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Spatial Variations in Relationships between Urbanization and Carbon Emissions in Chinese Urban Agglomerations

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Abstract: Urban agglomerations (UAs) are the main battlefield of urbanization and the most concentrated areas of carbon emissions (CEs). Nevertheless, limited studies have examined the impact of urbanization level (UL) on CEs in UAs in China. This study aimed to identify the spatial relationship between UL and CEs in Chinese UAs and to conduct a comprehensive analysis of the differences in CEs caused by urbanization. The findings would provide scientific support for the China's dual-carbon goals and the achievement of green and low-carbon urban development. Spatial variations in UL and CEs in 19 Chinese UAs were assessed in 2000, 2010, and 2020 using distribution dynamics and spatial regression models. The results indicated that the UL of UAs in China evidently increased over time, and UAs contributed approximately 80% of the national CEs. Significant spatial dependence was identified between urbanization factors and CEs. The regression results indicated that an increase in UL promoted the growth of CEs, and the form of the urban land had a significant and highly variable impact on CEs. Our findings provide a valuable case study for exploring relationships between UL and CEs in other UAs worldwide.

Keywords: carbon emissions; urbanization level; bivariate spatial autocorrelation; multiscale geographically weighted regression; urban agglomerations; China

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1. Introduction

Climate change, particularly global warming, exerts a significant impact on the natural ecosystem and socioeconomics [1]. Extreme climates, such as deadly heat extremes, droughts, floods, and rising sea levels, are directly or indirectly caused by global warming and are being reported increasingly frequently [1]. The main culprit is ever-increasing carbon emissions (CEs) [2]. CEs caused by human activities have led to global warming [3], which is projected to increase another 1–5 °C over the next century [4]. As global attention to the issue of climate change continues to grow, the implementation of the Paris Agreement will face more challenges and opportunities. In 2020, global energy-related CEs exhibited the largest negative annual growth rate to date. However, the subsequent decline was not as rapid as anticipated, resulting in a new record high of 37.4 Gt in 2023. Urban areas are responsible for close to 70% of global CEs associated with energy consumption [5]. Globally, urban CEs are increasing, with per capita urban emission trends exceeding their national equivalents in nearly all regions. This suggests that urbanization will become a more significant challenge in the future [6].

China is the world's largest energy consumer and carbon emitter, accounting for approximately one-third of the world's CEs. Consequently, it is facing increasing international pressure to reduce CEs. China's current socioeconomic development is characterized by rapid urbanization [7], which has had a significant impact on CEs, with far-reaching consequences for society [8]. As the volume of CEs generated by human activities continues to increase [1], China is striving to assist in achieving the "30·60 dual carbon" goal proposed in 2020. It aims to actively and steadily promote dual-carbon goals and accelerate the green transformation of development mode. This entails advocating for green and low-carbon transitions across all sectors, with a particular focus on Chinese urban agglomerations (UAs). As the growth pole of economic development [9], UAs account for 29.39% of China's total area but contribute approximately 80% of the country's CEs. It is imperative to enhance urbanization strategies to advance socioeconomic development in China in a manner that mitigates environmental impact, thereby ensuring the realization of sustainable development [10,11]. Nevertheless, there is a paucity of research examining the spatial relationship between urbanization level (UL) and CEs at the UAs level. An investigation into the spatial variations in the relationships between UL and CEs in Chinese UAs would facilitate the implementation of green and low-carbon transformations.

The process of urbanization is a defining feature of modern civilization and is a crucial driver of economic growth [12]. Moreover, research has demonstrated that the phenomenon of accelerated urbanization can precipitate the deterioration of habitats and the diminution of ecosystem structure and functionality [13,14], which in turn influences CEs. Nevertheless, the impact of UL on CEs remains a topic of contention, with existing empirical studies yielding disparate results [15,16]. Zhu and Gao (2019) [17] reported that UL promoted CEs in the transport sector. However, Amin et al. (2020) [18] argued that UL did not significantly impact CEs. Dong et al. (2018) and Zhou et al. (2021) [19,20] demonstrated that UL can effectively reduce CEs with advances in technological progress. Moreover, Li et al. (2022) [21] have demonstrated that UL exerts a non-linear negative impact on CEs in the transport sector. A substantial body of research has addressed the intricate relationship between UL and CEs, and several key findings have emerged. Prior studies that have assessed the extent of UL have predominantly focused on social, demographic, economic, and spatial urbanization factors [22–24]. Meanwhile, existing studies have demonstrated that population urbanization has a significantly positive impact on CEs [25,26]. For example, Imhoff et al. (2000) and Milesi et al. (2003) reported that spatial urbanization could positively promote CEs because rapid advancement of urbanization accelerates the demand for urban land, which had the highest total CEs among all forms of land [27,28]. Moreover, previous studies have also revealed that the urban landform exerts a considerable influence on CEs, with a discernible discrepancy [29–33]. In conclusion, previous studies have primarily concentrated on individual urbanization factors, while the process of urbanization in UAs was inherently complex [34,35]. It is therefore imperative to undertake a comprehensive analysis of the impact of UL, including economic, population, social, and spatial urbanization factors as well as urban form, to identify the impact of UL on CEs in UAs.

A variety of methods have been utilized to ascertain the association between UL and CEs, including index and structural decomposition analyses [36–38]. The most commonly used methods at present are econometric techniques, including the logarithmic mean divisia index method [31], the environmental Kuznets curve [12], and the system-generalized method of moments [39]. A substantial number of studies were typically conducted at the national, regional, or prefectural scale at various stages of development. For example, Amin et al. (2020) employed ordinary least squares (OLS) and dynamic OLS estimations to study CEs in European countries. Zhu and Gao (2019) [17] explored CEs in countries of the "Belt and Road Initiative". Li et al. (2022) [21] used the decoupling index and panel threshold analysis to explore the relationship between UL and CEs in the transport sector. However, existing studies have rarely been conducted in Chinese UAs with high UL rates and CEs, even though UAs can play a dominant role in promoting a new-type urbanization that realizes green and low-carbon transformation [9,10]. As reported by Wang et al. (2022) [40], large UAs were areas with high urban CEs performance values. Consequently, an investigation into the spatial correlation between UL and CEs intensity in Chinese UAs may facilitate the formulation of enlightened policies.

The UAs comprise numerous sizable cities and have become a significant region of urbanization and economic growth in China [41–43]. It is of paramount importance to ascertain the influence of UL on CEs, both for the sustainable development of UAs and for the realization of China's double carbon target [44]. What is the spatial relationship between UL and CEs of UAs in China? What are the distinctions in the influence of disparate urbanization factors on CEs? What policy recommendations can be provided for green development, energy conservation, and emission reduction by studying the relationship between UL and CEs in Chinese UAs? These issues require further elucidation. To this end, this study employed kernel density estimation and the Markov chain model to initially examine the evolution and spatial development trends of CEs intensity in Chinese UAs in 2000, 2010, and 2020. Subsequently, the spatial autocorrelation and spatial econometric models were employed to analyze the spatial variations in the relationships between urbanization factors and CEs. The study attempted to address two key questions: (1) What are the spatiotemporal patterns of CEs intensity and UL in Chinese UAs? (2) What are the spatial variations in the relationships between urbanization factors and CEs intensity in Chinese UAs?

2. Materials and Methods

2.1. Study Area

UAs represent a high-level spatial form of urban development. A total of 19 UAs were proposed in China's 14th Five-Year Plan, which has become an important starting point for promoting China's high-quality development (Figure 1). Due to their advantageous natural conditions and substantial development potential, UAs accounted for the majority of China's total population, economic aggregate, and construction area, serving as the primary growth engine for China's economic expansion [23]. The 19 UAs in China accounted for approximately 29.39% of the country's total area and approximately 74% of the country's total population and generate approximately 83% of the country's GDP [45]. UAs represented the predominant form of new-type urbanization [9,46]. They served as spatial conduits and focal points for a multitude of activities, encompassing political, economic, ecological, cultural, and other domains. Additionally, they facilitated the aggregation and divergence of diverse production factors. CEs in UAs accounted for approximately 80% of the total CEs in China. However, the rapid and disorderly development of UAs has caused a series of eco-environmental problems that may have seriously affected China's "30·60 dual carbon" development strategies, among which the rapid increase in CEs was a typical example.

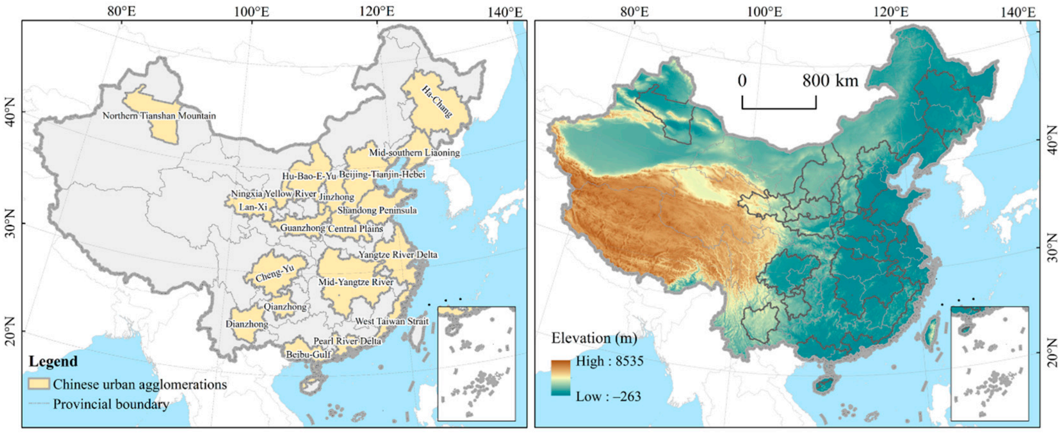

Figure 1. Depiction of the study area.

2.2. Data Sources and Processing

China's land-use remote sensing monitoring data, normalized difference vegetation index (NDVI) data, economic density data (spatial resolution of 1 km), and main road vector data for 2000, 2010, and 2020 were obtained from the Data Center for Resources and Environment, Chinese Academy of Sciences (http://www.resdc.cn, accessed on 16 June 2024). Population density data with a spatial resolution of 100 m were obtained from WorldPop (https://www.worldpop.org, accessed on 16 June 2024). The CEs data were primarily sourced from the global CEs raster data published by the Open-Data Inventory for Anthropogenic Carbon Dioxide from 2000 to 2022 (http://db.cger.nies.go.jp/dataset/ODIAC/data_policy.html, accessed on 16 June 2024). These data were widely used in CEs exploration, simulation, and prediction, and their simulation accuracy is greater than 80%. Basic geographic information data were obtained from the National Geomatics Center of China (http://www.ngcc.cn, accessed on 16 June 2024).

2.3. Kernel Density Estimation

Kernel density estimation is commonly employed to construct a probability distribution function that aligns with the original factor distribution [47–49]. The advantages of kernel density estimation are that it does not depend on a model and the method is robust, which is widely used to explore the dynamic evolution and spatial development of geographical factors [50–52]. Here, we used the method to describe the dynamic evolutionary trends of CEs intensity in Chinese UAs to reveal their quantitative change characteristics. The equations are as follows:

$$f(cei) = \frac{1}{NL}\sum_{i=1}^{N} K\left(\frac{CEI_i - cei}{L}\right) \quad (1)$$

$$K(cei) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{cei^2}{2}\right) \quad (2)$$

where cei is the mean CEs intensity in the UAs, L is the bandwidth, N is the number of observations, CEI_i is the CEs intensity of the i-th observation, and $K(cei)$ is the Gaussian kernel function. In this study, the bandwidth was 0.02. To achieve a better visualization effect, CEs intensity was normalized to the range of 0–1 before kernel density estimation.

2.4. Markov Chain Model

The Markov chain model, a stochastic process that exhibits no aftereffects, is typically employed to investigate the mutual transformation of factors over time. The model employs an $n \times n$ transition probability matrix to characterize transition probability and direction [51,53,54]. The spatial Markov chain model adds a spatial lag term, which converts the $n \times n$ transition probability matrix into an $n \times n \times n$ transition probability matrix. The spatial Markov chain model is based on the original Markov chain model and considers the spatial dependence of transfer factors [54,55]. In this study, we used the Markov chain to analyze the dynamic evolutionary trend of CEs intensity in Chinese UAs in the future to reveal its mutual transfer in different value domains.

2.5. Measurement of UL

Urbanization encompasses population growth, economic development, expansion of construction land, and rising living standards [56]. Rising living standards are the result of population growth, economic development, and the expansion of construction land [57,58]. The methods of measuring UL are diverse, with population growth being the core, land expansion being the guarantee, and economic growth being the engine [23,59]. An evaluation method for UL was constructed concerning previous literature [59,60]. Here, economic, population, and spatial urbanization factors were comprehensively analyzed to construct the UL assessment method due to data availability and measurability [23,58–61]. The equation is as follows:

$$UL_i = (ED_i + POP_i + DLP_i)/3 \quad (3)$$

where UL_i represents the urbanization level of the i-th county, ED_i, represents the economic density, POP_i, represents population density, and DLP_i, represents the construction land proportion of the i-th county.

2.6. Bivariate Spatial Autocorrelation Analysis

Bivariate spatial autocorrelation is employed to investigate the potential for a spatial auto-correlation between CEs intensity and UL [23,62]. The global bivariate Moran's I index was employed to investigate the overall spatial agglomeration intensity/direction of CEs intensity and UL, as delineated by Chen and Chi (2022) [23]. This study employed global spatial autocorrelation to quantify the extent of the autocorrelation between CEs intensity and UL, while local autocorrelation was utilized to illustrate the spatial clustering patterns of CEs intensity and UL.

2.7. Multiscale Geographically Weighted Regression

First, the OLS model was employed to explore the impact of UL on CEs intensity. The econometric model is constructed as follows:

$$CEI_i = \beta_0 + \beta_1 UL_i + \sum_{k=2}^{7} \beta_k X_{ki} + \varepsilon_i \quad (4)$$

where β_0 represents the intercept, β_1 represents the regression coefficient, i represents a district or county, CEI_i represents the CEs intensity in the i-th district, UL_i represents the UL in the i-th district, X_{ki} represents the control variable affecting the CEs intensity in the i-th district, and ε_i is the residual term.

Considering that UAs' UL is influenced by spatial factors, the traditional global regression model cannot identify potential spatial heterogeneity. Previous research has sought to assess the spatial non-stationarity of urbanization development through the use of the GWR model, which incorporates spatial factors into the analysis [63,64]. However, the GWR model has two inherent limitations. Firstly, although the GWR model considers spatial factors, it fails to account for the multi-scale test problem, resulting in an inability to accurately estimate local parameters. Secondly, the GWR model employs a fixed value for the optimal bandwidth, operating under the assumption that all variables exert an influence on the explained variables at an identical spatial scale. To address the aforementioned issues, the multi-scale GWR model does not scale for each independent variable within the same spatial context. Instead, it employs a multi-scale inference approach to identify the optimal bandwidth, thereby ensuring the reliability of local parameter estimates. Here, we introduced the multi-scale GWR model to analyze the spatially non-stationary response of CEs intensity to UL in Chinese UAs. The equation is as follows:

$$CEI_i = \beta_{bwi0} + \beta_{bwi1} UL_i + \textstyle\sum_{k=2}^{7} \beta_{bwik} X_{ki} + \varepsilon_i \quad (5)$$

where β_{bwi0} represents the intercept, β_{bwi1} represents the regression coefficient, bwi represents the optimal bandwidth of each variable, i represents a district or county, CEI_i represents the CEs intensity in the i-th district, UL_i represents the UL in the i-th district, X_{ki} represents the control variable affecting the CEs intensity in the i-th district, and ε_i is the residual term. MGWR V2.2.1 software was used to estimate and calibrate the parameters of the model, and the related maps were drawn using ArcGIS 10.8 software (Esri, Redlands, CA, USA).

Here, CEs intensity was expressed as CEs per unit area of each district and county. The core explanatory variable was UL, which was measured by the methodology outlined in Section 2.5. The measures of each control variable included patch density (PD), edge index (ED), cohesion index (COHESION), agglomeration index (AI) of urban land, elevation (digital elevation model, DEM), road density (RD), and vegetation cover (VC). Landscape pattern metrics, including PD, ED, COHESION, and AI, were selected to measure the form of urban land [30,32,33,65]. DEM and VC were selected to represent natural elements, while RD was selected to represent socioeconomic elements [66].

3. Results

3.1. Spatiotemporal Patterns of CEs Intensity in Chinese UAs

3.1.1. Spatiotemporal Patterns of CEs Intensity

Figure 2 illustrates the spatiotemporal patterns of CEs intensity in Chinese UAs from 2000 to 2020. In 2000, 2010, and 2020, the average CEs intensity of Chinese UAs was 1152.689, 3124.253, and 3811.584 tons/km^2, respectively. The CEs intensity growth rates during 2000–2010 and 2010–2020 were 171.040% and 22.000%, respectively. This indicated a decrease in the CEs intensity growth rate over time. Despite comprising only 29.390% of the country's total area, UAs were responsible for the vast majority of the country's total CEs. In 2000, 2010, and 2020, the total CEs in UAs contributed 78.347%, 78.927%, and 78.941% of the total national CEs, respectively, demonstrating a continuous upward trajectory. The highest CEs were observed in the Yangtze River Delta, while the lowest was recorded in the central Guizhou UAs. Moreover, the CEs intensity in UAs in eastern China (e.g., the Yangtze River Delta, Pearl River Delta, Shandong Peninsula, and Beijing-Tianjin-Hebei UAs) was observed to be higher than that in UAs in western China. Additionally, the CEs intensity in the core areas of UAs was found to be higher than that in the surrounding areas.

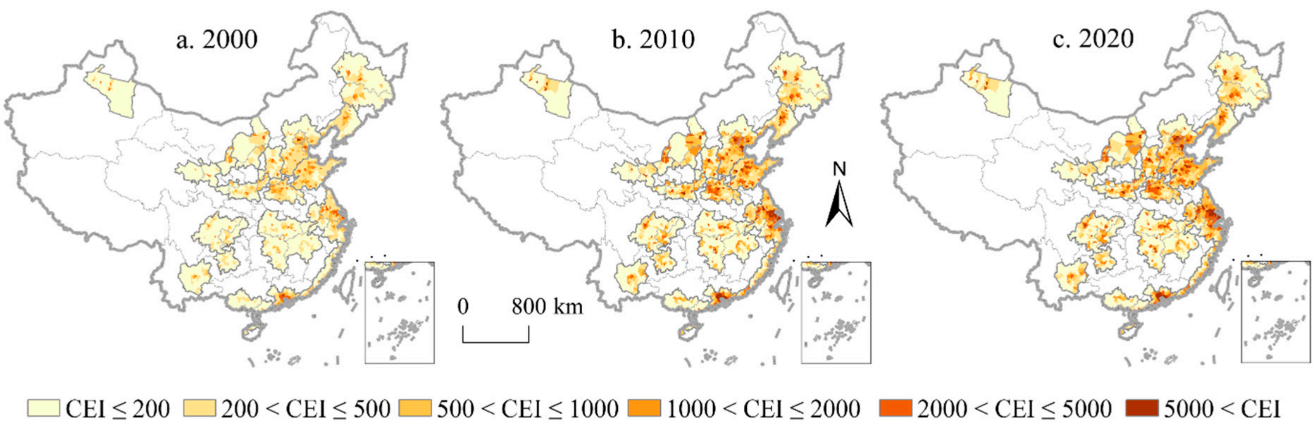

Figure 2. Spatiotemporal patterns of CEs intensity in Chinese UAs during 2000–2020.

3.1.2. Dynamic Evolution of CEs Intensity

Furthermore, unconditional and spatial static kernel densities were employed to investigate the dynamic evolution of CEs intensity in Chinese UAs (Figure 3). The concentration of unconditional kernel densities in proximity to the 45° diagonal suggested that CEs intensity did not undergo a notable change. The peaks in the unconditional kernel densities were primarily situated in areas with elevated CEs intensity-high UL and reduced CEs intensity-low UL, suggesting that CEs intensity underwent dynamic evolution in these regions. Regions with higher CEs intensity tended to convert to lower CEs intensity over time. This may have been due to a series of CEs reduction measures implemented in China from 2010 to 2020, which gradually reduced CEs intensity in regions with previously higher CEs intensity. Furthermore, the findings indicated that the highest CE intensity was concentrated in areas with low CEs intensity-low UL and medium CEs intensity-high

UL, suggesting that CEs intensity in UAs exhibited notable spatial clustering tendencies. Additionally, regions with elevated CEs intensity were situated close to UAs with similarly high CEs intensity.

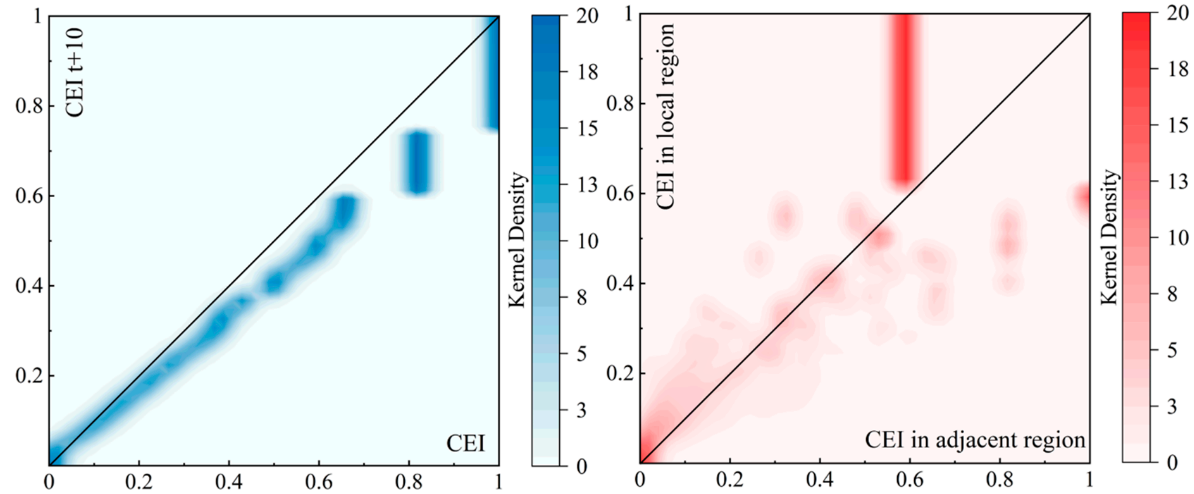

Figure 3. Contour map of CEs intensity kernel density in different regions.

In light of the spatial dependence of CEs intensity, a spatial Markov chain model was employed to quantify the dynamic transfer trends of CEs intensity in Chinese UAs, with CEs intensity for 2000, 2010, and 2020 sorted by size (Table 1) [51,52]. The transfer trends of CEs intensity in UAs were investigated across time slices of 10 and 20 years. As illustrated in Table 1, the value of the diagonal was greater than that of the off-diagonal. However, the value of the diagonal exhibited a gradual decline with increasing time slices, indicating that CEs intensity demonstrated notable mobility. Furthermore, the value of the upper part of the diagonal was considerably higher than that of the lower part, indicating that the probability of CEs intensity transferring to a high value was significantly greater than that of transferring to a low value. This suggests that CEs intensity in UAs increased at a steady rate. Furthermore, the greater probability of CEs intensity shifting to a high value under the premise of spatial lag indicated that CEs intensity in UAs had a spatial spillover effect.

Table 1. Spatial Markov transition probability matrix of CEs intensity.

Time Slice	Spatial Lag	Type	L	ML	MH	H
10	L	L	0.804	0.192	0.004	0
		ML	0.014	0.521	0.465	0
		MH	0	0	0.606	0.394
		H	0	0	0	1
	ML	L	0.697	0.297	0.006	0
		ML	0.010	0.599	0.383	0.008
		MH	0	0	0.681	0.319
		H	0	0	0	1
	MH	L	0.731	0.263	0.006	0
		ML	0.002	0.500	0.485	0.013
		MH	0	0	0.646	0.354
		H	0	0	0	1
	H	L	0.733	0.267	0	0
		ML	0	0.465	0.535	0
		MH	0	0	0.616	0.384
		H	0	0	0	1

Table 1. *Cont.*

Time Slice	Spatial Lag	Type	L	ML	MH	H
20	L	L	0.669	0.322	0.009	0
		ML	0.022	0.222	0.756	0
		MH	0	0	0.167	0.833
		H	0	0	0	1
	ML	L	0.495	0.480	0.025	0
		ML	0.004	0.312	0.665	0.019
		MH	0	0	0.325	0.675
		H	0	0	0	1
	MH	L	0.429	0.551	0.020	0
		ML	0.004	0.172	0779	0.045
		MH	0	0	0.204	0.796
		H	0	0	0	1
	H	L	0	1	0	0
		ML	0	0	0.800	0.200
		MH	0	0	0.058	0.942
		H	0	0	0	1

Notes: L, CEs intensity less than the lower quartile; ML, CEs intensity between the lower quartile and median; MH, CEs intensity between the median and upper quartile; and H, CEs intensity greater than the upper quartile.

3.2. Spatiotemporal Patterns of UL in Chinese UAs

Figure 4 illustrates the spatiotemporal UL patterns in Chinese UAs, indicating a notable increase in UL from 2000 to 2020. The mean UL were 0.029, 0.035, and 0.059 in 2000, 2010, and 2020, respectively. The growth rates of UL during 2000–2010 and 2010–2020 were 20.690% and 68.571%, respectively. As with CEs intensity, the UL of UAs in eastern China were markedly higher than those in western China, with those in the core UAs areas exhibiting even higher values than those in the surrounding regions. The regions exhibiting elevated UL were analogous to those displaying heightened CEs intensity.

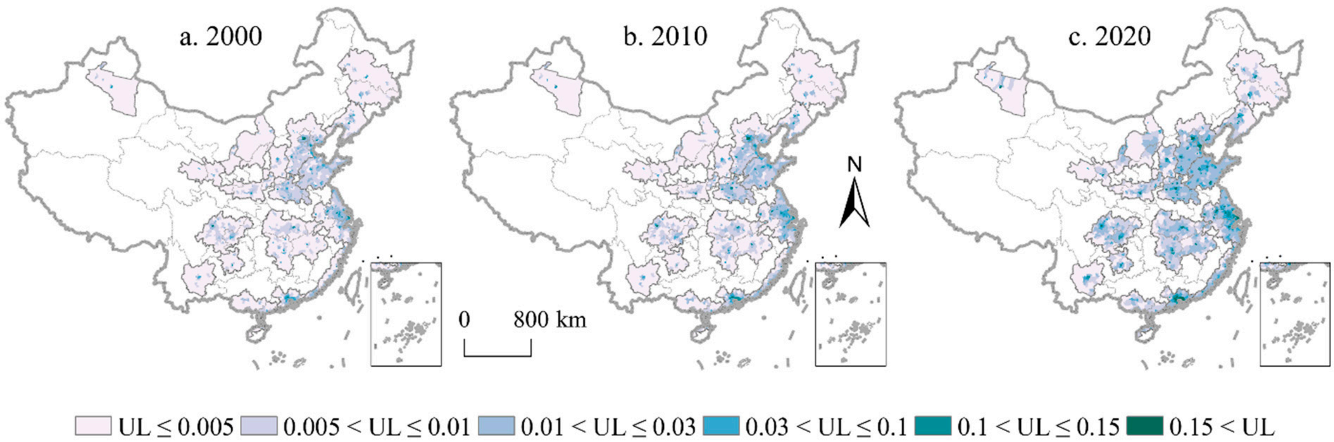

Figure 4. Spatiotemporal patterns of UL in Chinese UAs during 2000–2020.

3.3. Spatial Autocorrelation Analysis of CEs Intensity and UL in Chinese UAs

The global bivariate Moran's I were 0.468 (Z-value = 32.426), 0.510 (Z-value = 34.756), and 0.537 (Z-value = 36.646) in 2000, 2010, and 2020, respectively. The results demonstrated a significant (p = 0.0001) spatial autocorrelation between CEs intensity and UL in Chinese UAs. The LISA cluster map provided a visual representation of the specific patterns of spatial autocorrelation (Figure 5). In particular, low CEs intensity-low UL spatial correlations were the main type, followed by high CEs intensity-high UL spatial correlations. The results indicated a positive correlation between CEs intensity and UL. Low CEs intensity-low UL spatial correlations were predominantly distributed in the regions surrounding UAs, while high CEs intensity-high UL spatial correlations were primarily observed in the core area of UAs.

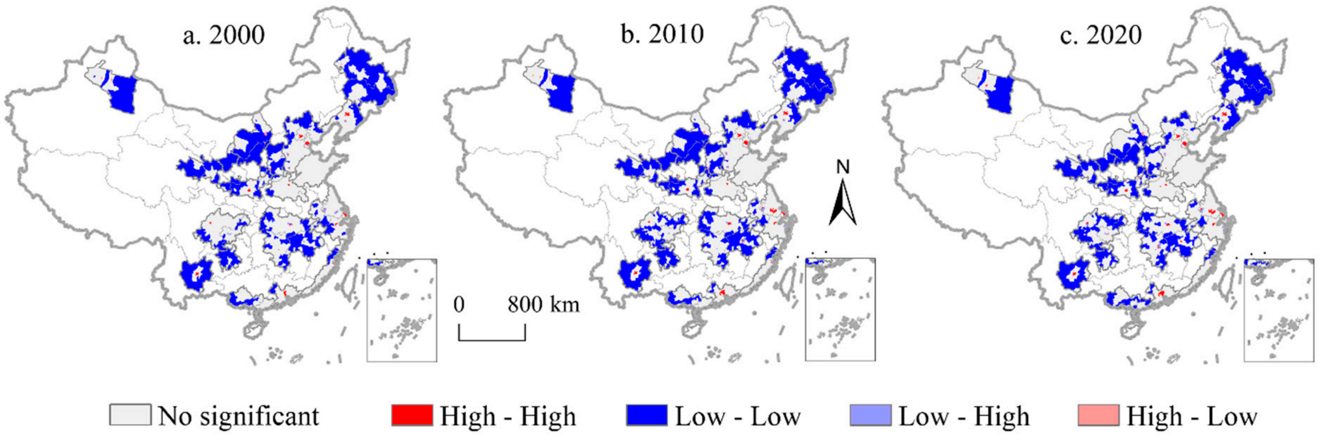

Figure 5. LISA cluster maps of CEs intensity and UL in Chinese UAs during 2000–2020.

3.4. Regression Results

3.4.1. Global Regression Results

In this study, the OLS model was initially employed to quantify the global impact of UL on CEs in urban areas. As demonstrated in Table 2, UL exerted a markedly positive influence on CEs intensity from 2000 to 2020 ($p = 0.001$), indicating that the advancement of urbanization resulted in a notable increase in CEs. Concurrently, the expansion of the economic scale was occurring at a rapid pace in conjunction with the continuous advancement of urbanization, which was resulting in elevated pollution emissions and a considerable surge in urban CEs. However, urban areas experience a significant influx of population during the urbanization process, which intensified energy consumption and land over-development, placing pressure on the urban environment and increasing urban CEs.

Table 2. Global estimation results of the impact of UL on CEs.

Variables	2000			2010			2020		
	Coef	t_Stat	Prob	Coef	t_Stat	Prob	Coef	t_Stat	Prob
UL	4.567 ***	7.890	0.000	5.175 ***	11.240	0.000	3.265 ***	8.901	0.000
PD	0.001 ***	3.770	0.000	64.265 ***	11.680	0.000	50.268 ***	10.586	0.000
ED	0.257 ***	3.790	0.000	−0.247 ***	−4.410	0.000	−0.201 ***	−4.365	0.000
COHESION	0.024 ***	8.110	0.000	0.039 ***	13.640	0.000	0.055 ***	17.711	0.000
AI	−0.009 ***	−5.450	0.000	−0.013 ***	−7.810	0.000	−0.016 ***	−7.845	0.000
DEM	−0.001 ***	−11.750	0.000	0.000 ***	−6.720	0.000	0.000 ***	−7.699	0.000
RD	0.811 ***	4.590	0.000	1.199 ***	7.670	0.000	0.000 ***	0.037	0.971
VC	−1.312 ***	−12.390	0.000	−1.244 ***	−12.700	0.000	−1.011 ***	−10.782	0.000
Con_s	5.323 ***	47.880	0.000	5.060 ***	41.580	0.000	4.860 ***	0.000	1.000
OLS method	*N*	R^2	A_VIF	*N*	R^2	A_VIF	*N*	R^2	A_VIF
diagnosis	1769	0.637	2.52	1769	0.726	3.38	1769	0.765	4.16

Notes: *** means $p \leq 0.001$; UL, urbanization level; PD, patch density; ED, edge index; COHESION, cohesion index; AI, agglomeration index; DEM, elevation; RD, road density; and VC, vegetation cover.

As evidenced by the results presented in Table 2, PD had a significant and positive impact on CEs intensity from 2000 to 2020. This finding aligns with expectations and suggests that increased urban land fragmentation has contributed to the growth of urban CEs. The effect of ED on CEs intensity was found to be significantly positive in 2000, but significantly negative in 2010 and 2020. This suggests that the impact of ED on CEs intensity was unstable. This may have been because continuous urban land improvement within UAs increased the degree of agglomeration, which was disadvantageous to the technological progress and economic development of marginal cities, resulting in a gradual positive impact on the marginal index of CEs intensity. The results indicate that an improvement in the cohesion index significantly promoted the growth of CEs intensity in 2000, 2010, and 2020. The results indicate that AI had a significantly negative effect on CEs intensity. This suggests that a higher degree of agglomeration within UAs facilitates economies of scale and technology spillover, thereby reducing CEs intensity. As anticipated, DEM and VC had a markedly adverse impact on CEs intensity, indicating that elevated altitudes and expansive vegetative coverage were conducive to reducing CEs intensity. As anticipated, the results demonstrated that RD had a markedly positive impact on CEs intensity. This finding suggests that elevated road densities were associated with increased pollution emissions, thereby facilitating the expansion of CEs intensity.

3.4.2. Spatial Heterogeneity Analysis Based on Multi-Scale GWR Model

Multi-Scale Analysis

The aforementioned estimation results, derived from the OLS model, failed to account for spatial effects, thereby impeding the identification of potential spatial heterogeneity. Accordingly, this study incorporated spatial factors through the use of the multi-scale GWR model, to evaluate the influence of UL on CEs intensity. The findings of the aforementioned traditional GWR model were also presented for comparison. As illustrated in Table 3, the bandwidth selections varied for each influencing factor in the multi-scale GWR model.

Table 3. Bandwidth comparison between multi-scale GWR model and GWR model.

Variables	Multi-Scale GWR			GWR		
	2000	2010	2020	2000	2010	2020
UL	1662	1074	1753	113	155	191
PD	155	170	184	113	155	191
ED	1673	1766	1766	113	155	191
COHESION	1607	198	1768	113	155	191
AI	1673	644	1766	113	155	191
DEM	79	157	1768	113	155	191
RD	450	47	49	113	155	191
VC	191	43	179	113	155	191
Con_s	354	548	43	113	155	191
R^2	0.824	0.836	0.836	0.830	0.827	0.841
Adj. R^2	0.797	0.814	0.824	0.797	0.803	0.824
AICc	2498.758	2299.793	2075.145	2572.331	2413.653	2156.661

The bandwidths of UL were considerable in 2000 (1662), 2010 (1074), and 2020 (1753), indicating that spatial differences in UL had a limited impact on CEs. Additionally, the spatial scale of other factors influencing CEs intensity exhibited a significant variation from 2000 to 2020. To illustrate, the bandwidth of DEM was relatively narrow in 2000, indicating that spatial variations in DEM had a considerable influence on CEs intensity in that year. However, the bandwidth of DEM was markedly larger in 2020, indicating that spatial differences in DEM had a markedly diminished impact on CEs intensity in 2020. These findings suggest that the multi-scale GWR model more accurately reflected the varying influence of each factor on CEs intensity compared to the fixed scale in the GWR model.

Multi-Scale GWR Model Regression Analysis

The descriptive statistical results of the multi-scale GWR model are presented in Table 4. From 2000 to 2020, the estimated regression coefficients for UL were found to be significant at the $p < 0.1$ level, with all coefficients exhibiting a positive sign. These findings illustrate that UL exerted a significant influence on CEs intensity. In addition to the aforementioned influencing factors, approximately 50% of the PD regression coefficients were significant at the $p \leq 0.01$ level from 2000 to 2020, with over 70% of the coefficients falling at the $p \leq 0.1$ level. Furthermore, all PD coefficients were positive, indicating that PD was a significant factor influencing the growth of CEs intensity during this period. In contrast, the influence of ED on CEs intensity was relatively limited. In 2000, only 6.90% of the ED coefficients were at the $p \leq 0.1$ level, and this proportion gradually decreased in 2010 and 2020. In contrast with the global estimation results based on the OLSmodel, the impact on the marginal index of CEs intensity was found to be significantly reduced after consideration of spatial factors. The proportions of the COHESION and AI regression coefficients that were at the $p \leq 0.01$ level increased in 2010 and 2020, reaching 100% in both cases. Furthermore, all coefficients were positive, indicating that COHESION and AI gradually became important factors leading to CEs intensity growth with the advancement of urbanization. The level of significance and ratio of positive to negative results for the DEM regression coefficients exhibited fluctuations from 2000 to 2020. However, the overall effect was found to be significantly negative, indicating that DEM exerted a detrimental influence on the growth of CEs intensity. The proportion of RD and VC regression coefficients that were significant at the $p \leq 0.1$ level was less than 50% from 2000 to 2020. This indicated that RD and VC had a relatively limited impact on CEs intensity during this period.

Table 4. Descriptive statistics of multi-scale GWR model regression parameters.

Year	Variable	Mean	STD	Min	Max	$p \leq 0.01$	$p \leq 0.05$	$p \leq 0.1$	+ (%)	− (%)
2000	UL	0.224	0.032	0.176	0.281	100.00	100.00	100.00	100.00	0.00
	PD	0.176	0.123	0.019	0.629	49.41	62.52	74.05	100.00	0.00
	ED	0.062	0.002	0.06	0.074	0.00	0.00	6.90	100.00	0.00
	COHESION	0.245	0.098	0.05	0.495	82.14	94.12	96.21	100.00	0.00
	AI	−0.069	0.06	−0.171	0.012	33.63	35.27	40.81	3.11	96.89
	DEM	−0.246	0.27	−0.887	0.394	56.70	70.49	73.94	17.81	82.19
	RD	0.213	0.285	−0.233	1.346	21.93	29.85	40.31	78.86	21.14
	VC	−0.128	0.218	−0.742	1.184	25.16	34.26	39.80	23.29	76.71
	Con_s	0.12	0.112	−0.071	0.267	53.70	58.00	66.31	77.44	22.56
2010	UL	0.208	0.004	0.2	0.216	100.00	100.00	100.00	100.00	0.00
	PD	0.178	0.113	0.037	0.556	46.52	69.87	82.42	100.00	0.00
	ED	0.054	0.002	0.051	0.064	0.00	0.00	4.92	100.00	0.00
	COHESION	0.333	0.001	0.33	0.336	100.00	100.00	100.00	100.00	0.00
	AI	−0.125	0.003	−0.133	−0.115	100.00	100.00	100.00	100.00	0.00
	DEM	−0.467	0.001	−0.469	−0.464	100.00	100.00	100.00	0.00	100.00
	RD	0.173	0.187	−0.109	0.891	23.29	34.65	40.87	83.89	16.11
	VC	−0.051	0.128	−0.316	0.184	33.13	51.16	58.90	35.73	64.27
	Con_s	0.153	0.431	−0.683	1.477	47.99	55.96	61.16	65.23	34.77
2020	UL	0.212	0.008	0.197	0.235	100.00	100.00	100.00	100.00	0.00
	PD	0.165	0.097	0.004	0.468	54.55	66.53	72.87	100.00	0.00
	ED	0.004	0.008	−0.008	0.03	0.00	0.00	0.00	60.66	39.34
	COHESION	0.55	0.011	0.529	0.571	100.00	100.00	100.00	100.00	0.00
	AI	−0.144	0.006	−0.157	−0.133	100.00	100.00	100.00	100.00	0.00
	DEM	−0.315	0.392	−1.258	0.75	51.10	59.81	65.52	21.14	78.86
	RD	0.037	0.07	−0.045	0.286	13.85	19.39	27.42	59.81	40.19
	VC	−0.071	0.099	−0.281	0.108	30.02	38.33	43.19	24.65	75.35
	Con_s	−0.069	0.202	−0.328	0.2	76.31	84.28	86.09	52.57	47.43

3.4.3. Spatial Heterogeneity Analysis of Local Parameters in Multi-Scale GWR Model

The primary factors influencing CEs intensity in the multi-scale GWR model were analyzed using ArcGIS 10.3 software, and the spatial heterogeneity of their influence is illustrated in Figure 5. UL was the core factor influencing the growth of CEs intensity, with regression coefficients ranging from 0.1760 to 0.2810. From the perspective of spatial heterogeneity between 2000 and 2020, the regression coefficients of UL exhibited a decline over time from north to south, indicating that the impact of UL on CEs intensity in southern China was relatively limited. In 2000 and 2010, the areas with the highest UL regression coefficients were primarily located in the Ha-Chang, mid-southern Liaoning, Beijing-Tianjin-Hebei, Hu-Bao-E-Yu, and Northern Tianshan Mountain UAs in northern China. However, in 2020, only the Northern Tianshan Mountain UAs exhibited high UL regression coefficients, while the majority of northern UAs demonstrated a notable decline in UL regression coefficients, indicating a diminished impact of UL on CEs intensity in the Northern Tianshan Mountain UAs. This effect can be attributed to the ongoing process of new-type urbanization construction in China, which placed a premium on the protection and development of urban ecological environments, thereby contributing to a reduction in CEs intensity.

There was a positive association between AI and CEs intensity in many counties and a negative association in most counties. The results demonstrate that the element agglomeration gives rise to disparate spatial spillover effects for UAs at varying stages of development [67]. They also indicate that reducing CEs intensity was advantageous in UAs with a higher degree of agglomeration. The regression coefficients for AI exhibited a positive association and demonstrated a tendency to spread from the northwest to the central plains. In 2000, only the Northern Tianshan Mountain UAs indicated a positive association between AI and CEs intensity. However, a gradual increasing trend was identified in 2010 and 2020. In particular, in 2020, positively correlated AI regression coefficients were identified in the Hu-Bao-E-Yu, Lanxi, and Jinzhong UAs, as well as in some areas of the Guanzhong Plain UAs. The varying degree of UAs at different levels of economic development gives rise to the phenomenon whereby the agglomeration of population, economy, industry, and other factors will lead to positive spatial spillover effects, thereby increasing the CEs intensity. This is particularly the case in UAs with weak core driving capabilities and where the overall UL is still on the rise. In contrast, AI was significantly and negatively correlated with CEs intensity in the Yangtze River Delta, Pearl River Delta, and West Taiwan Strait UAs, indicating that the effects of economies of scale and technology spillover owing to UAs were conducive to reducing CEs intensity.

As illustrated in Figure 6, a positive association was observed between COHESION and CEs intensity, with the regression coefficients ranging from 0.0499 to 0.4950. From the perspective of spatial distribution between 2000 and 2020, the influence of COHESION on CEs intensity exhibited temporal variation. Specifically, areas with high COHESION regression coefficients in 2000 were mainly distributed in the Northern Tianshan Mountain UAs in the northwest and middle reaches of the Yangtze River and Yangtze River Delta UAs in the southeast. In 2010, the areas with the highest COHESION regression coefficients were primarily concentrated in UAs in the northwest, north, and northeast regions of China. In 2020, the areas exhibiting high coefficients of association extended further from the northeast to the northwest of China. These findings suggest that the cohesion index played a progressively facilitating role in the growth of CEs intensity in UAs in northern China, whereas its promoting effect on CEs intensity growth in southern China was markedly diminished in comparison. The siphon effect of UAs on resources and their radiation and driving capabilities on surrounding areas result in the relatively concentrated distribution of resources such as capital, professional knowledge, and technology. Technology, in turn, leads to green development and production, thereby reducing CEs.

While the distribution patterns of the influence of ED on CEs intensity exhibited temporal variation, they demonstrated overall consistency. The positively associated ED regression coefficients were primarily concentrated in the northern region and exhibited a decreasing gradient from north to south. The ED regression coefficients ranged from 0.0596 to 0.075, indicating that ED exerted a relatively minor influence on the growth of CEs intensity. Concurrently, the high ED regression coefficients observed in the northern region demonstrated a gradual upward trajectory between 2010 and 2020 when compared to those recorded in 2000.

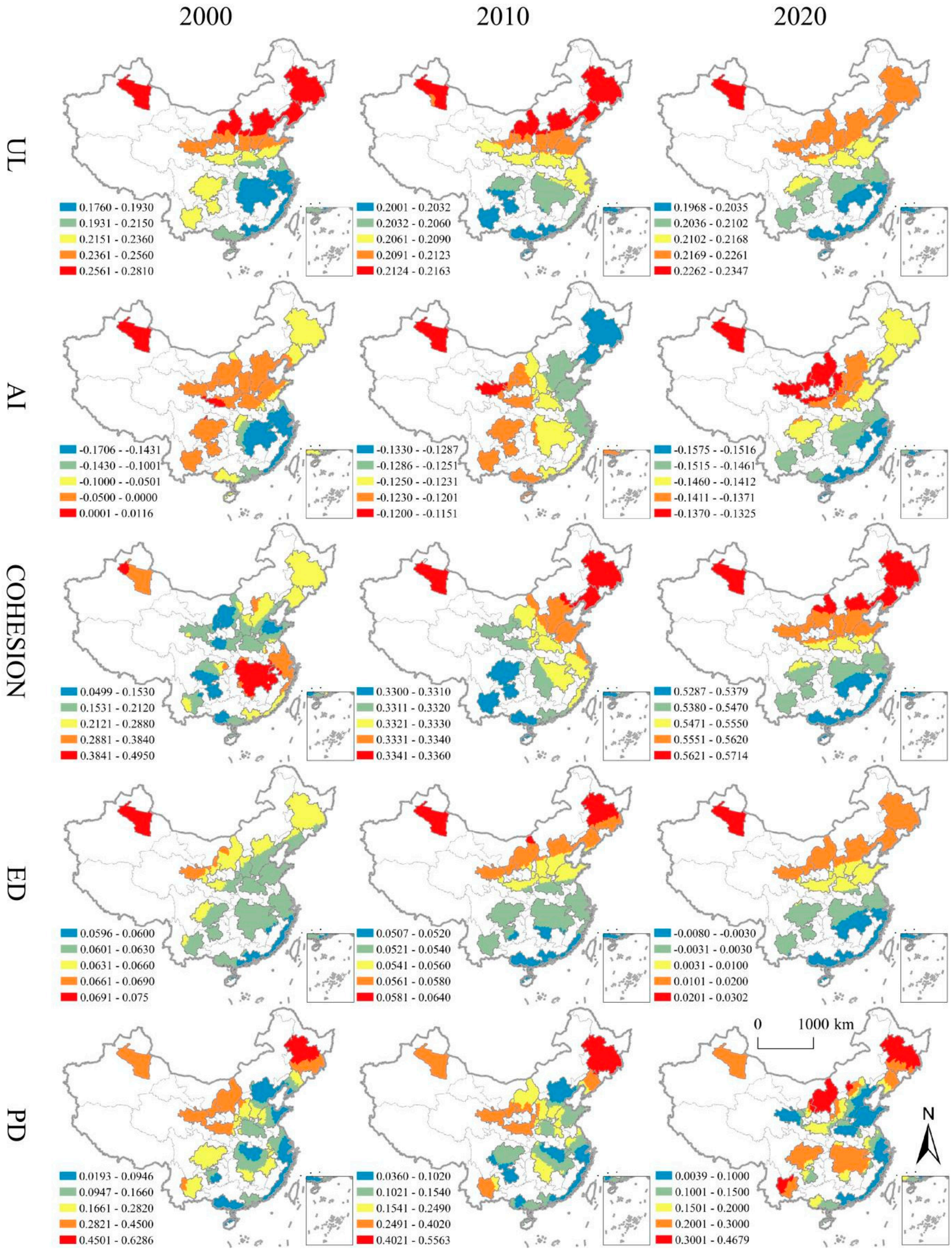

Figure 6. Regression coefficient of UL and urban form.

PD was positively associated with CEs intensity, displaying regression coefficients ranging from 0.0193 to 0.6282, which indicated that PD had a great impact on the growth of CEs intensity. Concerning the spatial distribution of heterogeneity between 2000 and 2020, areas with high PD regression coefficients in 2000 and 2010 were primarily situated in UAs in the northwest, northeast, and southwest regions of China. However, areas with high PD regression coefficients in 2020 displayed a distinct tendency to expand towards the central region, suggesting that the influence of PD on CEs intensity growth was progressively intensifying.

Furthermore, we examined the impact of distinct urbanization factors on CEs intensity, and the findings are presented in Figure S1 (all control variables have been controlled). In general, the various types of UL had a positive effect on CEs intensity. However, there was considerable spatial heterogeneity in the impact of different types of UL on CEs intensity. In particular, the process of population urbanization was observed to exert a more pronounced influence on CEs intensity in northern UAs than in southern UAs. The impact of land urbanization on CEs intensity was more pronounced and substantial in western UAs, yet the significant areas exhibited a gradual shift towards the south over time. The least impact on CEs intensity was observed in UAs in the North China Plain and Northeast China, while a more significant impact was evident in other regions.

4. Discussion

4.1. Summary of Findings

From 2000 to 2020, the CEs intensity of Chinese UAs increased continuously, but the growth rate slowed down evidently. High-intensity energy consumption, rising incomes, and population growth triggered by rapid socioeconomic development led to an increase in the contribution of UAs' CEs to total national CEs [68,69]. As urbanization improved, the impact of UL on local CEs changed from positive to negative [70]. Subsequently, the negative effect gradually diminished [70]. Due to differences in the spatial distribution of economic development, leading industrial structures, energy consumption, production, and lifestyles in Chinese UAs, the spatial distribution pattern of CEs intensity was significantly higher in coastal UAs than in inland UAs, with obvious spatial agglomeration characteristics [71].

This study found that CEs intensity of Chinese UAs was significantly and positively associated with UL. The regression results indicated that UL positively influenced the growth of CEs, urban land fragmentation aggravated the growth of CEs, and increased agglomeration reduced CEs. Previous studies have conducted extensive research between UL and CEs intensity. Zhang et al. (2016) [72] showed that China's urbanization process had a positive impact on CEs. Zhou and Dai (2013) [73] reported that urbanization led to an increase in CEs, and every 1% increase in the urbanization rate corresponded to a 1.61% increase in CEs. Guo and Liu (2012) [74], Zhao and Wang (2021) [75], and Xu and Zhou (2011) [71] also believed that UL would continue to amplify the increase of CEs and had a greater impact on eastern China, which was consistent with the results of this study. However, some researchers have proposed different views. Bi (2015) and Sun et al. (2013) [76,77] believed that UL had a dual effect of driving and braking CEs, and different stages of urbanization development showed significantly different modes of action. Fan and Zhou (2019), Feng and Li (2018), and Liu (2012) [78–80] further discussed the *U*-shaped relationship between UL and CEs, that is, the effect of UL on CEs showed a dynamic pattern of initial decrease followed by increase.

We also found apparent spatial heterogeneity in the influence of UL on CEs. There, high CEs intensity-high UL spatial correlations were mainly distributed in the core area of UAs, while low CEs intensity-low UL spatial correlations were mainly distributed in regions surrounding UAs. The siphoning effect of the core area has gradually increased, constantly attracting outflows of quality resources from neighboring areas. As a result, urbanization was also at a relatively low level with a relatively weak resource base in the peripheral cities [70]. In a previous study, UL and CEs in the whole country and eastern region showed an inverted *N*-type relationship, whereas UL and CEs in the central region showed an *N*-type relationship [81]. However, Wang and Shao (2014) [82] reported that UL and CEs in the eastern region were directly proportional, whereas urbanization in central and western China was inversely proportional to CEs. In addition, Hu and Jiang (2015) [83] proposed that urbanization in the Yangtze River Delta UAs had a restraining effect on CEs, while that in the Beijing-Tianjin-Hebei UAs had a significantly positive effect on CEs, and that in the Pearl River Delta UAs had a *U*-shaped relationship with CEs.

4.2. Policy Implications

4.2.1. Controlling Urban Expansion and Optimizing Spatial Layout

The findings of this research suggested that, in general, the process of urbanization in Chinese UAs continued to exert a positive influence on CEs. It is therefore imperative to exercise reasonable control over the scale of urban expansion and construction, particularly in eastern coastal UAs with high ULs. It is important that considerations be made concerning the ecological environment, and that the development scale and boundaries of various land types be controlled reasonably to ensure the integrity of the ecological environment [84]. Furthermore, researches has demonstrated that an increase in the fragmentation of urban landscapes can also increase CEs intensity. From the perspective of the urban landscape, it is essential that UAs prioritize considerations of land shape and compact layout while pursuing a reasonable expansion of construction land. Firstly, it is of utmost importance to avoid the excessive dispersion of urban land and instead seek a moderate concentration for low-carbon urban land layout to reduce CEs. Secondly, the phenomenon of the "heat island effect", which is caused by the excessive concentration of urban land, can also increase CEs. Accordingly, in the context of land use and layout, it is essential to prioritize the enhancement of ecological land design and the augmentation of carbon sequestration capabilities [85].

4.2.2. Implementing Differential Carbon Reduction Policies

The influence of UL on CEs exhibited notable regional variations. This also served to accentuate the spatial disparities in CEs intensity. It is therefore recommended that local governments implement differentiated emission reduction policies to reduce regional differences in CEs in UAs. Firstly, an investigation should be conducted into the development of land use CEs standards applicable to different UAs in China. This should be followed by the establishment of a mechanism that ensures a balance between the occupation of carbon sink space and the implementation of compensation measures. Core areas of UAs leverage the advantages of technological advancements to enhance energy efficiency and curtail CEs intensity while ensuring the continued sustenance of economic growth. Furthermore, marginal areas of UAs should facilitate the transformation of the industrial structure and the construction of a green industrial structure system that aligns with objective reality. This should be done in a manner that minimizes CEs generated along with economic growth and promotes the synchronous realization of low CEs and high-quality urbanization [86]. Secondly, it is possible to enhance regional collaboration within each UAs, fully capitalize on their respective advantages, collectively address pollution and other concerns, and effectively advance the implementation of emission reduction policies [84].

4.2.3. Promoting the Low Carbon Transition Development of New-Type Urbanization

As a principal component of the new-type urbanization paradigm, UAs bear a significant burden of responsibility for achieving energy conservation and emission reduction in China. Since the 18th National Congress of the Communist Party of China, the construction of new-type urbanization has been guided by ecological civilization. This has resulted in the integration of energy conservation and emission reduction as a significant component of the development process, to achieve a green and low-carbon urbanization model [87]. Consequently, in the context of promoting new-type urbanization, it is imperative to move beyond mere expansion of city size or increase in the urbanization rate. There is a need to pursue a sustainable urbanization path that is driven by scientific and technological innovation. Firstly, eastern and southern UAs, which demonstrate greater socioeconomic sustainability, should persistently investigate novel avenues for energy conservation and emission reduction. They should capitalize on the advantages and driving forces of their core regions, establish a networked system for energy conservation and emission reduction, and achieve coordinated regional emission reduction. Secondly, UAs in the central and western regions must expedite technological innovation, construct a green industrial system, facilitate the low-carbon transformation of leading industries, and enhance the economic vitality of the UAs. Finally, disparities in development levels among cities within the northern UAs underscore the necessity for strengthened regional coordinated development efforts. Furthermore, it is of paramount importance to expedite industrial modernization and diversification to fully realize the economic potential of the region.

4.3. Limitations and Future Directions

This study analyzed the spatiotemporal patterns of CEs intensity and UL, as well as the spatial non-stationary response of CEs intensity to UL in Chinese UAs. It aimed to elucidate the relationship between CEs and UL. However, the study has some shortcomings as follows. (1) The analysis of the spatiotemporal non-stationary response of CEs intensity to UL was conducted using a cross-sectional model, and the spatial impact of UL on CEs intensity was not analyzed based on a panel model. In subsequent studies, a panel model analogous to the spatial Durbin model could be employed to analyze the impact of UL on CEs intensity. (2) The relationship between UL and CEs intensity has not been explored from the perspective of telecoupling, which is particularly important in the 21st century. In subsequent research, the perspective of telecoupling could be introduced to analyze the telecorrelation between UL and CEs intensity.

5. Conclusions

In this study, the spatial patterns of CEs in Chinese UAs were analyzed using distribution dynamics models. The spatial relationships between UL and CEs were identified through the use of bivariate spatial autocorrelation analysis and multi-scale GWR. This study addressed the current deficiencies in understanding the relationship between UL and CEs in China's UAs. Furthermore, it examined the association between urban land patterns and CEs. The data thus provided a basis for promoting the low-carbon transformation and development of new-type urbanization, thereby facilitating the achievement of China's energy conservation and emission reduction targets. The principal findings were as follows. The results showed that CEs in Chinese UAs contributed about 80% of the total national CEs, with a gradually increasing trend. High CEs intensity was concentrated in the core area of the UAs. A significant spatial autocorrelation was found between UL and CEs intensity, among which low CEs intensity-low UL spatial dependence was the main type identified. The regression results indicated that UL positively influenced the growth of CEs, urban land fragmentation exacerbated the growth of CEs, and increased agglomeration reduced CEs. In addition, the effect of UL on CEs intensity showed significant spatial heterogeneity. From the perspective of spatial heterogeneity between 2000 and 2020, the regression coefficients of UL showed a decline over time from north to south, indicating that the impact of UL on CEs intensity in southern China was relatively weak. The overall regional development level of UAs in the south was higher than that in the north. The association between AI and CEs intensity was found to be positive in many counties and negative in most counties, indicating that a higher degree of agglomeration within UAs facilitated economies of scale and technology spillover, thereby reducing CEs intensity. DEM, COHESION, and VC had a significantly negative effect on CEs intensity, while RD had a significantly positive effect on CEs intensity.

In light of these findings, the CEs reduction strategies proposed in this study—controlling urban sprawl, optimizing spatial layouts, implementing differentiated carbon reduction policies, and fostering low-carbon transformation in new-type urbanization—offer valuable guidance for global UAs. These strategies can contribute to alleviating resource pressures, reducing CEs, enhancing land use efficiency, improving urban environments, fostering equitable development, and leading the global trend towards low-carbon transformation.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/land13081303/s1, Figure S1: Regression coefficient of different urbanization factors.

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Abbreviations

UAs, urban agglomerations; CEs, carbon emissions; UL, urbanization level; DEM, elevation; OLS, ordinary least squares; GWR, geographically weighted regression; NDVI, normalized difference vegetation index; AI, agglomeration index; ED, edge index; PD, patch density; COHESION, cohesion index; RD, road density; and VC, vegetation coverage rate.

References

1. Sun, W.; Ren, C. The impact of energy consumption structure on China's carbon emissions: Taking the Shannon-Wiener index as a new indicator. *Energy Rep.* **2021**, *7*, 2605–2614. [CrossRef]
2. Le Quere, C.; Jackson, R.B.; Jones, M.W.; Smith, A.J.; Abernethy, S.; Andrew, R.M.; De-Gol, A.J.; Willis, D.R.; Shan, Y.; Canadell, J.G.; et al. Temporary reduction in daily global CO_2 emissions during the COVID-19 forced confinement. *Nat. Clim. Change* **2020**, *10*, 647. [CrossRef]
3. Schuerch, M.; Spencer, T.; Temmerman, S.; Kirwan, M.L.; Wolff, C.; Lincke, D.; McOwen, C.J.; Pickering, M.D.; Reef, R.; Vafeidis, A.T.; et al. Future response of global coastal wetlands to sea-level rise. *Nature* **2018**, *561*, 231–234. [CrossRef] [PubMed]
4. Qiao, W.; Lu, H.; Zhou, G.; Azimi, M.; Yang, Q.; Tian, W. A hybrid algorithm for carbon dioxide emissions forecasting based on improved lion swarm optimizer. *J. Clean. Prod.* **2020**, *244*, 118612. [CrossRef]
5. Seto, K.C.; Dhakal, S.; Bigio, A.; Blanco, H.; Carlo Delgado, G.; Dewar, D.; Huang, L.; Inaba, A.; Kansal, A.; Lwasa, S.; et al. *Human Settlements, Infrastructure, and Spatial Planning*; Cambridge University Press: Cambridge, UK, 2014.
6. Luqman, M.; Rayner, P.J.; Gurney, K.R. On the impact of urbanisation on CO_2 emissions. *npj Urban Sustain.* **2023**, *3*, 6. [CrossRef]
7. Wang, Z.; Liao, J.; Chen, Z.; Zhang, D. Study of City Land Expansion and Carbon Emission Correlation Effect: Taking Changsha City as an Example. *J. Univ. South China (Sci. Technol.)* **2013**, *27*, 82–88. (In Chinese) [CrossRef]
8. Pan, S.P.; Guo, J.; Ou, M. Exploring the Coupling and Decoupling Relationship of Urbanization and Carbon Emissions in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 96808–96826. [CrossRef] [PubMed]
9. Fang, C. Progress and the future direction of research into urban agglomeration in China. *Acta Geogr. Sin.* **2014**, *69*, 1130–1144. (In Chinese) [CrossRef]
10. Fang, C.; Gao, Q.; Zhang, X.; Cheng, W. Spatiotemporal characteristics of the expansion of an urban agglomeration and its effect on the eco-environment: Case study on the northern slope of the Tianshan Mountains. *Sci. China Earth Sci.* **2019**, *62*, 1461–1472. [CrossRef]
11. Fang, C.; Liang, L.; Wang, Z. Quantitative simulation and verification of upgrade law of sustainable development in BeijingTianjin-Hebei urban agglomeration. *Sci. China Earth Sci.* **2019**, *62*, 2031–2049. [CrossRef]
12. Wang, Q.; Wang, X.; Li, R. Does urbanization redefine the environmental Kuznets curve? An empirical analysis of 134 Countries. *Sustain. Cities Soc.* **2022**, *76*, 103382. [CrossRef]
13. Micheli, F.; Mumby, P.J.; Brumbaugh, D.R.; Broad, K.; Dahlgren, C.P.; Harborne, A.R.; Holmes, K.E.; Kappel, C.V.; Litvin, S.Y.; Sanchirico, J.N. High vulnerability of ecosystem function and services to diversity loss in Caribbean coral reefs. *Biol. Conserv.* **2014**, *171*, 186–194. [CrossRef]
14. Xia, C.; Yeh, A.; Zhang, A. Analyzing spatial relationships between urban land use intensity and urban vitality at street block level: A case study of five Chinese megacities. *Landsc. Urban Plan.* **2020**, *193*, 103669. [CrossRef]
15. Fan, Y.; Liu, L.; Wu, G.; Wei, Y. Analyzing impact factors of CO_2 emissions using the STIRPAT model. *Environ. Impact Assess. Rev.* **2006**, *26*, 377–395. [CrossRef]

16. Xu, B.; Lin, B. How industrialization and urbanization process impacts on CO_2 emissions in China: Evidence from nonparametric additive regression models. *Energy Econ.* **2015**, *48*, 188–202. [CrossRef]
17. Zhu, C.; Gao, D. A research on the factors influencing carbon emission of transportation industry in "the Belt and Road Initiative" countries based on panel data. *Energies* **2019**, *12*, 2405. [CrossRef]
18. Amin, A.; Altinoz, B.; Dogan, E. Analyzing the determinants of carbon emissions from transportation in European countries: The role of renewable energy and urbanization. *Clean Technol. Environ. Policy* **2020**, *22*, 1725–1734. [CrossRef]
19. Dong, F.; Yu, B.; Hadachin, T.; Dai, Y.; Wang, Y.; Zhang, S.; Long, R. Drivers of carbon emission intensity change in China. *Resour. Conserv. Recycl.* **2018**, *129*, 187–201. [CrossRef]
20. Zhou, Y.; Poon, J.; Yang, Y. China's CO_2 emission intensity and its drivers: An evolutionary Geo-Tree approach. *Resour. Conserv. Recycl.* **2021**, *171*, 105630. [CrossRef]
21. Li, R.; Li, L.; Wang, Q. The impact of energy efficiency on carbon emissions: Evidence from the transportation sector in Chinese 30 provinces. *Sustain. Cities Soc.* **2022**, *82*, 103880. [CrossRef]
22. Friedmann, J. Four theses in the study of China's urbanization. *Int. J. Urban Reg. Res.* **2006**, *30*, 440–451. [CrossRef]
23. Chen, W.; Chi, G. Urbanization and ecosystem services: The multi-scale spatial spillover effects and spatial variations. *Land Use Policy* **2022**, *114*, 105964. [CrossRef]
24. Tian, Y.; Jiang, G.; Zhou, D.; Li, G. Systematically Addressing the Heterogeneity in the Response of Ecosystem Services to Agricultural Modernization, Industrialization and Urbanization in the Qinghai-Tibetan Plateau From 2000 to 2018. *J. Clean. Prod.* **2021**, *285*, 125323. [CrossRef]
25. Dong, F.; Long, R.; Li, Z.; Dai, Y. Analysis of carbon emission intensity, urbanization and energy mix: Evidence from China. *Nat. Hazards* **2016**, *82*, 1375–1391. [CrossRef]
26. Zhang, Y.; Liu, Z.; Zhang, H.; Tan, T. The impact of economic growth, industrial structure and urbanization on carbon emission intensity in China. *Nat. Hazards* **2014**, *73*, 579–595. [CrossRef]
27. Imhoff, M.; Tucker, C.; Lawrence, W. The use of multi- source satellite and geospatial data to study the effect of urbanization on primary productivity in the United States. *IEEE Trans. Geosci. Remote Sens.* **2000**, *38*, 2549–2556.
28. Milesi, C.; Elvidge, C.D.; Nemani, R.R.; Running, S.W. Assessing the impact of urban land development on net primary productivity in the southeastern United States. *Remote Sens. Environ.* **2003**, *86*, 401–410. [CrossRef]
29. Dai, S.; Zuo, S.; Ren, Y. A spatial database of CO_2 emissions, urban form fragmentation and city-scale effect related impact factors for the low carbon urban system in Jinjiang city, China. *Data Brief.* **2020**, *29*, 105274. [CrossRef] [PubMed]
30. Fang, C.; Wang, S.; Li, G. Changing urban forms and carbon dioxide emissions in China: A case study of 30 provincial capital cities. *Appl. Energy* **2015**, *158*, 519–531. [CrossRef]
31. Li, R.; Wang, Q.; Liu, Y.; Jiang, R. Per-capita carbon emissions in 147 countries: The effect of economic, energy, social, and trade structural changes. *Sustain. Prod. Consum.* **2021**, *27*, 1149–1164. [CrossRef]
32. Tan, R.; Liu, Y.; Liu, Y.; He, Q.; Ming, L.; Tang, S. Urban growth and its determinants across the Wuhan urban agglomeration, central China. *Habitat Int.* **2014**, *44*, 268–281. [CrossRef]
33. Shi, F.; Liao, X.; Shen, L.; Meng, C.; Lai, Y. Exploring the spatiotemporal impacts of urban form on CO_2 emissions: Evidence and implications from 256 Chinese cities. *Environ. Impact Asses.* **2022**, *96*, 106850. [CrossRef]
34. Li, J.; Huang, X.; Chuai, X.; Yang, H. The impact of land urbanization on carbon dioxide emissions in the Yangtze River Delta, China: A multiscale perspective. *Cities* **2021**, *116*, 103275. [CrossRef]
35. Wang, W.; Liu, L.; Liao, H.; Wei, Y. Impacts of urbanization on carbon emissions: An empirical analysis from OECD countries. *Energy Policy* **2021**, *151*, 112171. [CrossRef]
36. Alcantara, V.; Duarte, R. Comparison of energy intensities in European Union countries. Results of a structural decomposition analysis. *Energy Policy* **2004**, *32*, 177–189. [CrossRef]
37. Chen, J.; Shi, Q.; Shen, L.; Huang, Y.; Wu, Y. What makes the difference in construction carbon emissions between China and USA? *Sustain. Cities Soc.* **2019**, *44*, 604–613. [CrossRef]
38. Hoekstra, R.; Van den Bergh, J.C. Comparing structural decomposition analysis and index. *Energy Econ.* **2003**, *25*, 39–64. [CrossRef]
39. Peng, Z.; Wu, Q.; Li, M. Spatial characteristics and influencing factors of carbon emissions from energy consumption in China's transport sector: An empirical analysis based on provincial panel data. *Pol. J. Environ. Stud.* **2020**, *29*, 217–232. [CrossRef] [PubMed]
40. Wang, S.; Wang, Z.; Fang, C. Evolutionary characteristics and driving factors of carbon emission performance at the city level in China. *Sci. China Earth Sci.* **2022**, *65*, 1292–1307. [CrossRef]
41. Chen, W.; Wang, G.; Zeng, J. Impact of urbanization on ecosystem health in Chinese urban agglomerations. *Environ. Impact Asses.* **2023**, *98*, 106964. [CrossRef]
42. Li, Y.; Zhang, X.; Xia, C. Towards a greening city: How does regional cooperation promote urban green space in the Guangdong-Hong Kong-Macau Greater Bay Area? *Urban For. Urban Green.* **2023**, *86*, 128033. [CrossRef]
43. Yeh, A.; Chen, Z. From cities to super mega city regions in China in a new wave of urbanisation and economic transition: Issues and challenges. *Urban Stud.* **2020**, *57*, 636–654. [CrossRef]
44. Chen, W.; Gu, T.; Fang, C.; Zeng, J. Global urban low-carbon transitions: Multiscale relationship between urban land and carbon emissions. *Environ. Impact Asses.* **2023**, *100*, 107076. [CrossRef]

45. Chen, W.; Wang, G.; Gu, T.; Fang, C.; Pan, S.; Zeng, J.; Wu, J. Simulating the impact of urban expansion on ecosystem services in Chinese urban agglomerations: A multi-scenario perspective. *Environ. Impact Assess. Rev.* **2023**, *103*, 107275. [CrossRef]
46. Fang, C. China's urban agglomeration and metropolitan area construction under the new development pattern. *Econ. Geogr.* **2021**, *41*, 1–7. (In Chinese) [CrossRef]
47. Quah, D.T. Empirics for growth and distribution: Stratification, polarization, and convergence clubs. *J. Econ. Growth* **1997**, *2*, 27–59. [CrossRef]
48. Yang, L.; Chen, W.; Zeng, J.; Pan, S. Regional differences in spatial determinants of land urbanization in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 119260–119274. [CrossRef] [PubMed]
49. Yang, L.; Xu, H.; Pan, S.; Chen, W.; Zeng, J. Identifying the impact of global human activities expansion on natural habitats. *J. Clean. Prod.* **2024**, *434*, 140247. [CrossRef]
50. Wu, J.; Feng, Z.W.; Anwar, S. Assessing the pollution convergence across Chinese cities by considering ecological indicators: A continuous distribution dynamics approach. *Ecol. Indic.* **2021**, *126*, 107552. [CrossRef]
51. Liu, H.J.; Guo, L.X.; Qiao, L.C.; Shi, Y. Spatial-temporal pattern and dynamic evolution of logistics efficiency in China. *J. Quant. Tech. Econ.* **2021**, *38*, 57–74. (In Chinese) [CrossRef]
52. Shen, L.; Zhang, H.Y.; Li, W.J. Regional differences and dynamic evolution of China's inclusive finance. *J. Quant. Tech. Econ.* **2019**, *36*, 62–80. (In Chinese) [CrossRef]
53. Yang, W.; Deng, M.; Tang, J.; Jin, R. On the use of Markov chain models for drought class transition analysis while considering spatial effects. *Nat. Hazards* **2020**, *103*, 2945–2959. [CrossRef]
54. Agovino, M.; Crociata, A.; Sacco, P.L. Proximity effects in obesity rates in the US: A spatial Markov chains approach. *Soc. Sci. Med.* **2019**, *220*, 301–311. [CrossRef] [PubMed]
55. Yang, L.; Fang, C.; Chen, W.; Zeng, J. Urban-rural land structural conflicts in China: A land use transition perspective. *Habitat Int.* **2023**, *138*, 102877. [CrossRef]
56. Bai, X.; Shi, P.; Liu, Y. Realizing China's urban dream. *Nature* **2014**, *509*, 158–160. [CrossRef] [PubMed]
57. Peng, J.; Shen, H.; Wu, W.H.; Liu, Y.; Wang, Y. Net primary productivity (NPP) dynamics and associated urbanization driving forces in metropolitan areas: A case study in Beijing City, China. *Lands. Ecol.* **2016**, *31*, 1077–1092. [CrossRef]
58. Peng, J.; Tian, L.; Liu, Y.; Zhao, M.; Hu, Y.; Wu, J. Ecosystem services response to urbanization in metropolitan areas: Thresholds identification. *Sci. Total Environ.* **2017**, *607*, 706–714. [CrossRef] [PubMed]
59. Su, S.; Xiao, R.; Jiang, Z.; Zhang, Y. Characterizing landscape pattern and ecosystem service value changes for urbanization impacts at an eco-regional scale. *Appl. Geogr.* **2012**, *34*, 295–305. [CrossRef]
60. Wang, J.; Zhou, W.; Pickett, S.; Yu, W.J.; Li, W. A multiscale analysis of urbanization effects on ecosystem services supply in an urban megaregion. *Sci. Total Environ.* **2019**, *662*, 824–833. [CrossRef] [PubMed]
61. Ouyang, X.; Tang, L.; Wei, X.; Li, Y. Spatial interaction between urbanization and ecosystem services in Chinese UAs. *Land Use Policy* **2021**, *109*, 105587. [CrossRef]
62. Chen, W.; Zeng, J.; Zhong, M.; Pan, S. Coupling analysis of ecosystem services value and economic development in the Yangtze River Economic Belt: A case study in Hunan Province, China. *Remote Sens.* **2021**, *13*, 1552. [CrossRef]
63. Fotheringham, A.S.; Yang, W.; Kang, W. Multiscale Geographically Weighted Regression (MGWR). *Ann. Am. Assoc. Geogr.* **2017**, *107*, 1247–1265. [CrossRef]
64. Shen, T.; Yu, H.; Zhou, L.; Gu, H.; He, H. On hedonic price of second-hand houses in Beijing based on multi-scale geographically weighted regression: Scale law of spatial heterogeneity. *Econ. Geogr.* **2020**, *40*, 75–83. (In Chinese) [CrossRef]
65. Li, W.; Xie, S.; Wang, Y.; Huang, J.; Cheng, X. Effects of urban expansion on ecosystem health in Southwest China from a multi-perspective analysis. *J. Clean. Prod.* **2021**, *294*, 126341. [CrossRef]
66. Kafy, A.A.; Faisal, A.; Al Rakib, A.; Fattah, M.A.; Rahaman, Z.A.; Sattar, G.S. Impact of vegetation cover loss on surface temperature and carbon emission in a fastest-growing city, Cumilla, Bangladesh. *Build. Environ.* **2022**, *208*, 108573. [CrossRef]
67. Zhou, M.; Shao, W.; Jiang, K.; Huang, L. How does economic agglomeration affect carbon emissions at the county level in Liaoning China? *Ecol. Indic.* **2024**, *158*, 111507. [CrossRef]
68. Wang, Y.; Yang, X.; Guan, Y. Carbon emissions, energy consumption and economic growth: Mediating effect model based on Chinese provincial panel data. *J. Appl. Stat. Manag.* **2023**, *1*, 1–15. (In Chinese) [CrossRef]
69. Wang, Q.; Lin, J.; Zhou, K.; Fan, J.; Kwan, M.P. Does urbanization lead to less residential energy consumption? A comparative study of 136 countries. *Energy* **2020**, *202*, 117765. [CrossRef]
70. Liu, F.; Liu, C. Regional disparity, spatial spillover effects of urbanisation and carbon emissions in China. *J. Clean Prod.* **2019**, *241*, 118226. [CrossRef]
71. Xu, Y.; Zhou, S. An empirical study on urbanization and CO_2 emissions in China. *Resour. Environ. Yangtze Basin* **2011**, *20*, 1304–1309. (In Chinese)
72. Zhang, T.; Yang, J.; Sheng, P. The impacts and channels of urbanization on carbon dioxide emissions in China. *China Popul. Resour. Environ.* **2016**, *26*, 47–57. (In Chinese) [CrossRef]
73. Zhou, K.; Dai, X. An empirical study on the relationship between urbanization and carbon emission in China. *China Popul. Resour. Environ.* **2013**, *23*, 41–48. (In Chinese) [CrossRef]
74. Guo, J.; Liu, C. Impact of urbanization on carbon emissions intensity. *Urban Probl.* **2012**, *5*, 21–28. (In Chinese) [CrossRef]

75. Zhao, M.; Wang, D. Spatial differentiation and influencing mechanism of nearby urbanization in central and western China. *Acta Geog. Sin.* **2021**, *76*, 2993–3011. (In Chinese) [CrossRef]
76. Bi, X. The impact mechanism of urbanization on carbon emissions. *Shanghai J. Econ.* **2015**, *10*, 97–106. (In Chinese) [CrossRef]
77. Sun, C.; Jin, N.; Zhang, X.; Du, H. The impact of urbanization on the CO_2 emission in the various development stages. *Sci. Geogr. Sin.* **2013**, *33*, 266–272. (In Chinese) [CrossRef]
78. Fan, J.; Zhou, L. The Mechanism and Effect of Urbanization and Real Estate Investment on Carbon Emissions in China. *Sci. Geogr. Sin.* **2019**, *39*, 644–653. (In Chinese) [CrossRef]
79. Feng, D.; Li, J. Impacts of Urbanization on Carbon Dioxide Emissions in the Three UAs of China. *Resour. Environ. Yangtze Basin* **2018**, *27*, 2194–2200. (In Chinese) [CrossRef]
80. Liu, H. The influence of urbanization on carbon dioxide emissions: An empirical evidence from China. *Shanghai J. Econ.* **2012**, *24*, 24–35. (In Chinese) [CrossRef]
81. Yang, X.; Chen, H. Effect of urbanization on CO_2 emissions in China: Empirical study based on provincial panel data. *J. China Univ. Geosci. (Soc. Sci. Ed.)* **2013**, *13*, 32–37. (In Chinese) [CrossRef]
82. Wang, X.; Shao, Y. Impact of urbanization on energy consumption and carbon dioxide emission: Empirical study based on China's provincial panel data during 1995–2011. *Technol. Econ.* **2014**, *33*, 55–63. (In Chinese)
83. Hu, J.; Jiang, X. Effects of urbanization on carbon emissions from the perspective of UAs. *J. China Univ. Geosci. (Soc. Sci. Ed.)* **2015**, *15*, 11–21. (In Chinese) [CrossRef]
84. Zhang, N.; Sun, F.; Hu, Y.; Tang, J. Regional difference and spatial convergence of land use carbon emissions in three urban agglomerations of Yangtze River Economic Belt. *Environ. Sci.* **2024**, *45*, 4656–4669. (In Chinese) [CrossRef]
85. Li, S.; Wen, R.; Li, J.; Yang, H.; Chen, T.; Zhu, N. Impact of land use landscape pattern on carbon emission performance in five major urban agglomerations in China. *Econ. Geogr.* **2023**, *43*, 1–12. (In Chinese)
86. Wu, X.; Guan, W.; Zhang, H.; Wu, L. Spatio-temporal coupling characteristics and driving factors of carbon emission efficiency and high-quality development in Yangtze River Delta urban agglomeration. *Resour. Environ. Yangtze Basin* **2023**, *32*, 2273–2284. (In Chinese) [CrossRef]
87. Liu, S.; Jia, L.; Zhang, F.; Wang, R.; Liu, X.; Zou, L.; Tang, X. Do New Urbanization Policies Promote Sustainable Urbanization? Evidence from China's Urban Agglomerations. *Land* **2024**, *13*, 412. [CrossRef]