40].

In the current research on quantitative factors, it is common for scholars to use a variety of methods, such as semi-structured interviews [5,41], unstructured interviews [42], and fieldwork [5]. These methods effectively collect rich data and deepen the understanding of industry drivers. However, a neglected perspective is the analysis of the industry's spatial layout. The research output must include the degree of agglomeration and distributional characteristics of industrial activities in geospatial econometrics, limiting the understanding of industry development drivers from a macro and holistic perspective. Focusing on the construction and demolition waste management sector, this research takes 12 pilot cities in the industry as case studies. It analyzes in detail the spatial distribution characteristics of the resourcing firms in each city. The paper also explores the key factors affecting these enterprises' industrial agglomeration and location, intending to provide a scientific basis for the spatial optimization of the industry and to formulate further strategies.

3. Data and Methodology

This section may be divided into subheadings. It should provide a concise and precise description of the experimental results, their interpretation, and the experimental conclusions that can be drawn.

3.1. Methodology

This study used GIS and two regression models as the primary analysis tools to analyze the spatial distribution characteristics of construction waste resource enterprises in depth.

GIS is the core analysis tool of the study, which plays a decisive role in spatial data processing and visualization. GIS can efficiently integrate geospatial data from multiple sources, including the enterprise location, transportation network, and environmental factors, providing a solid foundation for studying the spatial distribution of construction waste resource enterprises. Through the spatial analysis function of GIS, this study can reveal the spatial patterns and agglomeration characteristics of enterprise distribution and its relationship with environmental factors, thereby providing a scientific basis for enterprise site selection and industrial layout.

In order to quantify the key factors affecting the spatial distribution of construction waste resource enterprises, this study further used two regression models for analysis. The regression model is a predictive modeling method that can study the relationship between dependent variables (such as the number of enterprises) and independent variables (such as policy, economics, and transportation). By constructing multiple regression models and weighted geographic regression (GWR) models, this study can identify variables that significantly impact the spatial distribution of enterprises and evaluate their impact. The choice of this method helps us to deeply understand the driving mechanism of the spatial distribution of construction waste resource enterprises. It provides data support for policy formulation and industrial planning.

3.1.1. Spatial Pattern of Construction Waste Resource Treatment Enterprises

Point of interest (POI) is a type of spatial geographic information that describes geographic entities and their spatial attributes. It is widely used in research in several fields, including planning urban infrastructure, analyzing commercial spatial layout, and exploring residential distribution patterns [40]. In addition, with the mathematical computing capabilities of Geographic Information Systems (GIS), researchers can deeply analyze the patterns and regularities latent in geospatial data. This process helps researchers understand the city's spatial structure and make more scientific and rational planning and decision making [41].

The standard partial ellipse (SDE) method explores the spatial patterns of CDW enterprises, revealing distribution characteristics such as dispersion, concentration, and development trends [42]. The SDE provides a valuable tool for analyzing the path of spatial economic activities.

The average nearest neighbor analysis measures the proximity of CDW enterprises and reflects spatial agglomeration. The kernel density estimation method analyzes spatial aggregation and visualizes element concentration through continuous spatial change maps. The kernel density estimation method reflects the aggregation characteristics of elements and reveals the law of distance decay, an essential tool for analyzing the spatial distribution pattern [40].

Spatial autocorrelation analysis measures the degree of interdependence in the spatial distribution of CDW. This dependence is often also called spatial dependence. Multi-distance spatial cluster analysis (Ripley's K-function) was used to identify patterns of industry clusters across cities [43]. If the observed K is greater than the expected K for a given distance, the spatial distribution of these objects is more clustered. If the observed K is less than the expected K, the spatial distribution of these objects is more discrete than the random distribution at that distance. If the observed K is greater than the HiConf value, the spatial clustering at this distance is statistically significant. If the K observation is less than the lower confidence interval (Low Conf) value, the spatial dispersion for that distance is statistically significant.

3.1.2. Correlation Analysis, Multiple Linear Regression Analysis

Pearson's correlation coefficient is used to characterize the degree of linear relationship between two variables, as seen in Formula (1) [43]:

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \quad (1)$$

where r is the correlation coefficient; $\overline{x}$ and $\overline{y}$ are the mean values of the variables x and y, respectively; and x_i and y_i are the ith observation of variables x and y, respectively. The larger the absolute value of r, the stronger the correlation between variables x and y. The sign r indicates the direction of the correlation.

Regression analysis is a predictive modeling method that uses available observations to study the relationship between dependent and independent variables. The method is commonly used to forecast and analyze time series models and find causal relationships between two or more variables.

3.1.3. Weighted Geographic Regression Models

Weighted geographic regression (GWR) modeling is a special local linear regression technique for constructing models based on spatially varying relationships. The GWR methodology constructs a separate model for each geographic area under study. Each model describes relationships within a localized region and accurately resolves variables' local spatial associations and heterogeneity. By incorporating the spatial structure into the traditional linear regression framework, the GWR model effectively identifies and characterizes the non-stationary nature of spatial relationships.

3.2. Study Area and Data

The POI data obtained in this paper includes enterprise name, category, address, and coordinate information. Beijing, Guangzhou, Hangzhou, Nanjing, Nanning, Ningbo, Qingdao, Xiamen, Shanghai, Shenzhen, Xi'an, Chongqing, and 12 other pilot cities of national CDW resourcing enterprises were selected as the study area. The data for the study were obtained from regional statistical yearbooks, regional and national economic and social development bulletins, and corresponding policy documents on the official websites of local governments.

3.3. Selection of Indicators for Influencing Factors on the Spatial Distribution of CDW Resourcing Enterprises

Based on the relevant theories and the availability and quality of variable data, the dependent variable in this study is the number of CDW resourcing enterprises in the administrative areas of 12 cities. Table 1 lists the 12 independent variables for the study of factors affecting spatial distribution.

Table 1. The influences on the spatial distribution of CDW resourcing enterprises.

Variant		Significance of Variables and Reasons for Their Selection	Quote
Policy factors	Site support X1	The land is the primary requirement for business creation. Land-use planning and policy incentives can simplify enterprises' entry and approval processes and promote industrial agglomeration.	[44]
	R&D incentive X2	The R&D incentive policy encourages enterprises to cooperate with scientific research institutions and universities, promotes technology transfer, reduces R&D costs, and accelerates industrial technology upgrading.	[45]
Economic factor	Financial subsidy X3	Financial subsidies are important in the early stages of industrial development. They directly reduce enterprises' operating costs and help them sustain development in the initial high-investment stage.	[46]
	Land price X4	High land prices increase the cost of construction and operation, which is detrimental to CDW companies with large land areas.	[5]
	Building construction area X5	Expansion of the construction area has led to an increase in construction waste. CDW companies depend on adequate waste sources, so the demand is higher in large construction areas.	[9]
	Value added by the secondary industry X6	The clustering of secondary industries brings about economic economies of scale, reducing costs, increasing efficiency and resource utilization, and attracting firms to relocate to developed regions for access to convenient services and opportunities for cooperation.	[47,48]
Transportation factor	Railroad density X7	Fixed and high-capacity railroad lines are suitable for rapidly transporting large quantities of goods over long distances, facilitating the sale of recycled products.	[49]
	Road network density X8	The dense road network area facilitates the road transportation of raw materials and reduces the production costs of enterprises.	[49]
Social factor	Industrial land area X9	Adequate land ensures that companies can handle large quantities of construction waste, raising the upper limit of scale and room for growth.	[50]
	Population density X10	The CDW resource enterprise is a neighborhood facility based on a site to avoid high-density areas and reduce negative impacts on the surrounding environment.	[47,51]
	Number of building material markets X11	The building material market is both CDW resourcefulness enterprises' sales market and raw material supply source, and the two sides form a close cooperation model.	[52]
Environmental factor	River network density X12	CDW resourcing enterprises must avoid rivers and lakes to prevent hazardous substances from polluting the ecosystem. Long-term stockpiling can cause environmental damage.	[53]

3.4. Correlation Analysis of Influencing Factors

Table 2 shows the results of the correlation analysis. The correlation coefficients between the respective variables remain below 0.7. This indicates that they have not reached a strong correlation with each other, and it is initially judged that there is no autocorrelation problem, which aligns with the basic premise of the regression analysis. It was further observed that the *p*-values of the correlation coefficients between all the independent variables and the dependent variable, except for the independent variable X5 (i.e., the area of residential building construction), were significantly less than 0.05. This implies that, except for X5, all the independent variables were statistically significantly correlated with the dependent variable. Based on the above analysis, it was decided to exclude X5 from the subsequent multiple linear regression analysis to ensure the accuracy and validity of the model.

Table 2. Results of correlation analysis.

Variant	Y	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Y	1												
X1	0.191 *	1											
X2	0.331 **	0.532 **	1										
X3	0.346 **	−0.011	0.257 **	1									
X4	−0.167 *	−0.224 **	−0.134	0.245 **	1								
X5	0.018	−0.039	0.011	0.181 *	0.219 **	1							
X6	0.500 **	0.039	0.172*	0.240 **	−0.078	0.234 **	1						
X7	−0.242 **	−0.011	−0.135	0.057	0.453 **	0.125	−0.170 *	1					
X8	0.392 **	0.101	0.149	0.098	−0.102	0.163 *	0.460 **	−0.250 **	1				
X9	0.471 **	0.073	0.140	0.209 **	−0.167 *	0.118	0.587 **	−0.198 *	0.466 **	1			
X10	−0.250 **	0.023	−0.103	0.203 **	0.579 **	0.274 **	−0.068	0.712 **	−0.192 *	−0.246 **	1		
X11	0.507 **	0.087	0.124	0.317 **	−0.095	0.248 **	0.505 **	−0.162 *	0.383 **	0.466 **	−0.126	1	
X12	−0.228 **	0.095	0.160*	0.279 **	0.385 **	0.215 **	−0.056	0.555 **	0.014	−0.008	0.629 **	−0.084	1

* $p < 0.05$, ** $p < 0.01$.

3.5. Regression Analysis of Impact Factors

The data in Table 3 shows the results of the multiple regression. The adjusted R^2 value is 0.495, showing that the model fit is good. The Durbin–Watson value is 2.030, close to the ideal value of 2, indicating that the independent variables are independent and have no autocorrelation problem. The result shows that the *p*-value is equal to 0.000, which is much less than the significance level of 0.05, indicating a significant linear relationship between the eleven independent variables studied and the number of CDW resourcing firms. The result shows that the regression analysis results for further analysis are considered reasonable. In the covariance test, the VIF values of all variables are less than 5, indicating that the covariance problem between variables is not significant. Seven variables (X2, X3, X6, X8, X9, X11, and X12) reached 0.05 at the specific significance level. Among them, the regression coefficient of X12 was negative, implying that the river network density negatively affects the number of enterprises. The regression coefficients of the other six variables (X2, X3, X6, X8, X9, X11) are positive, indicating that they positively contribute to the number of enterprises. Excluding X1, X4, X7, and X10, which did not pass the significance test, the equation of this regression analysis is as follows:

$$\overline{\mathrm{Y}} = 0.263\overline{\mathrm{X}}2 + 0.200\overline{\mathrm{X}}3 + 0.154\overline{\mathrm{X}}6 + 0.148\overline{\mathrm{X}}8 + 0.153\overline{\mathrm{X}}9 + 0.170\overline{\mathrm{X}}11 - 0.355\overline{\mathrm{X}}12 \quad (2)$$

Here, $\overline{\mathrm{X}}\mathrm{i}$ is the value of the Xi, which is the normalized result.

Based on the absolute values of the regression coefficients of the variables, it is possible to assess the degree of influence of the independent variables on the number of CDW resourcing firms in descending order:

River network density > R&D incentives > financial subsidies > number of building material markets > value added by the secondary industry > industrial land area > road network density.

Table 3. Multiple regression model results.

Mold	R	R^2	Adjustment of R^2	Standard Error of Estimate	Durbin Watson
1	0.727 [a]	0.529	0.495	2.775	2.030

[a] Predictor variables: (constants), X1, X2, X3, X4, X6, X7, X8, X9, X10, X11, X12; Dependent variable: Y.

3.6. Weighted Geographic Regression Analysis

The results in Table 4 show that Sigma = 0.774, indicating the model's high prediction accuracy. Meanwhile, the adjusted R2 value is 0.498, showing that the model's fit is slightly higher than that of the global regression model. Based on the above analysis, the study confirms that the constructed GWR model is valid.

Table 4. GWR model fit metrics.

Neighbors	Residual Squares	Effective Number	Sigma	AICc	R^2	Adjusted R^2
125.000	65.588	21.451	0.774	326.520	0.565	0.498

In comparing the results, the sign of the coefficients of X2, X3, X6, X8, and X12 is consistent with the global regression model. This implies that financial subsidies, R&D incentives, value added by the secondary industry, and road network density have significant positive driving effects on the number of firms in all sample points. Conversely, river density significantly negatively affects the number of firms at all sample points. The sign of the coefficients of X9 (industrial land area) and X11 (number of building material markets) is inconsistent with the global regression model at some sample points, showing a negative sign. The results reveal that the increase in the industrial land area and the number of building material markets reduces the number of CDW resourcing firms at some specific sample points. Nevertheless, the absolute values of the negative coefficients of X9 and X11 are relatively small, suggesting that the extent of this adverse effect is relatively limited.

4. Spatial Distribution of Construction Waste Resource Treatment Enterprises

4.1. Spatial Distribution Analysis

The results in Table A1 show the market situation in each city where CDW resourcefulness companies are located.

Table A1 shows that the number of CDW resourcing enterprises varies significantly by city. Beijing has the most resourcing enterprises at the top of the list. Xiamen, in contrast, has the fewest. On average, each city has about 45 CDW resourcing enterprises. It is worth noting that cities with high economic development, prosperous secondary industries, extensive housing construction areas, and strong policy support generally have more CDW resourcing enterprises.

4.2. Average Nearest Neighbor Analysis

Table A2 lists the nearest neighbor index (ANN) for each city. Nanjing, Xiamen, and Shanghai all have ANNs greater than 1, and the absolute value of the z-score is less than 1.96. This suggests that the spatial distributions of CDW resourcing firms do not differ significantly from the stochastic model, and there is no significant spatial agglomeration. Shanghai has the largest ANN among the three cities, indicating that it has the highest degree of discrete resource-based enterprises. Guangzhou and Hangzhou have ANNs of less than 1. However, the absolute value of the z-scores is at most 1.96, indicating that the probability of randomly generating this clustering pattern is high and not statistically significant. The remaining seven cities have ANNs of less than 1, indicating significant spatial aggregation of resourcing firms in these cities. The degree of clustering, in descending order, is Nanning, Shenzhen, Qingdao, Xi'an, Chongqing, Ningbo, and Beijing. In particular, Chongqing's average nearest neighbor observation distance is 17,363.0828 m, the most significant among these cities.

4.3. Kernel Density Analysis

Figure 1 demonstrates the different characteristics and patterns of spatial distribution of CDW resourcing enterprises in the pilot cities. Guangzhou, Chongqing, Nanning, Xi'an, Ningbo, Beijing, Shenzhen, and Qingdao show apparent clustering phenomena.

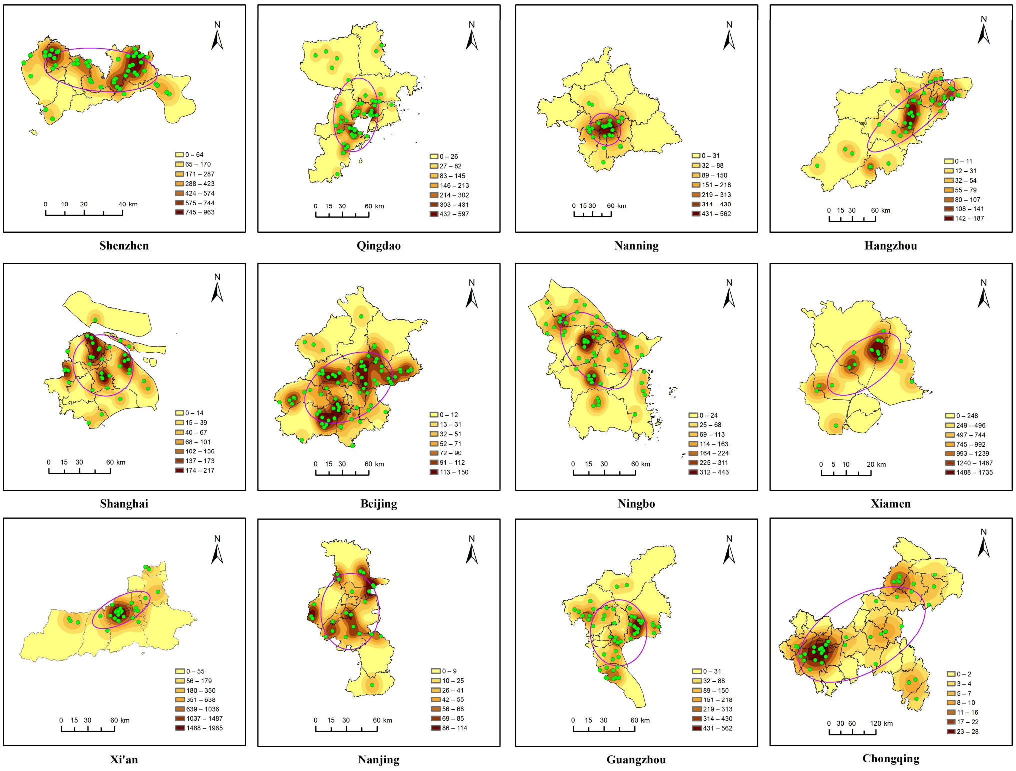

Figure 1. Standard deviation ellipse as well as kernel density maps for the 12 pilot cities.

4.4. Standard Deviation Elliptic Analysis

The results in Table A3 illustrate the significant differences in azimuth between cities. However, the distribution of firms in each city largely caoincides with the city's geographical development direction. At the same time, each city's standard deviation elliptic oblateness also shows significant differences, reflecting the diversity of the strength of the directionality of enterprise distribution. The standard deviation elliptic flatness of Guangzhou, Nanning, and Shanghai is less than 0.2, which indicates that the spatial distribution of enterprises in these cities is weak. The standard deviation elliptic oblateness of the remaining nine cities is more than 0.2, showing obvious spatial distribution directionality. Among these cities, Hangzhou has the most significant directionality in the spatial distribution of enterprises.

4.5. Spatial Autocorrelation Analysis

Global spatial autocorrelation is used to assess the overall degree of spatial correlation and difference between regions. This property is usually measured by Moran's I index. According to Figure 2, the value of Moran's I is 0.136281. Meanwhile, the z-score is 3.008854, and the *p*-value is 0.002622. These values indicate that the CDW resourcing firms exhibit an aggregated distribution at the 99% confidence level. Further, this clustered distribution shows positive spatial autocorrelation.

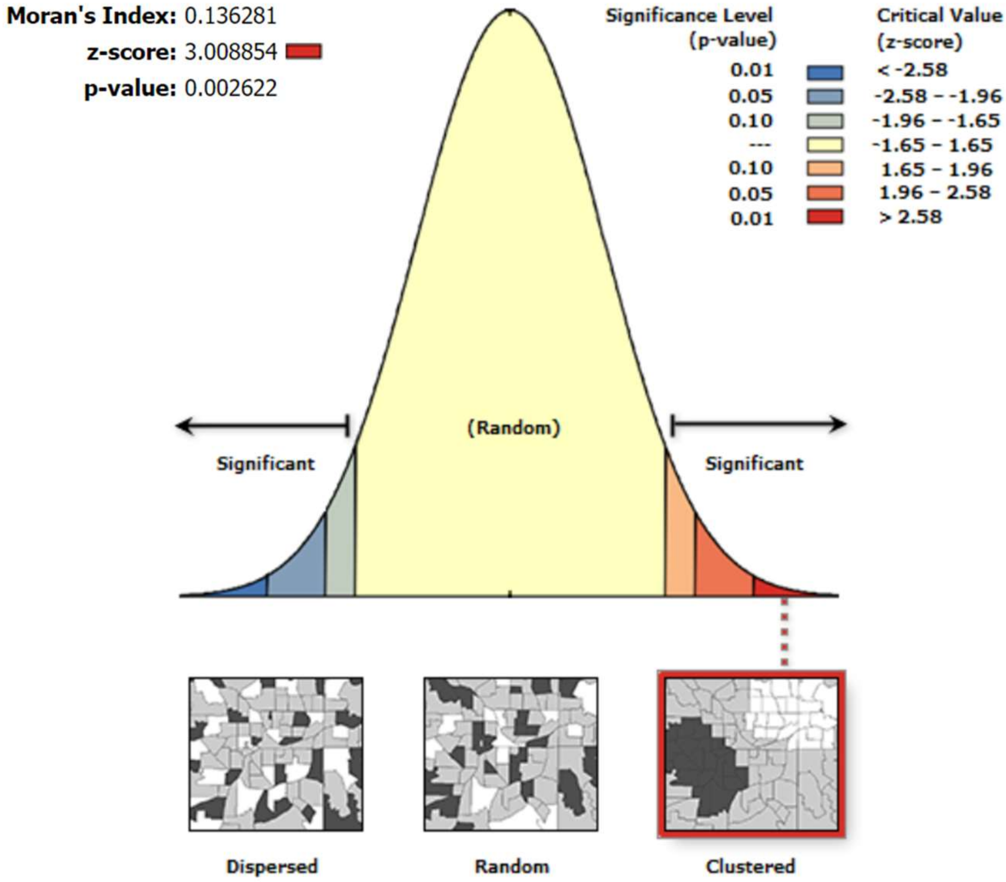

Figure 2. Graph of global spatial autocorrelation analysis results. Clustered; Relevance is average; irrelevant.

Local spatial autocorrelation helped identify spatially clustered regions of various types and locations. The phenomena of high–high clustering and low–low clustering reveal the presence of high spatial positive correlation (as seen in Table 5). This means that the sample points exhibit clustering and similarity within these regions. On the other hand, high–low clustering and low–high clustering reflect strong negative spatial correlation. In these regions, the sample points show heterogeneity.

Table 5. Local spatial autocorrelation analysis results.

Statistic	High–High Clustering	Low–Low Clustering	High–Low Clustering	Low–High Clustering	Insignificant
Amount	10	17	5	4	130
percentage	6.02%	10.24%	3.01%	2.41%	78.31%

The high–high clustering phenomenon is particularly significant in Ningbo, western Qingdao, and northern Beijing. Although Ningbo and Qingdao are not national leaders in the construction industry, both have implemented strong policies to promote construction waste resourcing. These policies have effectively incentivized local firms and rapidly prompted many resource-based companies to set up factories in each administrative district. Beijing has a long history of developing its construction waste recycling industry, which has entered a market-oriented stage. Given its well-developed construction industry and high level of urbanization, the northern part of Beijing is characterized by high–high clustering.

Low–low clustering is widespread in the central metropolitan area of Chongqing, mainly concentrated outside the central region. Chongqing is a vast area with many districts and counties, and the development of the construction industry is relatively balanced outside the central urban area. At the same time, the road networks in these areas are relatively sparse, which affects the distribution of CDW resourcing enterprises. Relevant enterprises occupy many administrative districts, but the number is limited, showing a low–low clustering characteristic.

The high–low clustering phenomenon is particularly evident in the center of Chongqing's main metropolitan area, eastern Shanghai, and central Nanjing. Shanghai's construction waste resourcing industry still relies on government support, with the Pudong, Minhang, and Baoshan districts becoming the main clusters of resourcing companies under government planning. In contrast, the number of enterprises in other regions of Shanghai is small. The central part of Nanjing stands out for its industrial agglomeration, with its well-developed secondary industry, well-developed road network, and high-level economy attracting many chemical resource enterprises, the number of which far exceeds that of the surrounding regions.

The low–high clustering phenomenon is mainly distributed in northeastern Ningbo, northern Guangzhou, and southern Shenzhen. Northeastern Ningbo is the city center area, which is limited in size and economically prosperous, and it is not cost-effective for resource-based enterprises to locate there. On the contrary, the low–high clustering areas in Guangzhou and Shenzhen are located far away from the city center, in areas with high topographic relief and less developed transportation.

4.6. Analysis of the Rootedness of Industrial Clusters

K-function plots were constructed for the 12 cities, each with 99% confidence intervals, and the results are shown in Figure 3. Each city's construction waste resource utilization industry was analyzed in depth by comparing the observed K values with the expected K values. On this basis, the spatial scales of the 12 cities under the clustering model were determined. The summary results of all relevant data have been organized in Table A4.

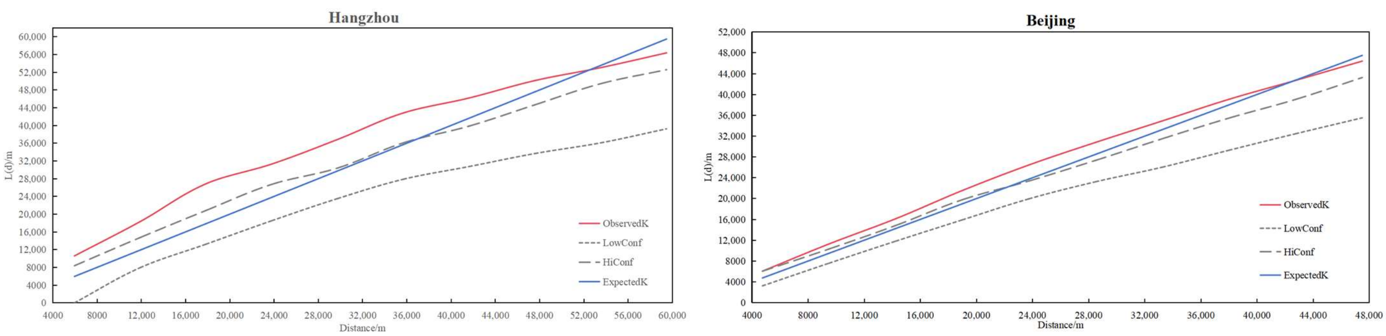

Figure 3. *Cont.*

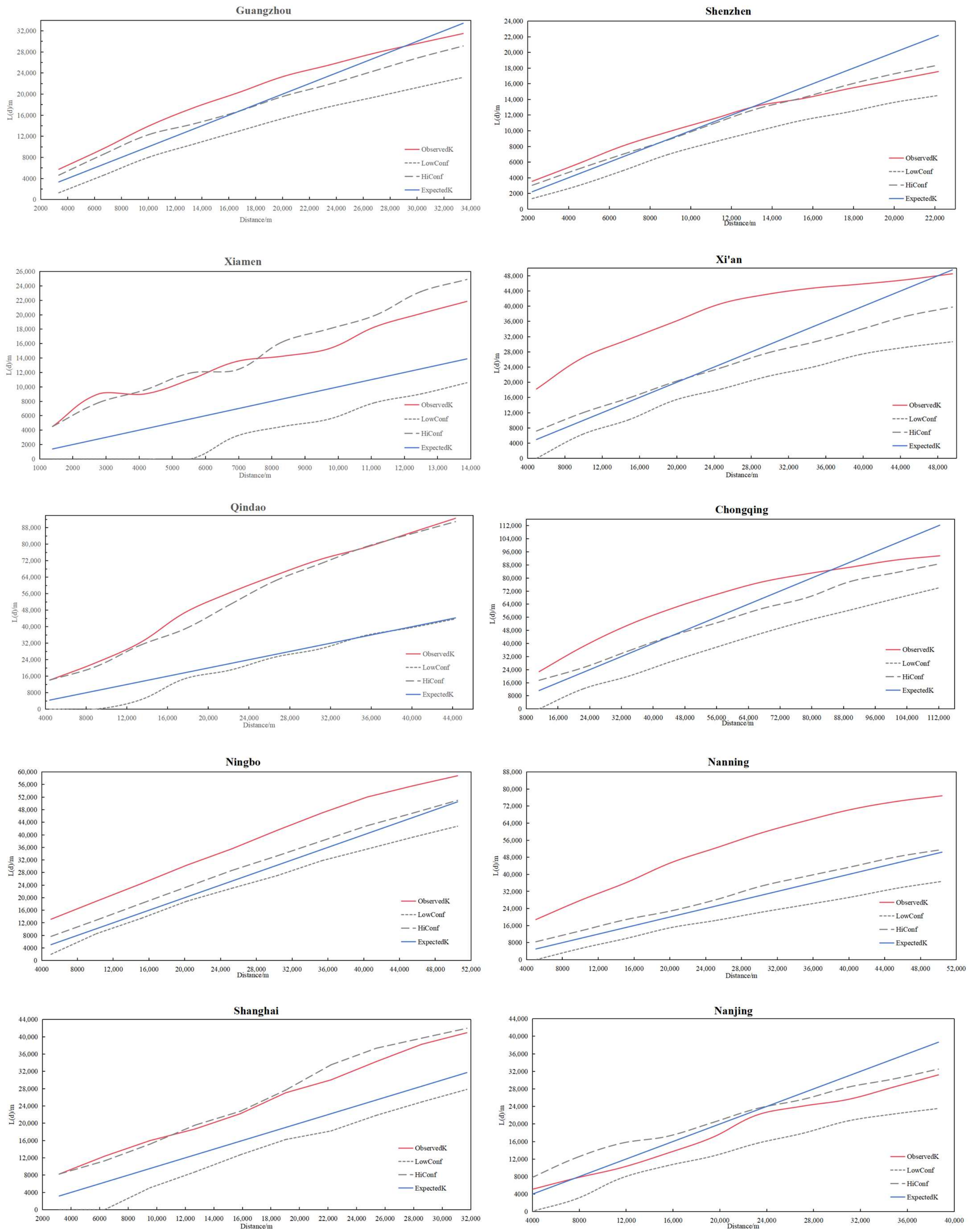

Figure 3. K-function plots for the 12 pilot cities.

The results in Table A4 show that, except for Nanjing, the remaining 11 cities exhibit the phenomenon of clustering in the construction waste resource utilization industry. In terms of the spatial scale of agglomeration, Chongqing has the widest scope, and the data indicate that the spatial scale of agglomeration of its construction waste resource chemical enterprises reaches 84,803 m, showing its broad geographical radiation power. Xiamen is the most compact, with its agglomeration scales concentrating between 1452 and 3733 m and 6114 and 7588 m, indicating that Xiamen's resource-based enterprises are densely clustered in a relatively small area. Due to its vast territory, Chongqing has strong radiation power for resourcing enterprises. Supporting enterprises such as construction units and wholesalers of recycled products are also clustered widely. Nanjing does not have significant cluster characteristics related to the even distribution of its resourcing firms. Only a few financial institutions are clustered there, and the number of resourcing enterprises needs to be increased, limiting synergistic development. The size of the spatial scale of clusters reflects the scale of industrial cluster areas, and industrial clusters are present in the whole area of Nanning and Ningbo. The GDP share of machinery and equipment manufacturing in these two cities is high. The two industries serve as pillars, providing a favorable development environment for resource-based industries and promoting the rise in enterprises and the division of specialties. Beijing, Xi'an, Hangzhou, and Qingdao have similar spatial clustering scales, while Guangzhou and Shenzhen are slightly behind.

5. Discussion

5.1. Policy Drivers for CDW Industry Development

With the increased emphasis on low-carbon sustainable construction in China, several cities are actively seeking innovative directions for treating the solid waste from construction. Policies have become the key driving force that promotes solid construction waste reduction, resourcefulness, and harmless treatment. As a pioneer in solid waste treatment, Beijing has shown foresight and in-depth practice in construction waste management. In 2020, we saw the introduction of the Beijing Construction Waste Disposal Management Regulations. The policy was further upgraded to clarify the principles of minimization, resource utilization, and harmlessness. The regulations have built a management system that is government-led, socially participatory, categorized for disposal, and supervised throughout the entire process, providing detailed guidance for construction waste management.

Guangzhou City has implemented a strategy combining policy guidance and market incentives in solid waste disposal, especially in managing construction waste. The government reduces the operating costs of recycling enterprises through tax incentives, such as value-added tax and income tax exemptions. These preferential policies enhance economic efficiency and the return on investment of recycling enterprises and motivate them to participate in waste recycling. The results of these policies are remarkable, and the total amount of recycling has increased significantly as a result. VAT and CIT incentives have become significant drivers of the industry's growth.

Shenzhen is one of the few cities in China that publicizes construction waste data. In 2020, the Measures for the Administration of Construction Waste in Shenzhen were comprehensively upgraded to specify the requirements for the whole management chain, covering various aspects such as definition, classification, generation, discharge, and transportation. These measures set out in detail the specific links of transit, sorting, recycling, and elimination to ensure that there are no omissions in management. Shenzhen has strengthened the supervision process and ensured effective policy implementation through emission authorization, electronic joint-order management, and statistical reporting.

5.2. Driving Factors Influencing the Development of the CDW Industry

Previous studies have focused on the government's role in industry development, especially in formulating policies and regulations. This study finds that R&D incentives and financial subsidies significantly impact the CDW industry, with correlation coefficients of 0.263 and 0.200, respectively. In contrast, the land-use support policy does not significantly affect the CDW industry. The R&D incentive policy encourages the technological innovation of enterprises to improve the efficiency and effectiveness of waste resource utilization. Technological progress reduces treatment costs, improves product quality, and enhances market competitiveness. Financial subsidies alleviate the financial pressure on enterprises and enhance their operational capacity. They are used for equipment purchase, technology R&D, and market expansion, which enhances enterprises' competitiveness and sustainable development ability. Financial subsidies also serve as an incentive mechanism to attract investors and entrepreneurs to the field of construction waste resource utilization. On the other hand, the effectiveness of the land use support policy, despite providing favorable land-use conditions, is constrained by market demand, economic environment, and other factors. Therefore, the land-use support policy has not significantly impacted the growth of enterprises.

The impact of economic factors on industrial development has received equal attention from scholars, including GDP per capita and industrial structure. This empirical study found that the value added by the secondary industry is a significant driver for the construction waste treatment industry, with a correlation coefficient of 0.154. In contrast, land prices and the residential building construction area do not significantly affect this industry. The agglomeration effect of secondary industries brings about an economic scale effect, and their added value reflects the scale and dynamism of the regional industrial economy. Regions with developed industrial economies have a high demand for construction materials and are prone to produce large amounts of construction waste. Resource-based enterprises can utilize these wastes for treatment and reuse.

Among transportation factors, scholars often focus on the impact of transportation infrastructure on industrial development. In this research, road network density was a significant industry driver with a correlation coefficient of 0.148, while railroad density had no significant effect. The findings are related to the current means of automobile transportation in CDW. A well-developed road network reduces transportation costs and improves logistics efficiency. Construction waste transportation relies on an efficient and convenient logistics system, and areas with high road network density help reduce transportation costs. High road network density ensures smooth waste transportation from generation to treatment to the market, reducing enterprises' operating costs.

Among the social factors, industrial development studies focus on the degree of marketization, population density, and education level. This study specifically focuses on the mechanisms of the industrial land market, building material market, and population density. The industrial land area and the number of building material markets were significant industry drivers, with correlation coefficients of 0.153 and 0.170, respectively. In contrast, the effect of population density on industrial development did not show significance. The large industrial land area provides more space for industrial activities, including the disposal and recycling of construction waste. Large industrial land areas reduce the land acquisition cost of enterprises and enhance their development space security. The rational planning of industrial land through policies prioritizing the layout of construction waste treatment enterprises in industrial parks can help industrial development. At the same time, centralized construction waste treatment centers are promoted to adopt intensive production methods and improve land-use efficiency. This approach can reduce the environmental and resource waste caused by decentralized treatment. The number of building material markets directly reflects the demand size for the building material market. An increase in the number of building material markets indicates an increase in demand for building materials, which broadens sales channels and market space for CDW enterprises, which can use these markets to sell recycled building materials, realize profits, and promote business expansion.

Environmental factors have a significant impact on industrial development. In previous studies, environmental factors have either caused constraints or facilitated them. In our study, river network density was found to have a significant constraining effect on the CDW industry. Its correlation coefficient was −0.355, and this negative regression coefficient highlights the tension between environmental protection regulations and industry development. The long-term accumulation of construction waste may pollute groundwater, threatening river and lake ecosystems. With stricter government regulations, dense river network areas are often regarded as environmentally and ecologically sensitive. Due to environmental regulations and land-use restrictions, CDW industries are difficult to establish in high river network density areas. Environmental policies should be strengthened to mitigate the negative impact of high river network density on the CDW industry. Strict waste discharge management and environmental monitoring must be implemented for construction projects in riverine areas. At the same time, environmentally friendly construction waste treatment technologies are being developed to reduce the risk of water pollution. For example, closed treatment systems and high-efficiency wastewater treatment equipment are used to ensure that wastewater discharges meet standards.

5.3. The Role of Urban Planning in Promoting the CDW Industry

The distribution of CDW industries at the district (county) level is characterized as follows: there is almost no distribution in city-center administrative districts; the distribution of CDW industries in remote suburban districts (counties) is small and scattered; and the distribution of CDW industries is most concentrated in the administrative districts adjacent to the city center. These features prevail in the major pilot cities. In urban planning, the central city is mainly used for commercial and residential purposes, and industrial activities, including CDW industries, are restricted. CDW industries are difficult to set up in the city center due to exceptional land and transportation needs and low land price affordability and are significantly inhibited by urban planning. Weak infrastructure, inconvenient transportation, and insufficient market demand in remote suburban areas have led to the scattered distribution of CDW enterprises. However, the attractiveness of distant suburbs to CDW enterprises can be enhanced through transportation network improvement, infrastructure development, and policy enhancement. Administrative districts adjacent to city centers are ideal locations for CDW industries to cluster due to convenience and cost advantages. Urban planning needs to coordinate land use and upgrade infrastructure in these areas to facilitate the concentration of CDW industries.

Cities with high levels of economic development and developed secondary industries, such as Beijing and Guangzhou, have thriving and widely distributed CDW industries. These cities have intensive construction activities and generate large amounts of construction waste. Well-developed logistics networks and extensive market demand also provide favorable conditions for the local CDW industry. The growth of the CDW industry is further promoted through urban planning, optimization of land use, improvement of transportation facilities, and construction of industrial parks. Demonstration cities with a lower level of economic development, such as Nanning, have a relatively concentrated and limited distribution of CDW industries. Despite the demonstration role, insufficient market demand limits the expansion of CDW industries. Guiding industrial agglomeration through urban planning and providing necessary infrastructure and policy support can enhance the attractiveness of CDW industries.

Cities with strong policy support have rich and evenly distributed CDW industries. Policy support is an essential driving force for developing the CDW industry. In urban planning, utilizing financial subsidies, tax breaks, and technical support to reduce operating costs can attract more enterprises to the CDW industry. For example, Ningbo has realized a balanced distribution of the CDW industry in the city through diversified incentive policies. This balanced distribution helps to meet the needs of different regions better.

CDW industries are primarily located in flat areas and avoid nature reserves. In urban planning, the impact of terrain on industrial layouts needs to be considered. Flat terrain can reduce the construction and transportation costs of CDW industries and improve operational efficiency. Nature reserves are avoided when choosing locations due to high environmental requirements and restrictions on industrial activities. Enterprises choose flat and convenient transportation sites to comply with environmental regulations and reduce risks. For example, enterprises are scarce in the mountainous areas in the eastern part of Baiyun District in Guangzhou and the central part of Huangpu District, as well as in Huairou District and the northern part of Pinggu District in Beijing. In urban planning, terrain conditions should be evaluated, industrial land use should be rationally arranged, and restricted areas such as nature reserves should be avoided to balance economic and environmental needs.

CDW industries cluster near industrial parks in most cities. Industrial parks provide centralized and well-developed infrastructures, convenient logistics conditions, and preferential policy support, which provide a suitable environment for enterprises to develop. CDW industries clustering near industrial parks can enjoy shared infrastructures, reduce operating costs, and gain business opportunities through neighboring industrial chains. For example, areas such as Hangzhou Hezhuang Industrial Park and Xixucun Industrial Park have many clustered CDW resourcing enterprises. These enterprises have improved their overall competitiveness and market responsiveness through the agglomeration effect. In urban planning, forming an industrial agglomeration effect through constructing and improving industrial parks can enhance the industrial chain's synergy effect and market responsiveness.

5.4. Integration of CDW Industry Chain in Various Cities

From the perspective of industrial clustering, except for Nanjing, the construction waste resource utilization industry in the remaining 11 cities shows the clustering phenomenon. Specifically, each city has four modes of construction waste industry clustering: uniform distribution, centralized distribution, multi-center clustering, and belt-shaped distribution.

Shanghai, Xiamen, and Hangzhou are evenly distributed. Shanghai's solid waste treatment enterprises are scattered throughout the city, especially outside the city center. These enterprises are mainly concentrated in the eastern areas of Pudong New Area, Minhang District, and Baoshan District. Under the government's planning and coordination, many CDW resourcing enterprises are concentrated in these areas, forming a high–low clustering phenomenon.

Xi'an and Chongqing exhibit centralized distribution and regional agglomeration. The CDW resource utilization enterprises in Chongqing are mainly concentrated in the central city's metropolitan area, but the overall distribution is somewhat decentralized. This is because the central city metropolitan area has a well-developed transportation network, low land costs, and well-developed infrastructure, which makes it an ideal area for enterprises to cluster.

Guangzhou, Shenzhen, Beijing, Ningbo, and Qingdao City exhibit multi-center Clustering. Guangzhou shows prominent characteristics of industrial clusters in CDW resource utilization, with a vast concentration of related enterprises. Regarding spatial distribution, Guangzhou presents two high-density core areas and a belt-shaped agglomeration area. The high-density core area is located southwest of Zengcheng District and at the junction of Huadu District and Baiyun District. The belt-shaped agglomeration area is distributed along the north–south direction of the Huangpu, Panyu, and Nansha districts.

Nanning exhibits belt-shaped distribution. The Xingning, Xixiangtang, and Yongning districts have attracted many enterprises due to their transportation advantages and lower land costs. This clustering pattern not only enhances the synergy effect among enterprises but also helps centralize the treatment of construction waste and improve resource utilization efficiency.

5.5. International Comparison and Enlightenment

This study analyzes the spatial distribution characteristics of CDW resource utilization industries in 12 pilot cities in China. It explores the industrial layout's driving mechanism, mutual policy promotion, and economic and environmental factors. In CDW management, 12 Chinese cities demonstrate empirical experience in urban planning, policy, and economy and location sample data. The research results are universal and can provide a reference for other large cities worldwide. The following is a detailed comparison of international experiences.

In terms of urban planning and location, a lack of data is a significant obstacle for emerging economies in designing effective waste management systems [54]. This study provides case-city data. The 12 Chinese city cases show that urban spaces, transportation, resources, and the economy will support and influence CDW operations. The CDW industries, in the case of these cities, are most concentrated in administrative districts adjacent to the city center. The spatial network structure of Chinese cities significantly impacts the intensity of CDW generation. The spatial network characteristics of CDW have a center-edge structure [55]. The industrial planning of CDW needs to be comprehensively considered based on the spatial distribution of cities, the composition of urban centers and satellite towns, river and road resources, and the scale of upstream and downstream industries. When formulating industrial planning and facility support, it is necessary to focus on constraints such as the river network density, number of building material markets, added value of the secondary industry, industrial land area, and road network density. Studies on foreign cities have shown that urban planning and location impact CDW management. The case study of Chennai, a city in India, showed that transportation costs were 50% higher than the cost of recycled materials [54], which slowed the progress of CDW. A sensitivity analysis of the Lombardy Region in Italy also confirmed that CDW transportation plays a key role [56]. Minimizing waste transportation can improve the performance of the management system. The recommended measures of this study are to promote industrialization by appropriately locating recycling plants within the region and promoting connections between recyclers and builders.

Regarding policy framework, the core driving forces of the Chinese case cities are fiscal subsidies and R&D incentives. The case cities can promote the development of the CDW industry by reducing enterprise costs and upgrading technology. The effectiveness of fiscal subsidies and R&D incentives depends on the regional economic level (such as the industrial agglomeration of Beijing and Guangzhou). However, the land support policies of the case cities did not pass the significance test, indicating that policies need to be more integrated with market demand and transportation resources. These experiences are worth referring to for international cities when formulating management policies.

International researchers also believe CDW policies and practices are key issues that must be considered [57]. International researchers focus on education, government incentives, laws, community environmental protection, and corporate responsibility. Several studies in Brazil [58], Hong Kong [59], and other countries have proven that government intervention measures such as policies, taxes, and incentives can promote waste recycling. The EU has set a mandatory 70% CDW recycling target through the Waste Framework Directive [60]. Its legislative means are more potent than economic incentives, providing a target-oriented supplementary model for China. The United States emphasizes the responsibility of developers and incorporates stakeholders into the management chain through "zero CDW emission rewards" [61]. Market-driven mechanisms can provide a reference for China to optimize policy coordination.

Regarding economic and technological drivers, the added value of the secondary industry and the industrial land area in the Chinese case cities significantly affect the layout of the CDW industry, reflecting the dual role of industrialization and land resources. International cities also use economic and technical methods. Some European countries have achieved up to 100% recycling rates for CDW due to effective waste control frameworks and management plans tailored to regional needs rather than relying solely on national policies [62]. Achieving CDE objectives requires investments in local municipalities to enhance logistical efficiency, engage stakeholders, and develop the secondary materials market and local economies. Singapore supports technology upgrades through a special fund to encourage the purchase of demolition equipment for recycling concrete [63]. The South Korean government has implemented quality standards and quality certificates for recycled aggregates to enhance consumer confidence while using an online market system to increase transparency in CDW management to improve waste tracking and management [63]. The Netherlands has reduced customers' and contractors' fear of using recycled materials by introducing quality labels and promoting the use of recycled materials in construction [63]. Japan emphasizes waste reduction during the design phase and requires waste producers to dispose of waste responsibly within a strict legal framework [64]. Different experiences reference cities' entire life-cycle management in various countries.

Regarding environmental constraints, the density of China's river network significantly restricts the location of enterprises. Cities need to reduce the risk of environmental pollution through environmental protection technologies (such as closed-loop treatment systems). Cities worldwide have also issued environmental constraints on river and soil protection. Sweden has promoted an increase in resource utilization by prohibiting the landfill of combustible waste [63]. The strictness of environmental regulations can provide policy inspiration for areas with dense river networks. Australia's state-level landfill tax and circular economy framework [65] show that the "economic lever + policy target" combination strategy is universal and complementary to the fiscal subsidies of Chinese case cities.

In terms of law, global cities attach importance to law in CDW management. Chinese case cities have issued administrative management methods, tending to administrative orders. Some cities provide quality standards. Shenzhen issued the "Technical Standards for Construction Waste Emission Reduction" to unify the technical standards of design, construction, and effect processes to promote the development of the CDW industry. The European Union adopts a legal legislation model. South Korea and the Netherlands have adopted a quality certification system to enhance consumer confidence through unified standards. In addition, South Korea's online CDW management system is worth learning from. Combined with GIS technology, it can improve the industrial chain's transparency and supervision efficiency.

6. Conclusions

Under the background of the country's vigorous development of a circular economy, the CDW resourcing industry has attracted much attention. Due to the differences in metropolitan area positioning, economic, social, and cultural characteristics, and city panel data, the layout characteristics of resource-based industries vary in different cities.

Taking 12 CDW pilot cities as examples, this paper reveals the characteristics and differences in the spatial distribution of CDW resourcing enterprises by extracting spatial hotspot information and mixing quantitative data to analyze the influencing factors quantitatively. This paper constructs a global regression model and finds seven factors that can significantly influence the spatial distribution of national CDW resource enterprises and the degrees of influence of different factors. The degrees of influence of these factors, from largest to smallest, are river network density, financial subsidies, R&D incentives, the number of building material markets, the value added by the secondary industry, the area of industrial land, and the density of the road network. According to the results, policy is a key driver for low-carbon sustainable construction, promoting the reduction, resourcing, and harmless treatment of construction solid waste (CDW). Financial subsidies and R&D incentives should be increased to support companies in the CDW industry. Industrial site selection should pay more attention to the density of the city's river network, the number of building material markets, the value added by the secondary industry, the industrial land area, and the road network's density. These factors will sustainably help future operations. The model passed the F-test, covariance test, and standardized residual test to ensure that the model is valid and has a high degree of fit. From the regional perspective, most of the CDW resourcing enterprises are located in areas with flat terrain, close to industrial parks, and adjacent to the central city. From the city level, cities with a high level of economic development and strong policy support have more resourcing enterprises, and their spatial distribution is roughly the same as the direction of the city's geographic development. The CDW resourcing enterprises show positive spatial autocorrelation on the global scale. They can be subdivided into four types of local clustering patterns: high–high, low–low, high–low, and low–height. Ningbo, western Qingdao, and northern Beijing showed high–high aggregation characteristics. Low–low aggregation characteristics exist in regions other than central Chongqing. High–low aggregation features are found in the center of the main city of Chongqing, eastern Shanghai, and central Nanjing. Low–high aggregation is distributed in northeastern Ningbo, northern Guangzhou, and southern Shenzhen. Regarding industrial agglomeration, except for Nanjing, industrial agglomeration of construction waste occurs in all 11 pilot cities. Among them, Shanghai, Xiamen, and Hangzhou have industries that are distributed evenly. Xi'an and Chongqing have centralized distributions of industries. Guangzhou, Shenzhen, Beijing, Ningbo, and Qingdao exhibit multi-center clustering of industries. Nanning's industry has a belt-shaped distribution.

This research examines the current status of the CDW industry in 12 CDW governance pilot cities in the Chinese region, which have geographical and temporal limitations. However, the Chinese region is characterized by a large volume of concrete solid waste removal, high potential for future technologies and industries, and urgent urban low-carbon operations, which are of research significance. These fundamental studies are helpful for City Information Modeling, industrial development, policy incentives, industrial planning, transportation economics, and spatial optimization decision making. Future research will be expanded to a global scale to include important international cities to increase the robustness of the study.

This research explores the micro level of the industry chain integration elements of the construction and demolition waste (CDW) industry, combined with two macro levels of incentive policies and urban planning, to jointly promote sustainable urban construction. In the future, the following research aims to tap into the information on human–land relationships and system engineering of big data and jointly promote the innovative direction of new engineering in urban science. Researching natural and social phenomena in built environments through discovery-driven and theory-led approaches and combining mechanistic and data-driven approaches is a new way. In the future, we will further combine the interdisciplinary disciplines of civil engineering, architecture, and urban science to explore the critical issues of sustainable urban construction for research with new perspectives.

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

Appendix A

Table A1. Basic data for pilot cities.

Municipalities	Number of Enterprises Resourced	Area (of a Floor, Piece of Land) (km²)	GDP (Billions of Dollars)	Value Added by the Secondary Industry (Billion Yuan)	Building Construction Area (10,000 Square Meters)	Site Support	Financial Subsidy	R&D Incentives
Beijing, the capital of the People's Republic of China	78	16,411	40,269	5244	91,155		√	
Guangzhou, a subprovincial city and the capital of Guangdong	54	7434	28,232	7723	39,222	√	√	
Hangzhou is a subprovincial city and capital of Zhejiang province in southeast China	40	16,850	18,109	5441	33,132		√	
The capital of China at different historical periods	23	6587	16,355	4454	26,470	√		
Zhuang: Namzningz	22	22,100	5121	1199	9625		√	
Ningbo, a subprovincial city in Zhejiang	68	9816	14,595	6975	10,779	√	√	√
Qingdao, a subprovincial city in Shandong	59	11,293	14,136	5109	21,906	√	√	√
Xiamen, a subprovincial city in Fujian	18	1700	7034	2828	16,435	√		
Shanghai	36	6340	43,215	11,543	54,802		√	
Shenzhen, asubprovincial city in Guangdong, a special economic zone close to Hong Kong	53	1997	30,665	9122	22,531		√	
Xian	34	10,108	10,688	3349	22,452	√	√	
Chongqing	42	82,400	27,894	11,185	37,895			

Table A2. Average nearest neighbor analysis.

Municipalities	Average Observation Distance (m)	Expected Average Distance (m)	Nearest Neighbor Index (NMI)	z-Score
Chongqing	17,363.0828	25,080.4427	0.692296	−3.814952
Shenzhen, a subprovincial city in Guangdong, a special economic zone close to Hong Kong	2298.8641	3425.3751	0.671128	−4.580323
Qingdao, a subprovincial city in Shandong	4551.3434	6630.6153	0.686413	−4.60802
Beijing, the capital of the People's Republic of China	6438.5103	7489.0327	0.859725	−2.370052
Guangzhou, a subprovincial city and the capital of Guangdong	4375.0117	5073.3291	0.862355	−1.935029
Hangzhou, a subprovincial city and the capital of Zhejiang province in southeast China	7597.1941	8662.4471	0.877026	−1.487898
Capital of China at different historical periods	8919.2389	8781.4355	1.015693	0.143976
Zhuang: Namzningz	3761.8718	6303.1002	0.596829	−4.363102
Ningbo, a subprovincial city in Zhejiang	4794.4384	5773.3427	0.830444	−2.674842
Xiamen, a subprovincial city in Fujian	3522.0230	3392.8359	1.038076	0.309046
Shanghai	6841.5237	6841.5237	1.067591	0.775837
Xian	4181.4428	6062.1861	0.689758	−3.460753

Table A3. Standard deviation ellipse analysis.

Municipalities	Center Coordinate	Long Axle (km)	Short Axle (km)	Azimuth (°)	Flatness
Beijing, the capital of the People's Republic of China	116.41° E, 40.04° N	53.28	34.63	60.63	0.35
Guangzhou, a subprovincial city and the capital of Guangdong	113.49° E, 23.18° N	32.17	27.53	0.38	0.14
Hangzhou, a subprovincial city and capital of Zhejiang province in southeast China	119.86° E, 30.00° N	70.74	20.98	51.20	0.70
Capital of China at different historical periods	118.80° E, 31.98° N	37.37	28.40	1.67	0.24
Zhuang: Namzningz	108.41° E, 22.83° N	26.98	23.38	149.66	0.13
Ningbo, a subprovincial city in Zhejiang	121.49° E, 29.84° N	43.60	25.35	139.55	0.42
Qingdao, a subprovincial city in Shandong	120.17° E, 36.23° N	41.77	24.83	6.44	0.41
Xiamen, a subprovincial city in Fujian	118.14° E, 24.67° N	17.26	8.74	52.94	0.49
Shanghai	121.47° E, 31.21° N	30.94	28.28	140.40	0.09
Shenzhen, a subprovincial city in Guangdong, a special economic zone close Hong Kong	114.15° E, 22.70° N	29.50	11.18	95.02	0.62
Xian	108.88° E, 34.24° N	35.69	14.79	62.92	0.59
Chongqing	107.49° E, 29.91° N	179.91	95.57	59.87	0.47

Table A4. Results of multi-distance spatial clustering analysis.

Municipalities	Spatial Scale of Clustered Distribution (m)
Beijing, the capital of the People's Republic of China	5417 < d < 44,616
Guangzhou, a subprovincial city and the capital of Guangdong	d < 29,432
Hangzhou, a subprovincial city and capital of Zhejiang province in southeast China	d < 52,521
Capital of China at different historical periods	-
Zhuang: Namzningz	Whole territory
Ningbo, a subprovincial city in Zhejiang	Whole territory
Qingdao, a subprovincial city in Shandong	4461 < d < 37,823
Xiamen, a subprovincial city in Fujian	1452 < d < 3733, 6114 < d < 7588
Shanghai	3276 < d < 11,553
Shenzhen, a subprovincial city in Guangdong, a special economic zone close Hong Kong	0 < d < 12,912
Xian	d < 48,245
Chongqing	d < 84,803

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