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Has Urban Construction Land Achieved Low-Carbon Sustainable Development? A Case Study of North China Plain, China

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Abstract: The rapid expansion of urban construction land (UCL) provides a guarantee to support rapid economic development and meet the social needs of urban residents. However, urban construction land is also an important source of carbon dioxide emissions. Therefore, it is of great research value to investigate the relationship between UCL and carbon emissions in depth. Based on this, using panel data of 57 cities in the North China Plain from 2007 to 2018, the study found that there is a strong positive correlation between UCL and CO_2 emissions. It can be seen that the expansion of UCL is an important source of CO_2 emissions. On the basis of this research conclusion, first, this paper uses the Tapio decoupling model to analyze the decoupling relationship between UCL and carbon emissions in the North China Plain. Then, the spatial autocorrelation analysis was applied to explore the spatial correlation characteristics of the carbon emission intensity of UCL in cities in the North China Plain. Finally, using the GTWR model to analyze the influencing factors of the carbon emission intensity of UCL, the following conclusions were drawn. In 2007–2015, the decoupling relationship performed well, but it deteriorated significantly from 2015 to 2018; in addition, there was a significant positive spatial correlation of carbon emission intensity of UCL. Various influencing factors have a significant impact on the carbon emission intensity of UCL, for example, the urbanization rate, industrial structure, economic development level, and population density have a positive impact, and environmental regulations, foreign investment intensity, land use efficiency and greenery coverage have a negative impact. The research results of this paper provide a scientific basis for making decisions and optimizing pathways to achieve carbon emission reduction from UCL in the North China Plain, as well as certain reference values for other regions to achieve low-carbon development of UCL. This is significant for exploring the optimal solution of land and carbon emissions and building a harmonious human–land relationship.

Keywords: urban construction land; carbon emission; carbon emission intensity of urban construction land; North China Plain; tapio decoupling model; geographically and temporally weighted regression (GTWR) model

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1. Introduction

Since the reform and opening up, China's economy has achieved rapid development, and the country's appearance has changed with each passing day. At the same time, China is also a big energy-consuming country. The extensive development model is accompanied by a large amount of energy consumption, making it the country with the largest carbon dioxide emission in the world. Currently, the increasingly serious climate warming and greenhouse effect are the most direct causes of various extreme weather events. It has become an important factor restricting the development of human society. In the face of the current severe emission reduction situation in society, China has made a commitment at the 75th United Nations General Assembly to achieve the two goals of carbon peaking and carbon neutrality before 2030 and 2060, which reflects China's efforts in addressing climate change, a major country's responsibility and firm determination on the issue of change. Adhering to a low-carbon economy and achieving sustainable development is an inevitable choice concerning the destiny of all mankind.

At the same time, land is the most important support and carrier of human activities, and human production activities also have an impact on the land; unreasonable production activities cause direct damage to land resources and increase the burden on land. Studies have shown that 60% of land changes are related to direct human activities [1]. Land use and cover change is the second most important cause of increased CO_2 emissions in the atmosphere, after fossil fuel combustion [2,3]. In recent years, China has been rapidly urbanizing, and UCL has increased significantly, which is one of the important sources of carbon emissions. The expansion of land use has resulted in tight land supply and demand, air pollution, and the greenhouse effect. From the source of carbon emissions, land expansion increases carbon sources, such as industry and housing; from the end of carbon emissions, land expansion reduces carbon sinks, such as forest vegetation. Therefore, how to reconcile land expansion and carbon emissions and minimize carbon emissions, while reasonably expanding land area and promoting economic and social development, has become a problem that must be addressed head-on. On the basis of this research purpose, this paper selects 57 cities in the North China Plain as research objects and, firstly, explores the coupling relationship between UCL and carbon emission and then further analyzes the spatial and temporal patterns and key driving forces of carbon emission intensity of UCL, which is important for fully exploring the emission reduction potential of UCL, reasonably planning the development direction of UCL, and improving the ecological environment.

The background, significance, and main structure of the study have been analyzed above; however, the question regarding how to better achieve the objectives of the study remains, which requires the selection of appropriate research methods. The decoupling theory provides a good theoretical framework for exploring the relationship between economic growth and resource consumption, and it has become an effective analytical method for academics to measure the relationship between the two changes. The decoupling theory was first proposed by the Organization for Economic Cooperation and Development (OECD) [4], and Tapio introduced the elasticity method to the decoupling theory to study the decoupling relationship between economic growth and carbon emissions in the European transport sector [5]; the model was later widely used to explore the relationship between resource consumption and environmental pollution. At present, a large number of scholars have applied the decoupling model at the international [6,7], national [8–13], regional [14–17], urban [18,19], and industrial levels [20–23]. For example, Zhao et al. analyzed the decoupling relationship between carbon emissions and economic development for 29 countries, based on the Tapio model, and the study found some differences in the decoupling status among countries in each period. Among them, the United States performed the best, followed by the four countries where the climate target process was legal (France, the United Kingdom, Hungary, and New Zealand) [6]. Using annual data on Qatar's economic income and CO_2 emissions from 1970 to 2018, Shannak and Contestabile find through empirical analysis that Qatar is currently experiencing an expanded relative decoupling [12]. Liu et al. explored the decoupling relationship between economic growth and industrial CO_2 emissions in 13 cities in Jiangsu Province and found that the three regions of southern, northern, and central Jiangsu experience weak decoupling, weak negative decoupling, and weak decoupling, respectively [16]. The study by Wang et al. found that Beijing and Shanghai both experienced weak decoupling in construction, expansive negative decoupling in transport, expansive coupling in trade, and weak decoupling in others over the period 2000–2015 [19]. Yan and Chen analyzed the decoupling state of economic development of construction industry and CO_2 emissions in different provinces of China during 2009–2019, and the results of the study showed that Beijing and Jiangsu reached the ideal strong decoupling state, and Heilongjiang had the worst decoupling state [21]. Through sorting and summarizing the existing literature, it is found that most of the literature applies the decoupling model to investigate the decoupling relationship between economic growth and environment, and very few literatures combine resources (especially land resources) and environment alone to study the decoupling status of the two. In the face of the increasingly serious situation of carbon emission reduction and unreasonable expansion of urban land, it is important to introduce UCL and carbon emission indexes into the decoupling model and investigate the change relationship between them, in order to further optimize the land policy for macro-control and ensure the sustainable and healthy development of land resources.

As described above, the decoupling model is used to assess the decoupling relationship between UCL expansion and carbon emissions, but the model does not provide an effective way to reduce carbon emissions from UCL. Since UCL is an important source of carbon emissions, it is of great importance to study how to minimize carbon emissions from UCL. Based on this research purpose, carbon emission intensity as an important indicator to measure the harmonious relationship between economic and social development and the ecological environment; it is essential to introduce the indicator of carbon emission intensity of UCL (carbon emission per unit of urban construction land) and analyze its influencing factors. Under the current increasingly serious situation of carbon emission reduction, the research on carbon emission intensity has also been a hot topic of academic research. Many scholars have conducted research on the carbon emission intensity of GDP (carbon dioxide emission per unit of GDP), and the research results are very fruitful, mainly including the measurement of carbon emission intensity of GDP and analysis of spatial and temporal evolution characteristics, change trends, regional differences, and influencing factors. Jiang and Liu studied the inter-provincial CO_2 emission intensity inequality in China during 2005–2015 by using the Thiel index, and their findings indicate that the inter-provincial CO_2 emission intensity inequality in China has significantly increased. Energy efficiency is the most important and positive factor regarding the inter-regional, eastern, central, and western inequality in China [24]. Wang et al. analyzed the characteristics of the spatially correlated network structure of carbon emission intensity in China's construction industry and its driving effects during 2006–2017. The results showed that the regional differences in carbon emissions were significant, and the carbon emission intensity of the construction industry showed a fluctuating trend. The overall network of carbon emission intensity shows an obvious "core-edge" state, and the hierarchical network structure is gradually broken [25]. Liu et al. found that the carbon emission intensity of China's transportation industry shows a spatial pattern of low in the southeast and high in the northwest, and there are regional differences in the effects of energy structure, population size, and industrial structure on carbon emission intensity, with energy intensity occupying a pivotal position among all drivers [26]. Through sorting and summarizing the existing literature, it was found that most of the previous literature focused the research on the carbon emission intensity of GDP, and little literature focused on the carbon emission intensity of UCL (carbon emission per unit of urban construction land). Studies have shown that land use change affects greenhouse gas emissions and sequestration and has become a key driver of global and regional carbon emissions change [3,27]. Among various land use types, the total and intensity of carbon emissions from UCL are obvious, and the expansion of construction land is one of the important factors affecting urban carbon emissions [28–33]. Therefore, the carbon emission effect caused by the expansion of UCL is worthy of academic discussion, and the in-depth investigation of the carbon emission intensity of UCL has great research space and value. It is also an important basis for formulating emission reduction policies and initiatives, and efforts to reduce the carbon emission intensity of UCL are essential for achieving low-carbon sustainable development. From this perspective, this paper will attempt to fill the gap in this research area and investigate what may be driving the increasing carbon intensity of UCL. Is there spatial heterogeneity in the effects of different drivers? The answer to this question will help to formulate a scientific strategy for low-carbon land development, which is of great theoretical and practical significance, in order to achieve carbon emission reduction and sustainable use of land resources.

The rest of this paper is organized as follows. Section 2 provides the research materials and methods. Section 3 shows the study results, mainly including the decoupling change relationship between UCL and carbon emissions, as well as the factors influencing the carbon emission intensity of UCL. Section 4 presents the discussions. Section 5 presents the conclusions.

2. Materials and Methods

2.1. Materials

2.1.1. Study Area

The North China Plain is located between 32–40° North latitude and 114–120° East longitude. With its flat terrain, numerous rivers and lakes, convenient transportation, and developed economy, the North China Plain is the political, economic, cultural, and transportation center of China. By the end of 2019, the North China Plain had a total area of 300,000 square kilometers (accounting for 3.1% of China's total land area), total population of 339 million people (accounting for 24.2% of China's total population), and gross domestic product of 25.16 trillion yuan (accounting for 25.4% of China's gross domestic product), as well as a per capita gross domestic product of 74,218 yuan in 2019. The North China Plain spans Beijing, Tianjin, Hebei Province, Shandong Province, Henan Province, northern Anhui Province, and northern Jiangsu Province, with a total of 57 cities, as shown in Table 1 and Figure 1. Figure 1 shows the spatial distribution of land use types in the North China Plain, with land use data from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences. Table 2 shows the percentage of each land use type. In addition, the soils in the North China Plain are mainly tidal soils, sand ginger black soils, brown soils, wind-sand soils, and saline soils.

The main considerations for choosing the North China Plain as the research area are as follows. (1) The North China Plain is one of the three major plains in China. Compared with plateaus and mountains, plains have natural topographical advantages, flat terrain, and sufficient water resources, which are extremely conducive to the expansion of construction land and formation of cities. According to the statistical data of China Urban Construction Statistical Yearbook 2018, the UCL area of cities in the North China Plain occupies about one-fifth of the total UCL area in China. (2) The North China Plain is also one of the areas with the most serious environmental problems in China. High pollution and emissions are the prominent features of environmental problems in the North China Plain. It is an important production and accumulation place of carbon dioxide and air pollutants in China.

Table 1. Classification of cities in North China Plain.

Study Area	Cities
Beijing	Beijing
Tianjin	Tianjin
Hebei Province	Shijiazhuang, Qinhuangdao, Tangshan, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui
Shandong Province	Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Taian, Weihai, Rizhao, Linyi, Dezhou, Liaocheng, Binzhou, Heze
Henan Province	Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang, Xuchang, Luohe, Sanmenxia, Nanyang, Shangqiu, Xinyang, Zhoukou, Zhumadian
Northern Jiangsu Province	Xuzhou, Lianyungang, Suqian, Huaian, Yancheng
Northern Anhui Province	Huaibei, Bozhou, Suzhou, Fuyang, Bengbu, Huainan

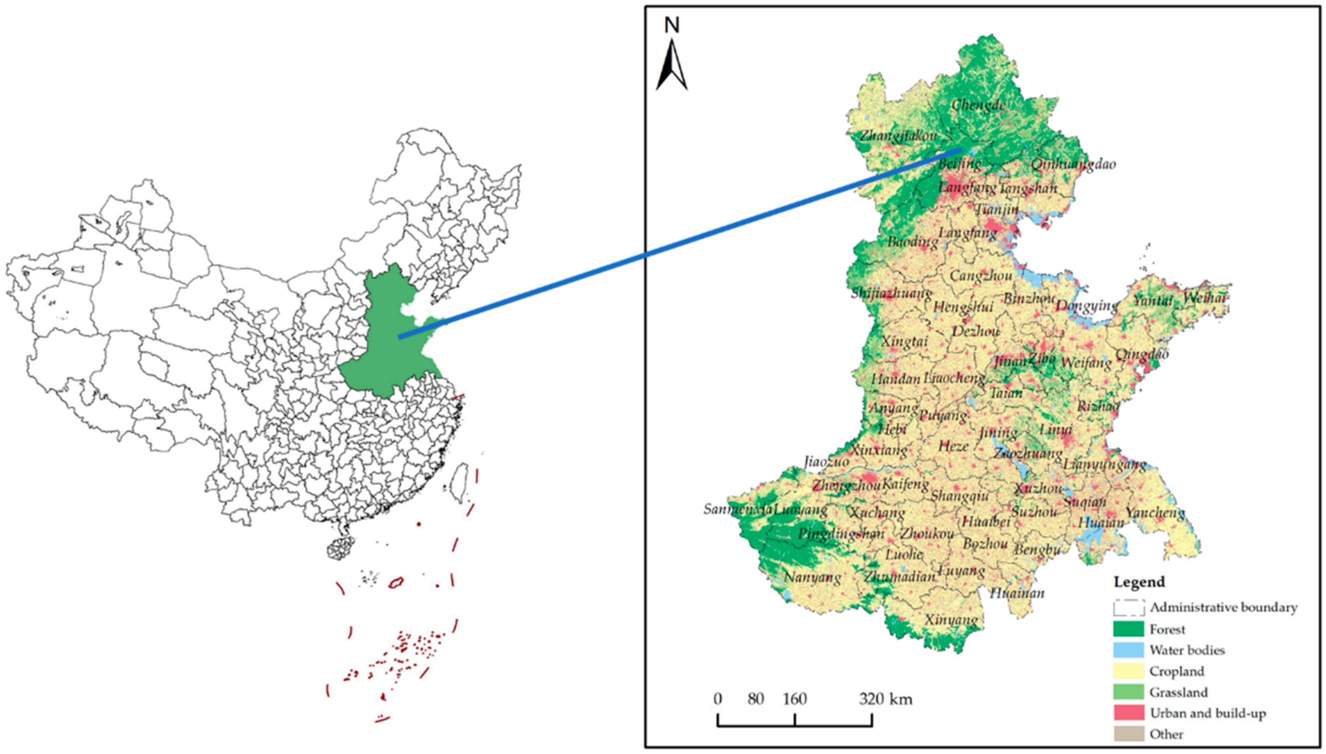

Figure 1. Location of the study area and distribution of land use types.

Table 2. Percentage of land use types in North China Plain.

Land Use Types	Percentage (%)
Forest	13.06
Water bodies	4.41
Cropland	58.88
Grassland	8.25
Urban and build-up	15.03
Other	0.37

2.1.2. Data Sources

The data of UCL area are from China Urban Construction Statistical Yearbook, and other data are from China Urban Statistical Yearbook. These datasets have been used in many studies, and a series of reliable findings have been obtained [34–40]. This proves that the datasets used in this study are valid and reliable.

2.2. Methods

In this paper, we obtain the data of urban construction land area and basic data of carbon dioxide emission from the statistical yearbook and calculate the carbon dioxide emission by the corresponding carbon dioxide emission estimation method. On this basis, the decoupling relationship between UCL and carbon emissions in 57 cities in the North China Plain was evaluated; then, the spatial autocorrelation analysis was used to explore the spatial distribution characteristics of carbon emission intensity of UCL Finally, the GTWR model is used to investigate the drivers of carbon emission intensity of UCL. The general research framework of this paper is shown in Figure 2.

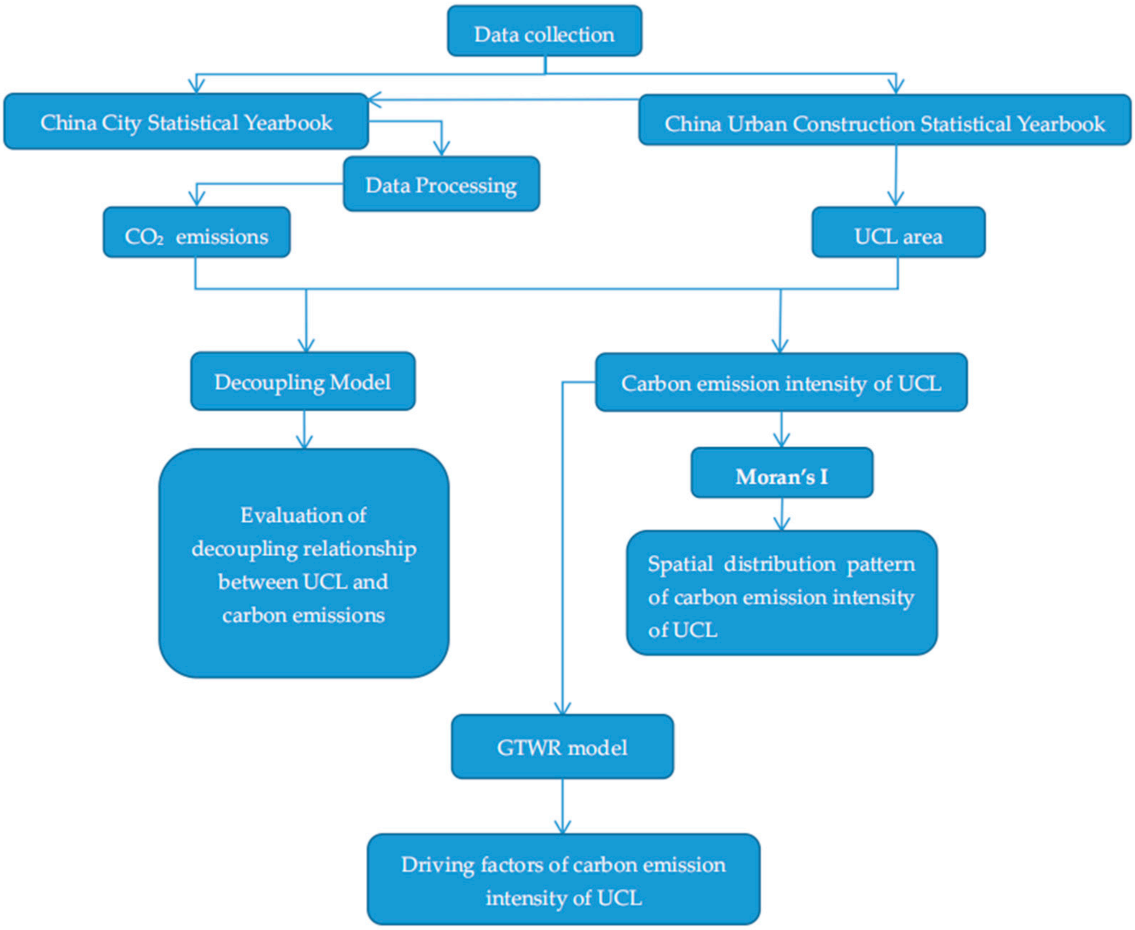

Figure 2. Research framework.

2.2.1. Tapio Decoupling Model

The "decoupling" is used to reflect the coupling between the changes of different systems with certain intrinsic correlation, and the OECD first proposed the "decoupling index" [4]; however, the OECD decoupling index is affected by the choice of the base period. The Tapio decoupling index is based on the elasticity of change and uses the ratio of the rate of change of two correlated variables in a certain period to measure the decoupling relationship, which is more flexible in calculation and makes up for the shortcomings of the OECD decoupling index. To investigate the decoupling relationships of urban construction land and carbon emissions in cities of the North China Plain, in this paper, Tapio decoupling model is used to calculate and classify the decoupling between UCL and carbon emissions in 57 cities in North China Plain.

The decoupling index between UCL and CO_2 emissions is calculated as follows:

$$\alpha = \frac{(L_t - L_0)/L_0}{(E_t - E_0)/E_0} = \frac{r_L}{r_E} \tag{1}$$

In the formula, α represents the decoupling index, and E_0 and L_0 represent the UCL area and CO_2 emissions in the base period of the study area, respectively; E_t and L_t represent the UCL and CO_2 emissions at the last period of the study area, respectively; r_E and r_L represent the change rate of UCL area and CO_2 emissions, respectively. The unit of UCL area is km^2, and the unit of total carbon emission is 10,000 tons.

In the actual study, in order to prevent the slight changes of the random variables from being interpreted too significantly, the decoupling elasticity value of 1.0 is generally considered to be in the linkage state, within the range of 20% above and below, with the elasticity index of 0.8 and 1.2 as the boundary. According to the calculated value of the decoupling elasticity index and the sign of r_E and r_L, the decoupling state is classified into 8 categories. The specific classification criteria are shown in Table 3. The strong decoupling of UCL and carbon emission is the most ideal state, while the strong negative decoupling is the most imbalanced state of UCL and carbon emission; the expansive connection or recessionary connection indicates that the change of UCL and carbon emission is about the same, which is the transitional state between decoupling and negative decoupling.

Table 3. Decoupling status classification criteria.

Decoupling Type	Changes in UCL	Change in CO_2 Emissions	Decoupling Index	Meaning
Strong decoupling	>0	<0	$(-\infty, 0)$	Increase in UCL area and decrease in CO_2 emissions
Weak decoupling	>0	>0	(0, 0.8)	Increase in UCL area and slow increase in CO_2 emissions
Expansive connection	>0	>0	[0.8, 1.2]	UCL area and CO_2 emissions increase at the same rate
Expansive negative decoupling	>0	>0	$[1.2, \infty]$	Increase in UCL area and significant increase in CO_2 emissions
Strong negative decoupling	<0	>0	$(-\infty, 0)$	Decrease in UCL area and increase in CO_2 emissions
Weak negative decoupling	<0	<0	(0, 0.8)	Decrease in UCL area and slow decrease in CO_2 emissions
Recessionary connection	<0	<0	[0.8, 1.2]	UCL area and CO_2 emissions decrease at the same rate
Recessionary decoupling	<0	<0	$[1.2, \infty]$	Reduced UCL area and significant reduction in CO_2 emissions

2.2.2. Spatial Autocorrelation Analysis

In this paper, Moran index is used to measure the spatial distribution characteristics of carbon emission intensity of UCL in the study area [41]. The global and local Moran indices are calculated as follows [42,43]:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \qquad I_i = \frac{n\left(Y_i - \overline{Y}\right)\sum_{j=1}^{n} w_{ij}\left(Y_j - \overline{Y}\right)}{\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2} \tag{2}$$

where, I and I_i represent the global and local Moran index of the carbon emission intensity of UCL. n represent the number of spatial locations, w_{ij} denotes the spatial weight matrix, and the spatial adjacency matrix is chosen; Y_i and Y_j represent the carbon emission intensity of UCL in i city and j city; and S^2 is the sample variance. If Moran index is greater than 0, it means there is spatial positive correlation; if Moran index is less than 0, it means there is spatial negative correlation; if Moran index is equal to 0, it means there is no spatial autocorrelation.

2.2.3. Geographically and Temporally Weighted Regression Model

Compared with the OLS, TWR, and GWR models, the GTWR model can take both temporal and spatial non-stationary characteristics into account [44], so the GTWR model can achieve better explanatory power and estimation results and effectively reduce model errors and parameter estimation errors [45–47]. Therefore, the GTWR model is used in this paper to explore the spatio-temporal heterogeneity of each factor affecting the carbon emission intensity of UCL under the constraints of spatio-temporal differences. By establishing a three-dimensional (longitude, latitude, and time) elliptical coordinate system [48], the GTWR model can describe the spatio-temporal effects using regression coefficients associated with the explanatory variables. The GTWR model expression is as follows [49]:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i \tag{3}$$

where (u_i, v_i, t_i) represents the spatiotemporal coordinates of the ith city; $\beta_0(u_i, v_i, t_i)$ represents the spatiotemporal intercept term of the ith city; p represents the number of independent variable; y_i represents the dependent variables of the ith city; x_{ik} represents the kth independent variable of the ith city; $\beta_k(u_i, v_i, t_i)$ represents the regression cofficient of x_{ik}; and ε_i represents the error term.

2.2.4. CO_2 Emission Estimation Method

CO_2 emissions from cities are mainly energy CO_2 emissions, including natural and liquefied petroleum gases, as well as CO_2 emissions from electricity and heat con-sumption [50]; therefore, the sources of urban CO_2 emissions can be divided into two categories: direct and indirect. Carbon emissions from direct sources (natural and liquefied petroleum gases) can be obtained by multiplying the end consumption of these energy sources by the relevant conversion factors provided by the United Nations Intergovernmental Panel on Climate Change (IPCC) in 2006. Indirect sources are carbon emissions from electricity and heat, where the carbon emissions from electricity are obtained by multiplying the baseline emission factors of each regional grid with the urban electricity consumption [51]. The carbon emission from thermal energy is calculated by first calculating the required amount of raw coal using heat supply, thermal efficiency, and raw coal heat coefficient, then calculating the amount of standard coal consumed for centralized heating using the raw coal conversion factor, and finally, calculating the carbon emission from thermal energy consumption using the emission factor provided by IPCC2006. The heat supply data are obtained from the China Urban Construction Statistical Yearbook, and the minimum standard of thermal efficiency of coal-fired industrial boilers in China is between 65% and 78%. Considering that the current Chinese central heating boilers are mainly small- and medium-sized coal-fired boilers, the value of thermal efficiency is taken as 70% [50]. Finally, the carbon emissions generated by the above four energy sources are summed up to get the total carbon emissions of each city.

3. Results

3.1. Time Series Changes of UCL Area and Carbon Emissions in North China Plain

As shown in Figure 3, the UCL area and total carbon emissions in the North China Plain, as a whole, show a more obvious upward trend, except for individual years. During the 12 years from 2007 to 2018, the area of UCL in the North China Plain expanded from 6884 km^2 in 2007 to 10,958 km^2 in 2018, while the total carbon emissions increased from 509 million tons in 2007 to 788 million tons in 2018, up by 59.2% and 54.8%, respectively. As can be seen from Figure 3, UCL has a strong positive correlation with total carbon emissions (the correlation coefficient is higher than 0.9 for all 12 years), thus indicating that the expansion of UCL causes a consequent increase in carbon emissions with a strong impact.

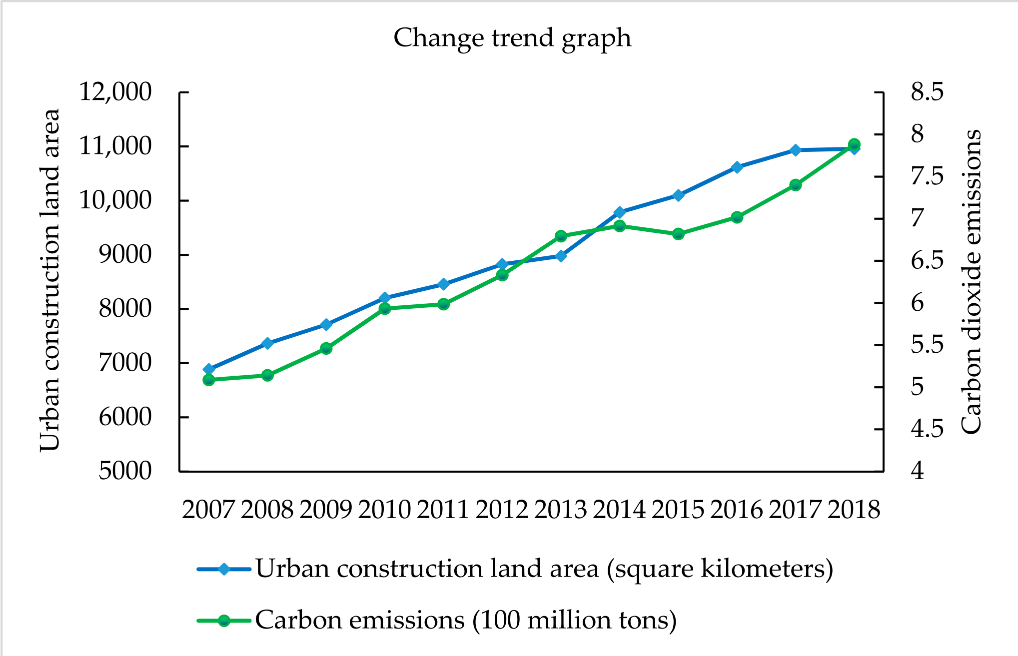

Figure 3. Changes in UCL area and carbon emissions in the North China Plain during 2007–2018.

3.2. Evaluation Results Analysis of Decoupling Effect of UCL and Carbon Emission

Based on the Tapio decoupling model, the decoupling relationship between UCL area and carbon emissions was studied in 57 cities in the North China Plain, and the Tapio decoupling elasticity index was used to identify and classify the decoupling of UCL area and carbon emissions in each city.

Considering that there may be a lagged relationship between UCL expansion and carbon emission increase, the study period is divided into three periods: 2007–2011, 2011–2015, and 2015–2018 for the convenience of analysis. Based on the relevant formulae and index data of 57 cities, the decoupling indices of each city in different time periods were finally calculated, and the decoupling types were identified, as shown in Figure 4. To facilitate the analysis, Table 4 shows the number of cities with different decoupling types in the four time periods at the same time.

Table 4. Number of cities of various decoupling types in different periods.

Decoupling Type	2007–2011	2011–2015	2015–2018
Strong decoupling	6	14	9
Weak decoupling	24	13	9
Expansive connection	6	5	10
Expansive negative decoupling	20	21	24
Strong negative decoupling	1	2	5
Weak negative decoupling		1	
Recessionary connection			
Recessionary decoupling		1	

As shown in Figure 4, the decoupling status of UCL and carbon emissions in the North China Plain is clearly distributed in a differentiated pattern. In the three time periods, the main decoupling types in North China Plain cities are weak decoupling, expansive negative decoupling, and expansive negative decoupling, in that order, and the overall decoupling situation shows a change from good to bad.

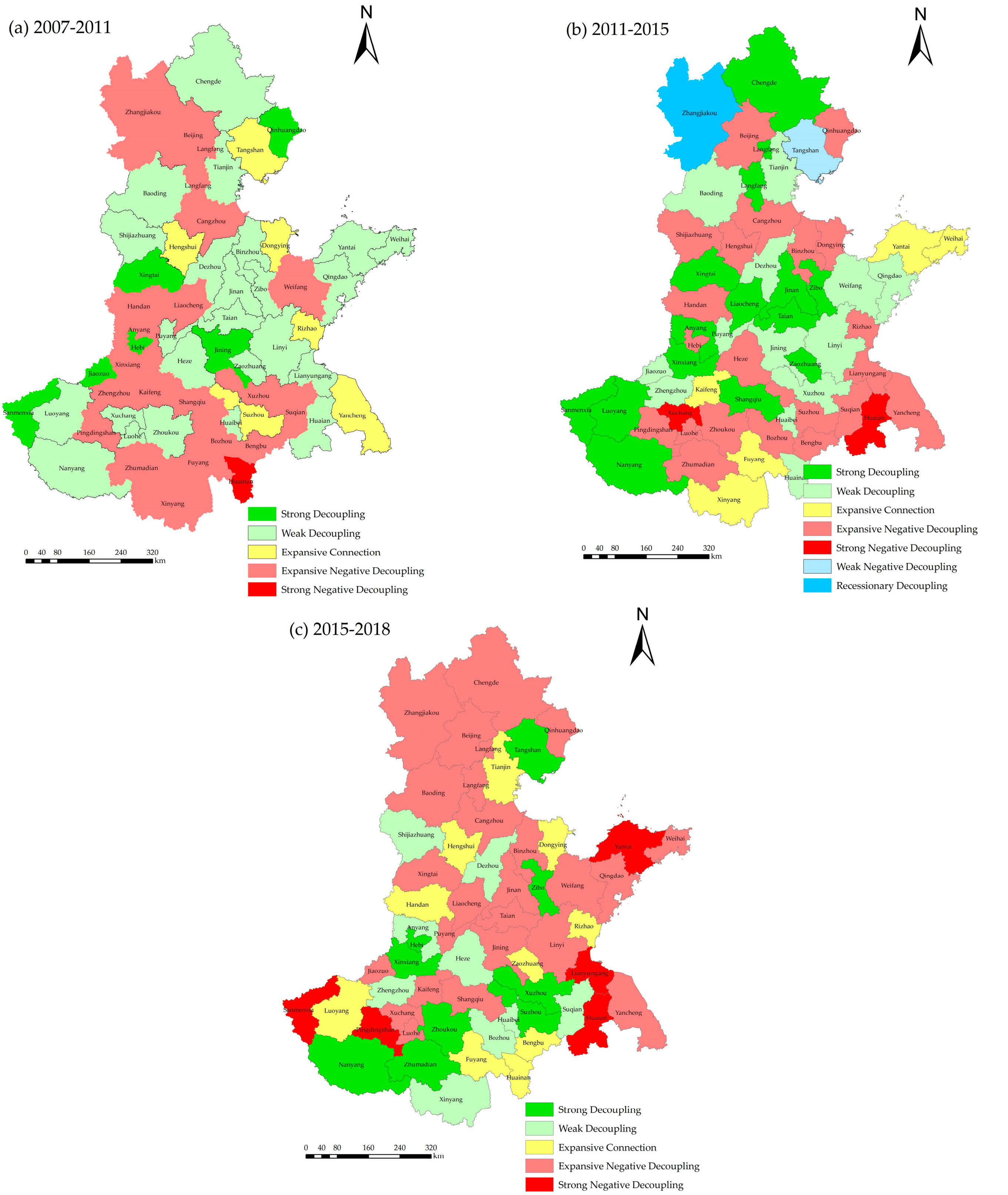

Figure 4. (**a**–**c**) Decoupling relationship between UCL and carbon emissions in different periods during (**a**) 2007–2011, (**b**) 2011–2015, (**c**) 2015–2018.

From 2007 to 2011, the overall decoupling status of the North China Plain was good, with more than half of the cities in strong and weak decoupling, which showed an increase in the area of UCL and decrease or slow increase in carbon emissions, thus achieving a low carbon development of UCL, which is a very desirable state. They are mainly located in the eastern, northern, and southwestern parts of the North China Plain, with most of the areas in Shandong showing strong or weak decoupling. The regions with poor decoupling performance are mainly distributed in Henan and central Hebei. These cities are in the state of expansive negative decoupling, which shows that the increase rate of carbon emissions is faster than the expansion rate of UCL, and UCL presents an extensive expansion trend. The worst performer is Huainan City, which is in a state of strong negative decoupling. As UCL shrinks, carbon emissions increase. The two are in a state of extreme dissonance.

In the period of 2011–2015, as can be seen from Figure 4, the most obvious change, relative to the period of 2007–2011, is that some cities in central Shandong and western Henan have improved their decoupling status from the previous weak decoupling status to a strong decoupling status; anyway, the decoupling status has not changed much, compared to the previous period.

Finally, during the period of 2015–2018, the overall decoupling performance in this period was poor, compared with the previous two periods, and the number of cities in strong and weak decoupling has decreased, among which, the number of cities in strong decoupling had decreased by 5 and the number of cities in weak decoupling had decreased by 4, compared with the previous period; the decoupling status of Shandong and Hebei has deteriorated significantly. It can be seen that, during the period of 2015–2018, Shandong and Hebei blindly expanded their UCL, while ignoring the ecological and environmental problems arising from it, which intensified carbon emissions and aggravated the greenhouse effect. In addition, the number of cities with strong negative decoupling increased to five during this period. Although these cities reduced UCL, carbon emissions increased, indicating that people in this region are more frequently engaged in various industrial production, construction, and commercial activities, which greatly increase the burden of land and are not conducive to the intensive use of land.

3.3. Calculation of Carbon Emission Intensity of UCL

In this paper, the carbon intensity of UCL indicates the carbon dioxide emissions per unit area of UCL and is expressed as the ratio of carbon dioxide emissions to the area of UCL.

In order to clarify the trend of carbon emission intensity of UCL in cities of North China Plain, this paper first measured the average value of carbon emission intensity of UCL in 57 cities of North China Plain.

As shown in Figure 5, in terms of time series, the average value of carbon emission intensity of UCL in 57 cities in the North China Plain increased from 68,026 tons/km^2 in 2007 to 73,326 tons/km^2 in 2018. After little fluctuation from 2007 to 2013, the carbon emission intensity showed a decreasing trend year-by-year, between 2013 and 2016, thanks to China's active implementation of the strictest arable land protection system and land conservation system in 2013, which provided an important guarantee for economic and social development, The Blue Book on China's Land Policy (2013) points out that the focus of land administration in that year changed from an emphasis on approval to supervision, increment to an emphasis on both stock and increment, and the introduction of policies to an emphasis on policy effects, with significant policy effects. Additionally, it is expected that, in 2014, the policy of saving and concentrating land will be fully implemented; the scale of land will be implemented to control the total amount and reduce the supply, increase the supply of stock construction land, and reduce new construction land. In 2016, the carbon emission intensity of UCL showed an increasing trend year-by-year, probably due to the local implementation of the central policy of land conservation and intensification of land use, which was gradually negative and lax, and began to pursue more economic growth and "face-saving projects" brought by the expansion of construction land. This has led to the rough expansion of UCL and intensified carbon emissions.

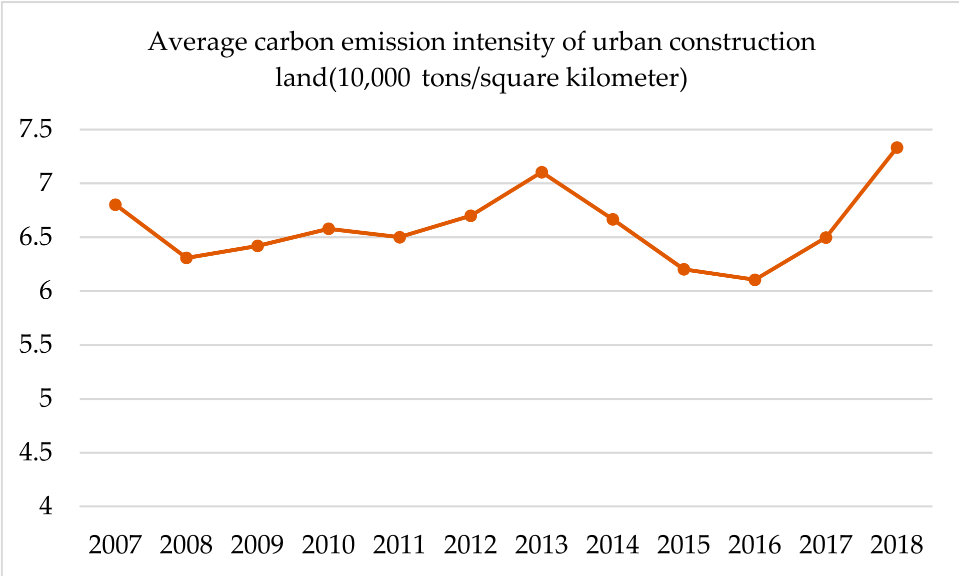

Figure 5. Average carbon emission intensity of 57 cities in the North China Plain in each year between 2007 and 2018.

3.4. Spatial Distribution Pattern of Carbon Emission Intensity of UCL

The carbon emission intensity of 57 cities in four years (2007, 2011, 2015, and 2018) was classified into five categories by using the natural breakpoint grading method with arcgis software, as shown in Figure 6. Spatially, the carbon emission intensity of UCL in the North China Plain shows an overall spatial distribution pattern of "high in the north and low in the south", with obvious clustering characteristics. The areas with high carbon emission intensity are mainly concentrated in Beijing–Tianjin–Hebei and the central and western part of Shandong, especially in the Beijing–Tianjin–Hebei region, which is the agglomeration of high carbon emission intensity, while the areas with low carbon emission intensity are mainly concentrated in the southern part of Henan, northern Jiangsu, and northern Anhui, which are the agglomeration of low carbon emission intensity.

From the observation in Figure 6, since the carbon emission intensity of UCL in the North China Plain shows agglomeration characteristics, we consider that there may be a spatial autocorrelation in the carbon emission intensity of UCL, in order to test whether it has a strong spatial correlation. By using GeoDa software, after 999 random permutations, the global Moran index was calculated for 12 years from 2007 to 2018, which described the spatial correlation and spatial difference of the carbon emission intensity of UCL each year. The calculation results are shown in Table 5.

Table 5. Global Moran's I for carbon emission intensity of UCL during 2007–2018.

Year	Moran's I	Z-Score	*p*-Value
2007	0.3011	3.8317	0.001
2008	0.3047	3.9230	0.001
2009	0.2694	3.4686	0.002
2010	0.2278	2.9870	0.003
2011	0.1245	1.7808	0.054
2012	0.1028	1.5960	0.062
2013	0.1678	2.4659	0.014
2014	0.1991	2.7429	0.008
2015	0.1917	2.6124	0.013
2016	0.1749	2.2830	0.016
2017	0.1401	1.8776	0.037
2018	0.0724	1.3499	0.085

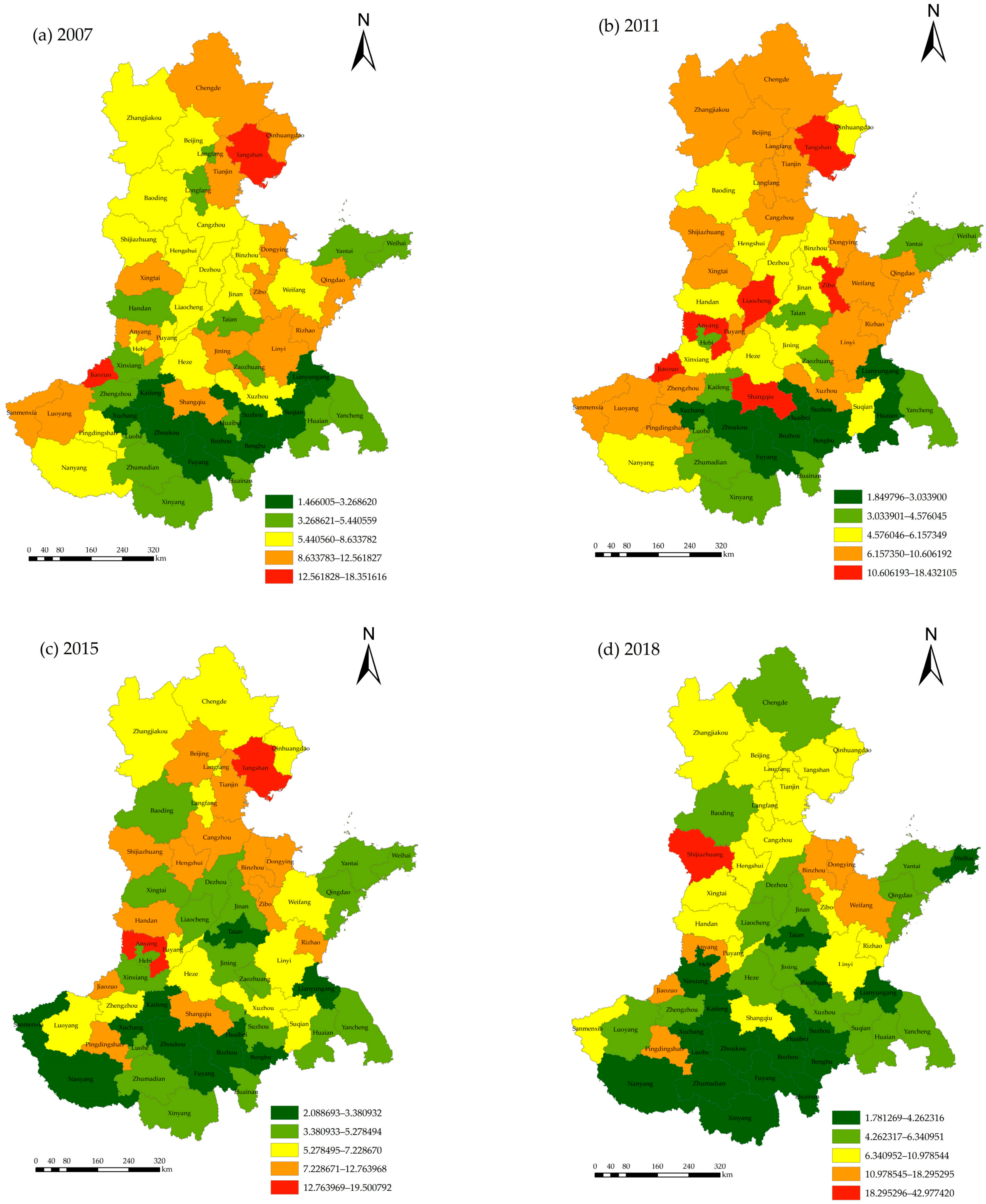

Figure 6. Carbon emission intensity distribution of UCL in North China Plain in (**a**) 2007, (**b**) 2011, (**c**) 2015, and (**d**) 2018.

As can be seen in Table 5, all 12 years passed the significance test, and Moran's I was greater than 0, indicating that there is a significant positive spatial correlation between the carbon emission intensity of UCL.

In Table 5, Moran's I roughly experiences three stages of "decline—rise—decline". From 2007 to 2012, the Moran's I showed a decreasing trend, and then started to rise again; in 2015, it again showed a decreasing trend year-by-year. Corresponding to the change of Moran's I, the carbon emission intensity of UCL shows a strong spatial clustering characteristic during 2007–2010, and the clustering characteristic transiently weakens during 2011–2012; the clustering characteristics continue to increase during 2013–2014, and then weaken year-by-year during 2015–2018.

To further clarify the local agglomeration distribution pattern of carbon emission intensity of UCL in 57 cities in the North China Plain, the data of four years (2007, 2011, 2015, and 2018) were selected to derive the Lisa agglomeration distribution map and classify the agglomeration types into four categories by using GeoDa software. Figure 7 shows the cities whose local spatial correlation statistics passed the significance test at the 5% level.

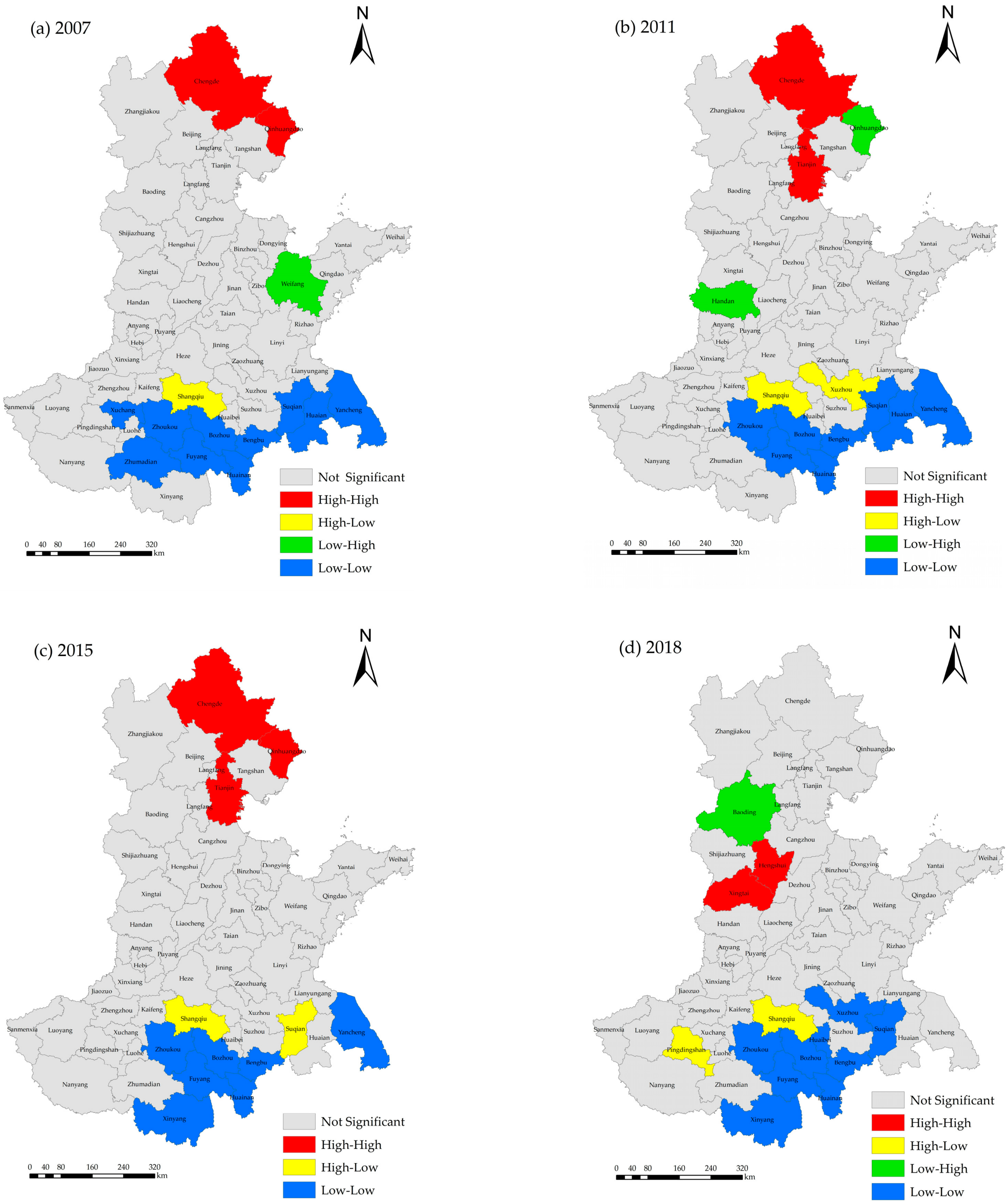

Figure 7. Lisa agglomeration map of carbon emission intensity of UCL in 57 cities in North China Plain in (**a**) 2007, (**b**) 2011, (**c**) 2015, and (**d**) 2018.

As can be seen from Figure 7, the carbon emission intensity of UCL in cities in the North China Plain is involved in all four forms of agglomeration. L-L agglomeration is dominant, i.e., cities with lower carbon emission intensity are surrounded by cities with lower carbon emission intensity, and these cities are mainly concentrated in southern Henan, northern Jiangsu, and northern Anhui. This is followed by H-H agglomeration, where cities with higher carbon emission intensity are surrounded by cities with higher carbon emission intensity; these cities are mainly located in Hebei and Tianjin. This is consistent with the results of the above analysis. The number of cities with L-H and H-L agglomeration is relatively small.

3.5. Analysis of Spatial and Temporal Heterogeneity of Factors Influencing Carbon Emission Intensity of UCL

In this paper, we synthesize the existing research literature [52–60] and select the corresponding indicators as influencing factors from eight aspects: urbanization rate, industrial structure, economic development level, population density, environmental regulation, foreign investment intensity, land use efficiency, and greenery coverage. The specific descriptions are shown in Table 6 (below).

Table 6. Selection and description of relevant variables.

Variable Type	Variable Name	Explanation of Variables	Unit
Dependent variables	Carbon emission intensity of UCL	Carbon emissions/UCL area	10,000 tons/km^2
Independent variables	Urbanization rate (UR)	Urban population/resident population	%
	Industrial structure (IS)	Output value of secondary industry/gdp	%
	Economic development level (EDL)	Real gdp per capita (2000 as base period)	10,000 yuan
	Population density (PD)	Total population/municipal area	100 people/km^2
	Environmental regulation (ER)	Comprehensive utilization rate of general industrial solid waste	%
	Foreign investment intensity (FII)	Actual amount of foreign capital utilized/gdp	%
	Land use efficiency (LUE)	Municipal area/real gdp	km^2/100 million yuan
	Greenery coverage (GC)	Green area/total land area	%

It is worth noting that, since the UCL is located in municipal districts, in order to ensure the reasonableness and rigor of the whole study, in the next selection of relevant indicators of influencing factors, except for the urbanization rate, the relevant data in the China Urban Statistical Yearbook are selected from the municipal district caliber.

3.5.1. Outcomes of Model Fitting

The regression results of the OLS model are shown in Table 7. Since the GTWR model cannot test the significance of each influencing factor, the OLS model is used to explore the influence of each influencing factor on the carbon emission intensity of UCL. As can be seen from Table 7, all factors have a significant effect on the carbon emission intensity of UCL, except for the land use efficiency, which is significant at the 10% level; all other influencing factors are significant at the 1% level. Among them, urbanization rate, industrial structure, economic development level, and population density have positive effects, while environmental regulations, foreign investment intensity, land use efficiency, and green coverage have negative effects. In addition, to avoid the effect of multicollinearity, the VIF (variance inflation factor) of each influencing factor was also calculated, as shown in Table 7, proving that there is no multicollinearity among the influencing factors.

Table 7. OLS model regression results.

Influencing Factors	Coefficient	Standard Error	t-Statistics	p-Value	VIF
UR	0.0556 ***	0.0143	3.89	0.000	1.86
IS	0.0483 ***	0.0126	3.82	0.000	1.12
EDL	0.2526 ***	0.0579	4.36	0.000	1.78
PD	0.1709 ***	0.0226	7.53	0.000	4.72
ER	−0.0385 ***	0.0069	−5.56	0.000	1.03
FII	−0.2954 ***	0.0581	−5.08	0.000	1.11
LUE	−0.0561 *	0.0293	−1.91	0.056	1.59
GC	−0.3255 ***	0.0464	−7.01	0.000	4.44

Note: * indicates $p < 0.1$; *** indicates $p < 0.01$.

To ensure the applicability and accuracy of using the GTWR model, the ols, TWR, and GWR models were introduced successively, and the estimation results were compared and analyzed, as shown in Table 8.

Table 8. Evaluating the performance of different models.

Model	R^2	RSS	AICc	Bandwidth
OLS	0.254	7442.11	3591.78	—
TWR	0.294	7055.52	3586.03	0.289735
GWR	0.566	4333.35	3345.45	0.140444
GTWR	0.710	2900.51	3325.10	0.118590

Based on the comparison of R^2, RSS, and AICc, it was found that the GTWR model has the largest R^2, smallest RSS, and smallest AICc among the four models, which indicates that GTWR model fits better than other models. In particular, the R^2 of the GTWR model is 0.71, indicating that the explanatory power of the GTWR model is 71%, which is 45.6%, 41.6%, and 14.4% higher than that of the OLS, TWR, and GWR models, respectively. In addition, the GTWR model has the smallest AICc among the four models, and the difference of AICc between GTWR model and other models is much larger than 3, which indicates that the overall fitness of the GTWR model is much better than the other models [47].

In summary, the GTWR model has the best applicability performance, followed by the GWR model, and the TWR and OLS models have poor performance, in terms of the factors influencing the carbon emission intensity of UCL in cities in the North China Plain from 2007 to 2018. That is, according to the superiority of applicability, GTWR > GWR > TWR > OLS.

In Table 8, we can also see that the GWR model possesses better fitting results and is more applicable than the TWR model, which reflects that the spatial factor is much more influential than the temporal factor in the carbon emission intensity of UCL in the North China Plain; that is, the spatial factor plays a dominant role in the influence of carbon emission intensity of UCL [61].

As can be seen from the quartile table (Table 9), the regression coefficients of each variable have a wide range of variation, with both positive and negative values, and the change of intensity is obvious, thus indicating that the intensity of influence factor on the carbon emission intensity of UCL has significant non-stationarity data, both in time and space [62].

Based on the above analysis, it can be seen that the GTWR model can more effectively and comprehensively explain the factors influencing the carbon emission intensity of UCL in the cities of North China Plain. In addition, the advantage of the GTWR model is that it can calculate the regression coefficients of the influencing factors in different times and in space, and it can also visualize the regression coefficients through ArcGIS 10.2, so as to explore more visually determine the differences regarding the degree of influence of each factor on the carbon emission intensity of UCL in different local areas. Therefore, this paper chooses to use the GTWR model to analyze the factors influencing the carbon emission intensity of UCL in detail, and then obtain the spatial and temporal variation of the regression coefficients of each factor.

Table 9. Test results of GTWR model.

Variables	Minimum	1/4 Quantile	Median	3/4 Quantile	Maximum
UR	−0.276	−0.002	0.051	0.114	0.500
IS	−0.510	0.033	0.067	0.129	0.343
EDL	−2.604	−0.080	0.314	0.825	2.666
PD	−0.230	0.063	0.153	0.313	1.807
ER	−0.162	−0.064	−0.034	−0.002	0.330
FII	−1.486	−0.495	−0.394	−0.292	0.318
LUE	−2.246	−0.129	−0.014	0.132	1.475
GC	−1.831	−0.462	−0.327	−0.226	0.093

3.5.2. Time Series Evolution of Factors Influencing Carbon Emission Intensity of UCL

This paper portrays the changes of regression coefficients of each factor affecting the carbon emission intensity of UCL in the North China Plain, in the form of boxplot from the time latitude, as shown in Figure 8.

(1) The urbanization rate (UR) shows an overall positive relationship with the carbon emission intensity of UCL, which is consistent with the regression results of the OLS model. This indicates that population urbanization can increase the carbon emission intensity of UCL. This is because, in the process of urbanization, rural residents flock to cities and become urban residents, leading to changes in their lifestyles, as well as employment fields. Due to the convenient transportation and living conditions in the cities, the consumption demand has been increased and diversified, thus resulting in a rapid increase in their demand for products such as automobiles and household appliances. In terms of employment fields, rural residents are mainly engaged in primary industries, while, when they become urban residents, their employment fields change from primary industries to secondary industries, bringing about rapid development of industries, as well as construction, which increases the burden of UCL and causes an increase in carbon emission intensity. However, in a few cities, population urbanization reduces the carbon emission intensity, which may be due to the fact that population urbanization can lead to more standardized and collective production and lifestyle; for example, centralized heating in urban areas facilitates energy saving and reduces carbon emissions, compared with decentralized direct coal-burning heating in rural areas [56]. At the same time, urban areas are also influenced by factors such as the inflow of talents, industrial structure optimization, and technological innovation to reduce their dependence on energy consumption and, thus, reduce carbon emission intensity.

(2) The industrial structure (IS) shows an overall positive relationship with the carbon emission intensity of UCL, which is consistent with the regression results of the OLS model. This indicates that the larger the proportion of the output value of the secondary industry in GDP, the higher the carbon emission intensity of UCL. This is because the secondary industries are mainly manufacturing, construction, and mining, which are resource-intensive industries, and high pollution and energy consumption are the main characteristics of these industries, which are the main sources of carbon emissions. The rapid development of China's secondary industries in recent years, especially before the 19th National Congress, has put more emphasis on "development quantity", rather than "development quality", and the rough development model has led to an increase in carbon emissions year-by-year.

(3) The economic development level (EDL) and carbon emission intensity of UCL show an overall positive correlation, which is consistent with the regression results of OLS model. That is, the higher the level of economic development, the higher the carbon emission intensity of UCL. This is because most production and business activities

are carried out on land, and economic development is based on land expansion. The area of UCL is closely related to the total economic volume; although the increase in the scale and intensity of human activities drives economic development, it also accelerates carbon emissions, while creating wealth.

However, in the initial years, the level of economic development in a small number of cities reduces the carbon emission intensity of UCL, which may be due to the fact that, in the early stage, various types of infrastructure are being built rapidly, when economic development has positive externalities; the agglomeration of economic activities generates economies of scale, and the economies of scale effect and the sharing of facilities reduce the carbon emission intensity. At this stage, the total economic volume is low and does not bring about large-scale CO_2 emissions. However, with the rapid expansion of the economy over time, the high intensity of economic activities, mainly heavy industry, consumes a large amount of energy, and consequent “increasing effect” of carbon emissions gradually become stronger than the “reducing effect” of carbon emissions caused by the economies of scale of economic agglomeration and sharing of facilities [63], which starts to push up the carbon emission intensity.

In addition, it is worth noting that the box shows an obvious upward trend year-by-year, as seen in the boxplot, which reflects that the level of economic development has played a stronger and stronger pulling role in increasing the carbon emission intensity.

(4) The population density (PD) shows an overall positive relationship with the carbon emission intensity of UCL, which is consistent with the regression results of the OLS model; that is, the greater the population density, the higher the carbon emission intensity of UCL. This is because higher urban population density will lead to the problem of uneconomical agglomeration, and excessive population agglomeration brings about the “congestion effect”; the impact of the “congestion effect” on carbon emissions is mainly manifested in transportation energy consumption. Increased population density puts pressure on urban transportation infrastructure, and traffic congestion is common [64], which has a negative impact on energy consumption, thus leading to higher carbon emission intensity.

In addition, it is worth noting that the box shows an obvious upward and longer trend, as seen in the boxplot. The upward shift of the box indicates that the regression coefficient is increasing year-by-year, which reflects that the pulling effect of population density on the increase of carbon emission intensity of UCL is increasing year-by-year. The longer box indicates that the regression coefficients become increasingly scattered, which may be due to the fact that it is a result of the large difference in population density among regions.

(5) Environmental regulation (ER) shows a negative relationship with carbon emission intensity of UCL, which is consistent with the regression results of OLS model; that is, the higher the comprehensive utilization rate of general industrial solid waste, the lower the carbon emission intensity of UCL, which indicates that environmental regulation can reduce the carbon emission intensity of UCL. This is because residual industrial solid waste is the waste slag, dust, and other wastes discharged into the environment during industrial production, and these wastes will produce a large amount of carbon dioxide if they are not treated properly. Improving the comprehensive utilization rate of general industrial solid waste can greatly avoid the carbon emission problems caused by improper treatment, thus reducing the carbon emission intensity.

In addition, it can be seen from the boxplot that the box shows a clear trend of becoming shorter, which indicates that the regression coefficients are becoming more concentrated and dispersion has decreased.

(6) Foreign investment intensity (FII) shows an overall negative correlation with the carbon emission intensity of UCL, which is consistent with the regression results of the OLS model, i.e., the higher the foreign investment intensity, the lower the carbon emission intensity of UCL. The relationship between foreign investment and energy

consumption is generally discussed in the literature around the "pollution refuge hypothesis" and "pollution halo hypothesis". The "pollution refuge hypothesis" argues that, although the infusion of FDI (foreign direct investment) expands the scale of the economy, it increases the pressure of the environment and resources, due to the transfer of some energy-intensive and high-polluting industries, thus leading to an increase in pollution and carbon emissions in the host country, while the "pollution halo hypothesis " argues that under the environmental regulation of the home country, FDI improves the technology level of the host country through knowledge and technology spillover, which improves the production process, thus enhancing the energy utilization efficiency and reducing the energy intensity [65,66]. This paper empirically verifies the "pollution halo hypothesis", which shows that the "increase effect" of carbon emissions caused by the "pollution refuge hypothesis" is weaker than the "decrease effect" of carbon emissions caused by the "pollution halo hypothesis" in the cities of North China Plain, has a significant inhibitory effect on foreign investment intensity on carbon emission intensity.

(7) Land use efficiency (LUE) shows an overall negative relationship with carbon emission intensity of UCL, which is consistent with the regression results of OLS model; that is, the higher the land use efficiency, the lower the carbon emission intensity of UCL. This is because when the ratio of land area to gdp is smaller, which proves that less land area is needed to create a unit of gdp, which proves that the land carries more intense human production activities; the land is overused, which increases the burden of land and pulls up the carbon emission intensity of UCL.

In addition, it is worth noting that, from the boxplot, it can be seen that the box has shown an obvious upward trend since 2012, and the regression coefficient began to change from negative to positive, which indicates that the land use efficiency and carbon emission intensity of UCL began to show a positive correlation. This may be because the local government has gradually realized the problem of excessive use of land resources. In particular, China has clearly defined the key tasks to promote the construction of ecological civilization in the 18th National Congress, and the report points out that it is necessary to optimize the spatial development pattern of the land, control the development intensity, adjust the spatial structure, and promote the intensive and efficient production space, in accordance with the principles of balancing population, resources, and environment, as well as unifying economic and social and ecological benefits. The implementation of the policy has reversed the overuse of land, and the carbon emission intensity of UCL has begun to decline.

(8) The greenery coverage (GC) shows an overall negative correlation with the carbon emission intensity of UCL, which is consistent with the regression results of the OLS model; that is, the higher the greenery coverage, the lower the carbon emission intensity of UCL. This is because increasing the green area of the land plays a crucial role in the reduction of carbon emissions from the land, and the increase of green area not only reduces carbon sources, such as various types of productive activities, but also greatly increases carbon sinks, such as forest vegetation, which is effective in reducing the carbon emission intensity of UCL and helps accelerate the achievement of carbon neutrality target.

In addition, it is worth noting that the box shows an obvious downward and longer trend from the boxplot. The downward shift of the box indicates that the inhibitory effect of greenery coverage on the carbon emission intensity of UCL is gradually increasing; the longer box indicates that the regression coefficients become increasingly dispersed, probably due to the large difference of greenery coverage in each region, which causes the degree of influence to become increasingly discrete.

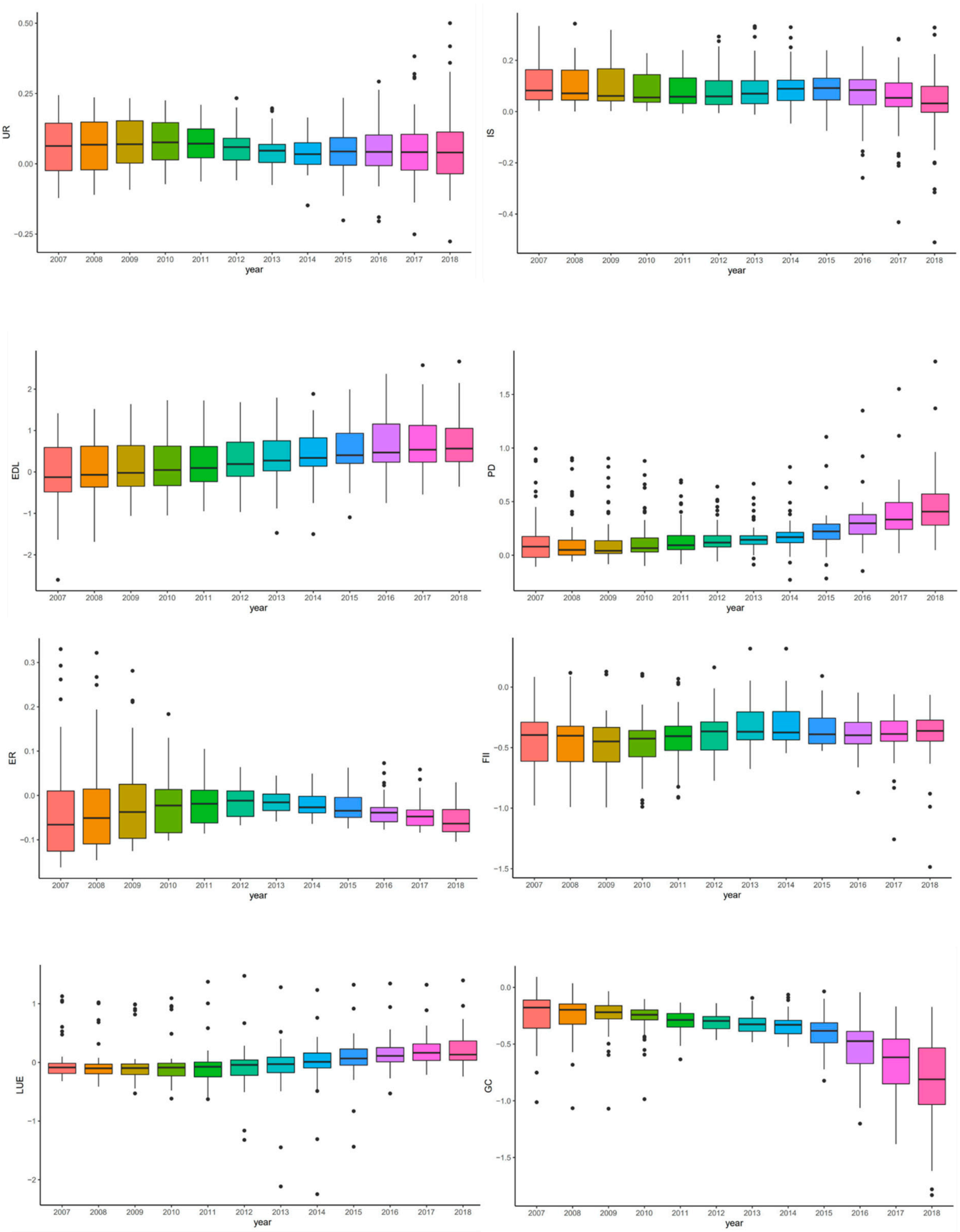

Figure 8. Time series change trend of GTWR regression coefficients.

3.5.3. Spatial Heterogeneity Analysis of Factors Influencing Carbon Emission Intensity of UCL

In order to more intuitively observe the spatial variability of the influence of each influencing factor on the carbon emission of UCL in different cities, the mean values of the regression coefficients of each influencing factor in different cities during 2007–2018 were calculated and visualized in this paper, as shown in Figure 9.

(1) The regression coefficients of urbanization rate (UR) and carbon emission intensity of UCL are positive in the majority of cities in the North China Plain, and the high impact areas are mainly concentrated in Beijing, Tianjin, Hebei, northwestern Shandong, and western Henan. In these areas, the increase of the urbanization level brings the concentration of population and production activities, which eventually leads to the increase of consumption level, as well as the corresponding energy demand, due to the high-intensity urban land development, and the urbanization mode of over-reliance on land finance and rough and sprawling land development in these places brings great pressure on urban emission reduction. However, the regression coefficients are negative in eastern and southern Shandong, eastern Henan, northern Jiangsu, and northern Anhui. This is because, as mentioned above, the urbanization rate reduces the carbon emission intensity in these regions, especially in the eastern coastal region, due to the influences of talent inflow, technological innovation, and industrial structure optimization.

(2) The regression coefficients of industrial structure (IS) and carbon emission intensity of UCL are positive in most cities in the North China Plain, and the high impact areas are mainly concentrated in Beijing, Tianjin, western and central Shandong, eastern Hebei, and northern Jiangsu, etc. A large proportion of these cities are heavy industrial cities, and the energy structure is dominated by coal, iron, steel, and other energy-intensive industries. The crude development model has greatly increased energy consumption, thus making the carbon emission intensity high.

(3) The regression coefficient between the level of economic development (EDL) and carbon emission intensity of UCL is positive in most cities in the North China Plain, and the high value is mainly concentrated in the southern part of the North China Plain, i.e., Henan, northern Jiangsu, and northern Anhui, where the high intensity of economic activities consumes a large amount of energy, thus causing an increase in carbon emission intensity of UCL.

However, in the Beijing–Tianjin–Hebei region, the regression coefficient is negative, i.e., economic development reduces carbon emission intensity of UCL, as mentioned above, which may be due to the fact that the "reduction effect" of carbon emission caused by the economy of scale effect and facility sharing is stronger than the "increase effect" of carbon emission caused by energy consumption. In order to verify this assumption, by examining the change trend of regression coefficients of economic development levels of cities in Beijing–Tianjin–Hebei region during 2007–2018, it is found that most of them show a negative to positive trend. It can be seen that, when the "increase effect" in other regions is already stronger than the "decrease effect", the "increase effect" in Beijing–Tianjin–Hebei region has a tendency to change from weaker than the "decrease effect" to stronger than the "decrease effect". This proves previous assumption.

(4) In most of the cities in the North China Plain, population density (PD) increases the carbon intensity of UCL, with the high impact areas mainly concentrated in the eastern and northern parts of the North China Plain, i.e., Shandong and Hebei, because, in these areas, the population density is relatively high, which brings about the "congestion effect", leads to higher energy consumption in transportation, and contributes to higher carbon emission intensity.

(5) Environmental regulations (ER) can reduce the carbon emission intensity of UCL in most cities in the North China Plain, with the high impact area mainly concentrated in the southwestern part of the North China Plain, i.e., Henan Province. This indicates that environmental regulations play a more effective role in reducing the carbon emission intensity of UCL in Henan Province, compared to other regions.

(6) In all cities of the North China Plain, without exception, the intensity of foreign investment (FII) significantly reduces the carbon emission intensity of UCL, which shows that the effect of foreign investment on reducing the carbon emission intensity of UCL is obvious. The "pollution halo hypothesis" is prevalent in the North China Plain, and foreign investment can improve local production technology and increase

the productivity of enterprises to achieve environmental improvement and carbon emission intensity reduction. As can be seen from Figure 9, the high impact value area is mainly concentrated in the western part of Henan Province. The main reason may be that, in these cities, local enterprises have lower energy saving and emission reduction technology, when foreign investment with high technology, low energy consumption and low pollution enters afterwards. The technology level gap can greatly play the technology spillover effect of foreign investment, which, in turn, significantly reduces carbon emission intensity.

(7) The spatially differentiated distribution of the regression coefficients of land use efficiency (LUE) in different cities is obvious, among which, the number of cities with positive and negative regression coefficients is large, and the areas with negative regression coefficients are mainly concentrated in Beijing, Tianjin, Hebei, and northern Henan, which shows that these regions rely too much on land finance, and the high-intensity human activities are challenging the land carrying capacity and increasing the land burden. Although the efficiency of land use has improved, it is also driving up the intensity of carbon emissions. However, in southern Henan, northern Jiangsu, northern Anhui, and some areas in Shandong, the regression coefficients are positive, which indicates that, in these areas, by reasonably controlling the intensity of land development and optimizing the structure and spatial layout of land, a reasonable allocation of land resources has been achieved, which, in turn, reduces the carbon emission intensity of UCL.

(8) In all cities of the North China Plain, the green coverage (GC) significantly reduces the carbon emission intensity of UCL, which shows that the carbon sink of green land can, indeed, effectively reduce the carbon emission intensity of UCL. Increasing the area of green land is an important way to enhance the carbon absorption capacity, so it is significant to build green water and green mountains. As can be seen from Figure 9, the high impact value areas are mainly concentrated in Shandong Peninsula and the western and southern parts of Hebei, as well as the eastern part of Henan Province, where the green land greatly reduces the carbon emission intensity of UCL and demonstrates a very prominent carbon reduction capacity.

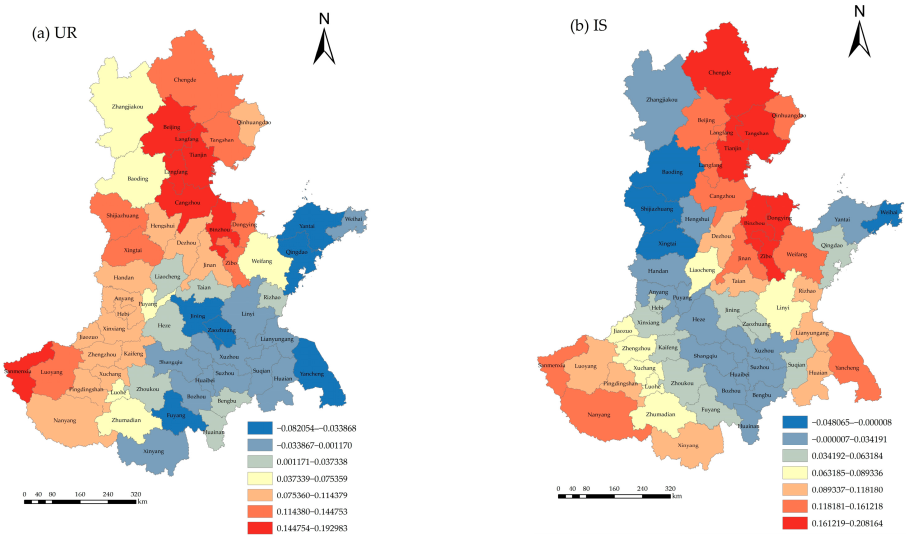

Figure 9. *Cont.*

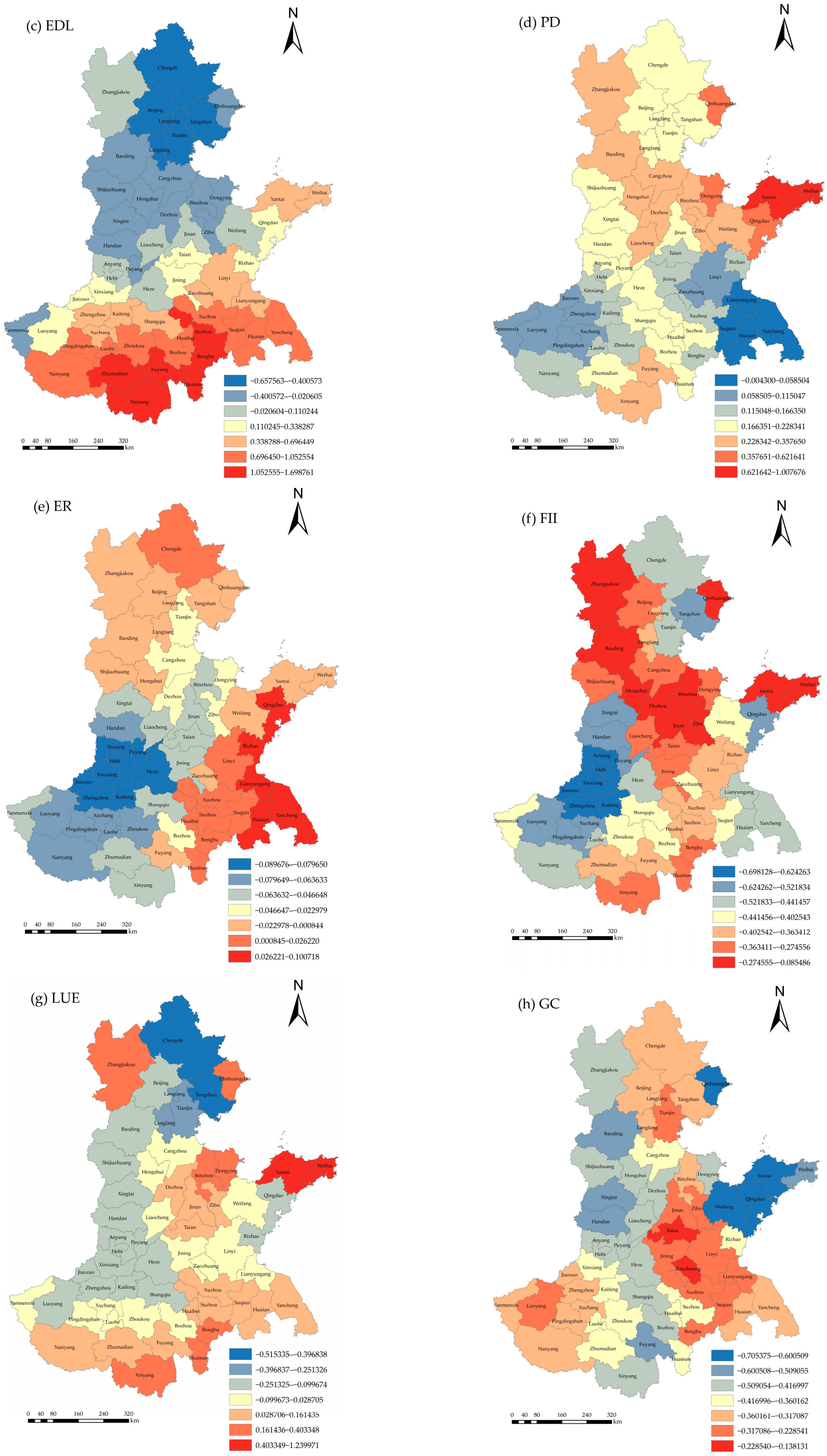

Figure 9. Spatial distribution of regression coefficients of influencing factors. (**a**)Regression coefficient of UR; (**b**) Regression coefficient of IS; (**c**) Regression coefficient of EDL; (**d**) Regression coefficient of PD; (**e**) Regression coefficient of ER; (**f**) Regression coefficient of FII; (**g**)Regression coefficient of LUE; (**h**)Regression coefficient of GC.

4. Discussion

4.1. Research Findings

Previous studies have analyzed the effects of urbanization rate, industrial structure, population density, and foreign investment on carbon emission intensity [52–60], and their findings are similar to this paper. However, in contrast to the previous findings, we found that there seems to be a possible "U"-shaped relationship between the level of economic development and the carbon intensity of UCL, with a negative, and then positive, relationship. The reason for this, as described above, may be that the "reduction effect" of carbon emissions caused by economies of scale and facility sharing is weaker, and then stronger, than the "increase effect" of carbon emissions caused by energy consumption. A previous study followed the environmental Kuznets curve hypothesis, which shows an inverted U-shaped relationship between economic development and carbon emission intensity [67]. We believe that this is not to say that the environmental Kuznets curve hypothesis is wrong, but we make a further conjecture based on the environmental Kuznets curve hypothesis, i.e., whether there is an "inverted N"-shape relationship between economic development level and carbon intensity of UCL. However, the second inflection point of the "inverted N"-shape has not been reached yet, and this hypothesis may not be confirmed in this paper, due to the limitation of sample size and study period. However, an inverted "N"-shaped relationship between economic agglomeration and carbon emission intensity has been found in the literature and proved by empirical analysis [63]. In conclusion, we believe that, in the future, economic development will inevitably reduce the intensity of carbon emissions. With the improvement of economic development, people can reduce carbon emission intensity by optimizing energy structure and developing energy-saving and emission reduction technologies, as well as by increasing people's awareness of environmental protection. The current volatile change situation is all about phase. When the second inflection point of the "inverted N" curve is reached, the level of economic development will significantly reduce the carbon emission intensity.

In addition, our study discusses the effect of land use efficiency on the carbon emission intensity of UCL. Overall, land use efficiency pulls up the carbon emission intensity of UCL, which is not difficult to understand. The decrease in land use efficiency (land area to real GDP ratio) also proves that land takes on more intense production activities, which most likely brings about an increase in carbon emission intensity. However, there are exceptions in southern Henan, northern Jiangsu, northern Anhui, and some parts of Shandong that draw our attention, and we speculate that it may not only be due to the optimal allocation of the structure and spatial layout of land in these areas, but also a reason that these areas (especially the coastal areas of Jiangsu and Shandong) have a higher level of science and technology development and higher number of high-tech industrial incubation parks. The economic development level (i.e., GDP) of these regions is more driven by technological innovation. The development of science and technology innovation can effectively curb carbon emissions, so that when the land use efficiency (land area to real GDP ratio) decreases, the carbon emission intensity will decrease. This finding can provide a reference value for policy makers' policy making. Promoting economic growth through scientific and technological innovation, rather than relying on energy-intensive industries with high pollution and energy consumption, can not only reduce the burden of land, but also reduce the carbon intensity of land, thus achieving the best of both worlds.

Finally, most previous studies have neglected the carbon reduction effect of green cover, which plays an important role in maintaining the concentration of greenhouse gases in the atmosphere through the carbon sink function of plants, which absorb carbon dioxide and release oxygen through photosynthesis. Taking this as the starting point, this paper analyzes the effect of green cover as an influencing factor on the carbon emission of UCL, and the research results support the above discussion; that is, green cover greatly reduces the carbon emission intensity of UCL, and urban green space system can reduce carbon emission in cities. The results of this study suggest that we should return more land to forests and guide regions to scientifically promote land greening, in order to achieve a balance of carbon emissions and effectively combat global warming. This is not only an important means to build a low-carbon urban land spatial form, but also an urgent requirement in the field of urban land planning to integrate the concept of ecological environment.

4.2. Policy Implications

At present, although the expansion of UCL has promoted economic development, the blind expansion of land and massive land acquisition are important reasons for the crude spread of land. According to the results of this paper, in recent years, the overall decoupling status of UCL and carbon emissions in the North China Plain has performed poorly, and the decoupling status varies among cities. Therefore, based on the advantages of local natural endowments and land carrying capacity, we should actively explore the emission reduction paths suitable for the region, gradually get rid of over-reliance on land finance, continue to optimize the industrial structure, accelerate the conversion of old and new dynamics, and gradually eliminate enterprises with high emissions, high energy consumption, and overcapacity, while actively developing green renewable energy.

Based on the findings of this paper, it is believed that the greening coverage of UCL can be appropriately expanded to enhance the "carbon sequestration" capacity of green areas, thus reducing the burden of land and promoting the low-carbon development of land. We should continue to deepen environmental regulation policy reform, improve environmental management capacity, and force enterprises toward green transformation and technological innovation; at the same time, we should increase the introduction of foreign investment, implement stricter entry conditions for foreign investment, and optimize the structure of foreign investment, so as to give full play to the emission reduction effect of knowledge and technology spillover brought by foreign investment. Anyway, over-urbanization should also be avoided, which is the main cause of big city disease, urban ecological deterioration, and resource tension. The corresponding strong measures should be taken to reasonably control the scale of cities and achieve a virtuous cycle of harmonious development of economy and environment under the constraints of resource carrying and environmental capacity.

The land is a very valuable non-renewable resource, and it is necessary to implement the strictest land protection policy, resolutely resist the rough management and overuse of land, strictly control the blind and rapid expansion of UCL, scientifically develop and utilize land, continue to optimize the structure and layout of UCL, and promote the coordinated development of the economic and environmental benefits of land use, which is the key to realizing the rational allocation and efficient use of land resources, promoting intensive land development, and ensuring the sustainable and healthy development of land.

4.3. Limitation and Further Research

(1) Due to the unavailability of some data, we only obtained relevant data for the period between 2007–2018, which is relatively old. In future studies, if the time span can be extended, different findings may be obtained, based on the findings of existing studies.
(2) In this paper, only 57 cities in the North China Plain were selected as research objects, and the corresponding research conclusions were obtained. Although some of the research conclusions are universal, the research conclusions are not comprehensive because the number of cities we selected only accounts for one-fifth of the total number of cities in China, and the development basis, development mode, and current situation of each city are different. In future studies, the sample can be expanded at the city level, and more targeted development strategies can be proposed, according to the differences in development status among cities to obtain more comprehensive research findings.
(3) In the analysis of the influencing factors of carbon emission intensity of UCL, the influence of individual influencing factors may not be linear, especially the influence

of economic development level. So, the model selection in this paper may have limitations. In future research, further optimization of the model can be made, i.e., by introducing some nonlinear models to explore the specific nonlinear relationships.

5. Conclusions

As the most important component of urban land, the total and intensity of carbon emissions from UCL are obvious. In the context of the two major goals of carbon peaking and neutrality that China will achieve by 2030 and 2060, achieving low-carbon development has become a new issue in the macro use regulation of UCL. Therefore, this paper uses a decoupling model to investigate the decoupling status of UCL and carbon emissions based on panel data of 57 cities in the North China Plain. The spatial autocorrelation and GTWR models were used to analyze the spatial distribution characteristics of carbon emission intensity of UCL in the North China Plain, as well as the influencing factors. The conclusions of the study are as follows:

(1) Urban construction land in the North China Plain shows an extremely strong correlation with carbon emissions; that is, the expansion of urban construction land significantly pulls up a significant source of CO_2 emissions, which is the basis of this study.
(2) The decoupling types of UCL and carbon emissions in the North China Plain are mainly weak decoupling and expansive negative decoupling types. The decoupling situation showed a general trend of improvement and then deterioration.
(3) Overall, the carbon emission intensity of UCL shows obvious clustering characteristics in both the north and south of the North China Plain; it is high in the north and low in the south.
(4) There is temporal and spatial variability in the effects of different influencing factors on the carbon intensity of UCL. Overall, urbanization rate, industrial structure, economic development level, and population density have positive effects; environmental regulations, foreign investment intensity, land use efficiency, and green coverage have negative effects.

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