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Spatiotemporal Variation and Development Stage of CO_2 Emissions of Urban Agglomerations in the Yangtze River Economic Belt, China

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Abstract: As the world's largest developing country, China has played an important role in the achievement of the global CO_2 emissions mitigation goal. The monitoring and analysis of CO_2 emissions in the Yangtze River Economic Belt (YREB) urban agglomerations is strategic to the carbon peak and carbon neutrality in China. In this paper, we revealed the spatial and temporal variations of CO_2 emissions in Cheng-Yu urban agglomeration (CY-UA), Yangtze River Middle-Reach urban agglomeration (YRMR-UA), and Yangtze River Delta urban agglomeration (YRD-UA) in YREB and investigated the carbon emission development stage of YREB urban agglomerations. Particularly, a carbon emission development stage framework that considered the relationship between economic growth and carbon emissions was built based on Environmental Kuznets Curves (EKCs). Meanwhile, multiscale geographically weighted regression (MGWR) was used to analyze the impact of different influencing factors, including population (POP), GDP per capita (GDPPC), the proportion of secondary industry (SI), carbon emission intensity (CI), and urbanization (UR), on the CO_2 emissions of three urban agglomerations. The results illustrate the following: (1) The CO_2 emissions of YREB urban agglomerations decreased, with YRD-UA having the highest CO_2 emissions among the three urban agglomerations and contributing 41.87% of YREB CO_2 emissions in 2017. (2) CY-UA, YRMR-UA, and YRD-UA reached the CO_2 emissions peak in 2012, 2011, and 2020, respectively, all of which are at the low-carbon stage. (3) POP and GDPPC show the greatest impact on the CO_2 emissions of the three YREB urban agglomerations.

Keywords: carbon emission; Yangtze River Economic Belt; urban agglomeration; influencing factor; multiscale geographically weighted regression

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1. Introduction

The 21st century is the fastest-growing period of CO_2 emissions in human history [1]. CO_2 accounts for more than 70% of greenhouse gases, which enhance the trend of global warming [2]. The current global temperature has increased by 0.86 °C compared to the average temperature of the 20th century, which was 13.9 °C [3]. According to the Intergovernmental Panel on Climate Change (IPCC) projections, CO_2 emissions in 2030 will be 30% higher than those in 2010 [4]. Global sustainable development will be threatened by increasing temperatures and unstable climate change. Global warming has become an important environmental issue around the world [5], which has caused widespread and rapid changes in human society. Over the past decades, the international community has signed the United Nations Framework Convention on Climate Change, the Kyoto Protocol, the Copenhagen Accord, the Glasgow Climate Agreement, etc., to enable global sustainable development [6]. Nowadays, more than 130 countries have proposed carbon neutrality targets, which is one of the most important issues in the world [7].

To achieve the carbon neutrality target, it is necessary to monitor and analyze the spatial distribution and temporal patterns of CO_2 emissions. In recent years, numerous studies have been proposed to investigate the spatiotemporal variation of CO_2 emissions as well as the influencing factors. Xiao et al. examined the spatiotemporal characteristics of carbon emission efficiency in 136 countries and analyzed the influencing factors of carbon emission efficiency using the Tobit model [8]. Andreoni et al. conducted a decomposition analysis of energy-related CO_2 emissions in 33 countries worldwide using the index decomposition method in order to explore the drivers of CO_2 emissions variation [9]. Grodzicki et al. assessed the impact of renewable energy usage and urbanization levels on CO_2 emissions in Europe from 1995 to 2018 using a spatiotemporal approach [10]. Namahoro et al. analyzed the long-term impacts of energy intensity, renewable energy consumption, and economic growth on CO_2 emissions across regions and income levels in over 50 African countries [11]. Fragkias examined the relationship between urban scale and CO_2 emissions for metropolitan and micropolitan areas in the United States [12]. Wen and Shao used a nonparametric additive regression approach to explore the spatial and temporal variations of CO_2 emissions in China and analyze the main influencing factors [13].

As a developing country, China has set a goal and committed to achieving a carbon peak in 2030 and carbon neutrality in 2060 [14,15]. The Chinese government has allocated emission reduction targets to different regions [16]. YREB in China is a globally influential inland economic region and a pioneering demonstration belt for the construction of ecological civilization [17]. Together with the Belt and Road and the coordinated development of the Beijing–Tianjin–Hebei region, YREB is one of China's major regional economic development strategies [18]. With the rapid economic growth of cities in YREB, a large number of major projects have been concentrated, which are the main sources of CO_2 emissions [19]. In 2017, YREB contributed 40.8% of China's GDP and 43.6% of China's CO_2 emissions [20]. Specifically, there are three national urban agglomerations in YREB, namely, the Cheng-Yu urban agglomeration (CY-UA), the Yangtze River Middle-Reach urban agglomeration (YRMR-UA), and the Yangtze River Delta urban agglomeration (YRD-UA). Urban agglomeration is the manifestation of urban spatial clustering [21], and its development is always guided by regional integration policies [22]. As an important part of the national economy as well as the most concentrated areas of industrialization and urbanization [23], urban agglomerations are important areas for achieving carbon neutrality in China [24]. In the YREB urban agglomerations, a lot of heavy industrial projects are concentrated, and the massive consumption of fossil energy contributed to the high CO_2 emissions [25]. In 2017, the three urban agglomerations contributed 65.31% of the GDP as well as 78.39% of the CO_2 emissions of YREB. Particularly, the resource endowment and economic development of the upper, middle, and lower reaches of YREB are unbalanced where the cities show different CO_2 emissions patterns [26].

As a pivotal economic region, YREB plays an important role in implementing a carbon neutrality strategy. Hence, studying the CO_2 emissions of YREB urban agglomerations is conducive to revealing the interaction between economic development and carbon emissions, which provides insights for urban planning and regional sustainable development. The goal of this study was to explore the spatiotemporal variation and development stage of CO_2 emissions in YREB urban agglomerations. Specifically, this study focused on the CO_2 emissions patterns of urban agglomerations in YREB, China, and developed a carbon emission development stage framework that takes economic development and carbon emissions into account. The main contributions are summarized as follows: (1) The spatial and temporal variations of CO_2 emissions in urban agglomerations in YREB were revealed. (2) The carbon emission development stages of CY-UA, YRMR-UA, and YRD-UA were analyzed on the basis of EKCs. (3) The influencing factors of CO_2 emissions in three urban agglomerations were discussed using the multiscale geographic weighted regression (MGWR) model.

The rest of this paper is as follows: In Section 2, the datasets and methods are introduced. Section 3 shows the results. In Section 4, the discussions are presented. In Section 5, the conclusion is presented.

2. Datasets and Methods

2.1. Study Area

YREB covers an area of about 205.23×10^4 km^2 with 11 provinces and municipalities, with the population and GDP accounting for over 40% of China [27]. Since the release of the Outline of the Yangtze River Economic Belt Development Plan in September 2016, YREB has formed a development pattern of "one axis, two wings, three poles, and multiple points". As shown in Figure 1, CY-UA, YRMR-UA, and YRD-UA are the three poles of YREB. The administrative boundary data were obtained from the Resource and Environment Science and Data Center (https://www.resdc.cn/, accessed on 2 January 2023). Table 1 lists the cities contained in three urban agglomerations.

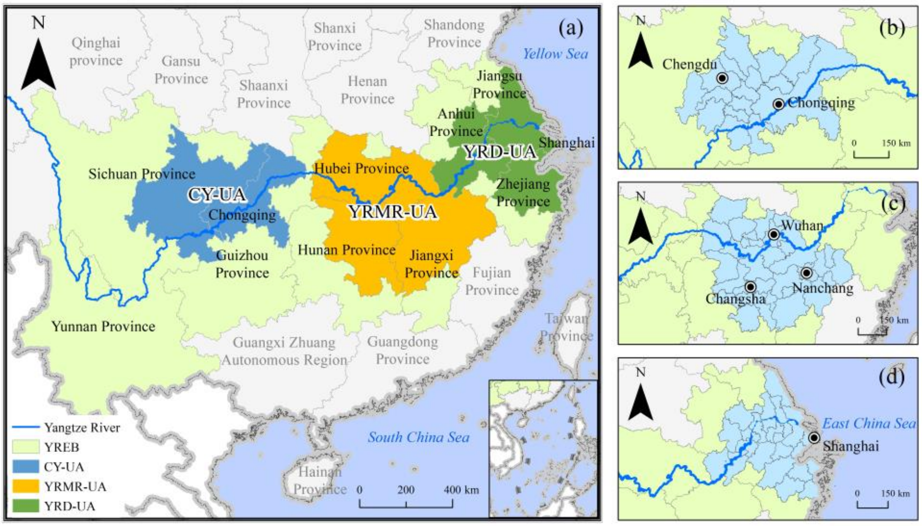

Figure 1. Locations of (**a**) YREB, (**b**) CY-UA, (**c**) YRMR-UA, and (**d**) YRD-UA.

Table 1. Cities in three YREB urban agglomerations.

	Cities
CY-UA	Chongqing, Chengdu, Dazhou, Deyang, Guangan, Leshan, Luzhou, Meishan, Mianyang, Nanchong, Neijiang, Suining, Yaan, Yibin, Ziyang, Zigong
YRMR-UA	Wuhan, Changsha, Nanchang, Changde, Ezhou, Fuzhou, Hengyang, Huanggang, Huangshi, Ji'an, Jingdezhen, Jingmen, Jingzhou, Jiujiang, Loudi, Pingxiang, Qianjiang, Shangrao, Tianmen, Xiantao, Xianning, Xiangtan, Xiangyang, Xiaogan, Xinyu, Yichang, Yichun, Yingtan, Yiyang, Yueyang, Zhuzhou
YRD-UA	Shanghai, Nanjing, Hangzhou, Anqing, Changzhou, Chizhou, Chuzhou, Hefei, Huzhou, Jiaxing, Jinhua, Ma'anshan, Nantong, Ningbo, Shaoxing, Suzhou, Taizhou, Taizhou, Tongling, Wuhu, Wuxi, Xuancheng, Yancheng, Yangzhou, Zhenjiang, Zhoushan

2.2. Datasets

2.2.1. CO_2 Emissions Data

CO_2 emissions data were obtained from the Multi-resolution Emission Inventory model for Climate and air pollution research (MEIC), which is a bottom-up multi-scale emission inventory model developed by Tsinghua University [28,29]. MEIC aims to build a high-resolution global-scale, multi-scale anthropogenic source greenhouse gas and air pollutant emission inventory model. The MEIC CO_2 emissions data at a 0.25-degree grid resolution contains industry sources, power sources, residential sources, and transportation sources (http://meicmodel.org.cn/, accessed on 29 May 2023). Based on China's measured emission factors, MEIC is more suitable than the IPCC method for the assessment of China's CO_2 emissions [30]. Meanwhile, MEIC has the advantages of objectivity, stability, high precision, and wide coverage and provides multi-year, different spatial scales, dynamic, and continuous CO_2 emissions monitoring information.

2.2.2. Socio-Economic Data

Based on numerous previous studies on CO_2 emissions from urban agglomerations [31–33], population (POP), GDP per capita (GDPPC), the proportion of secondary industry (SI), carbon emission intensity (CI), and urbanization (UR) were selected as the influencing factors of CO_2 emissions in this study. All data were derived from the China City Statistical Yearbook (2009–2018 editions).

Table 2 reports the influencing factors used in this study. POP represents the size of the population. GDPPC is the ratio of GDP to total population, which represents the regional economic development level. SI is the ratio of the value added of the secondary industry's GDP to total GDP, which represents the industrial structure. The resource endowments in the upper, middle, and lower reaches of YREB are unbalanced, and the industrial structure differs greatly [34]. CI is the ratio of total CO_2 emissions to GDP, which represents the technology level. UR represents the urbanization level.

Table 2. Brief description of influencing factors.

Factor	Abbreviation	Description	Unit
CO_2 emissions	CE	Total anthropogenic CO_2 emissions	10^4 tons
Population	POP	Total resident population	person
GDP per capita	GDPPC	GDP/Population	10^4 yuan/person
Proportion of secondary industry	SI	Added value of the secondary industry/GDP	%
Carbon emission intensity	CI	CO_2 emissions/GDP	ton/10^4 yuan
Urbanization	UR	Non-agricultural population/Population	%

POP, GDPPC, SI, CI, and UR were used to construct the MGWR model to analyze the influencing factors of CO_2 emissions in YREB urban agglomerations. Moreover, GDPPC was used in EKCs to depict economic growth.

2.3. Spatial Autocorrelation

2.3.1. Global Autocorrelation

Global Moran's I is a typical spatial autocorrelation index that measures the degree of spatial autocorrelation of CO_2 emissions in each urban agglomeration [35]. It determines whether the geographic phenomenon is aggregated. The calculation formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{y})(x_j - \overline{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)\sum_{j=1}^{n}(x_i - \overline{x})^2} \tag{1}$$

where n is the number of units in each urban agglomeration, x_i and x_j denote the CO_2 emissions of spatial units i and j, respectively, $\overline{x}$ denotes the average CO_2 emissions of each urban agglomeration, and W_{ij} denotes the spatial weight matrix.

The value of I ranges from -1 to 1. $I > 0$ indicates positive spatial autocorrelation, and the observations tend to be spatially clustered. The closer I is to 1, the stronger the aggregation. $I < 0$ indicates negative spatial autocorrelation, and the observations tend to be dispersed. The closer I is to -1, the more dispersed it is. I = 0 indicates that there is no spatial autocorrelation, and the observations are randomly distributed.

2.3.2. Local Autocorrelation

The local indicators of spatial association (LISA) are used to describe the correlation between a spatial unit and its neighboring unit [36], and the formula is as follows:

$$I_i = \frac{(x_i - \overline{x})}{S^2} \sum_{j=1}^{m} W_{ij}(x_j - \overline{x}), S^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \overline{x}_i)^2 \quad (2)$$

where x_i and x_j denote the CO_2 emissions of spatial units i and j, respectively, $\overline{x}$ denotes the average CO_2 emissions of the urban agglomeration, S^2 denotes the variance of CO_2 emissions of spatial units, W_{ij} denotes the spatial weight matrix, n denotes the number of spatial units in the urban agglomeration, and m denotes the number of neighboring units of unit i.

I_i > 0 means that the observations of this spatial unit and its neighboring units show a positive correlation, as high values are surrounded by high values (H-H), or low values are surrounded by low values (L-L). I_i < 0 shows a negative correlation, as high values are surrounded by low values (H-L), or low values are surrounded by high values (L-H).

2.4. Carbon Emission Development Stage

2.4.1. Environmental Kuznets Curve (EKC)

EKC depicts the inverted U-shaped relationship between economic growth and carbon emissions [37]. In this paper, CI, CO_2 emissions per capita (CEPC), and CE are selected as indicators of carbon emissions. Meanwhile, GDPPC is used as an economic growth indicator. In this study, the quadratic polynomial is used to represent EKC, and if the coefficients of the cubic term were not significant, the quadratic polynomial is used to represent EKC [38].

$$\ln(E) = \beta_0 + \beta_1(\ln G) + \beta_2(\ln G)^2 + \beta_3(\ln G)^3 + \varepsilon \quad (3)$$

where E denotes carbon emission index, β_0 is a constant term, $\ln G$ denotes the natural logarithm of GDPPC, β_1, β_2, and β_3 are the primary, secondary, and tertiary coefficients, respectively, and ε is the error term.

2.4.2. Carbon Emission Development Stage Division Based on EKCs

Urban agglomerations exhibit different carbon emission characteristics at different stages of economic development. It is necessary to consider the development stage of carbon emissions with the state of economic development. As shown in Figure 2, there are three types of EKCs that present a relationship between carbon emissions and economic growth [39]: (1) EKC with CI, where GDPPC is the independent variable and CI is the dependent variable; (2) EKC with CE, where GDPPC is the independent variable and CE is the dependent variable; and (3) EKC with CEPC, where GDPPC is the independent variable and CEPC is the dependent variable. There is a turning point for each curve, namely TP_1, TP_2, and TP_3. The development stage of carbon emissions can be divided into four stages based on the three TPs of the EKCs. S_1 is the rapid growth stage, where the carbon emission index increases rapidly with economic growth; S_2 is the pre-peak stage, where the carbon emission index continues to grow but at a slower rate and decreases until it reaches the peak; and S_3 is the over-peak stage, in which the carbon emission index starts to decrease. S_4 is the low-carbon stage, in which the carbon emission index gradually decreases to a lower level.

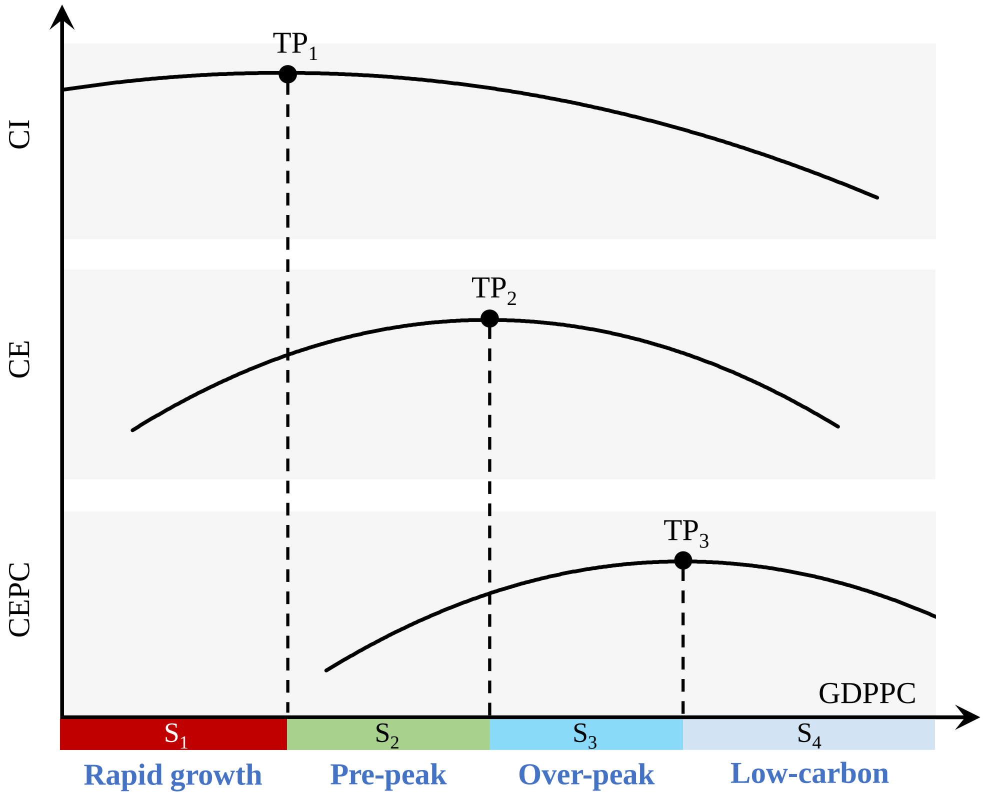

Figure 2. Carbon emission development stage based on EKCs.

2.5. MGWR Model

MGWR is an extension of geographic weighted regression (GWR) and has been widely used in the analysis of spatial relationships of explanatory variables. GWR is a model for geographic analysis that allows the model parameters to be verified based on a specific location [40]. The GWR model is formulated as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{n} \beta_j(u_i, v_i) x_{ij} + \varepsilon_i \tag{4}$$

where i represents the i-th unit, (u_i, v_i) are the latitude and longitude coordinates of city i, y_i is the CO_2 emissions of unit i, $\beta_0(u_i, v_i)$ is the intercept at i, $\beta_j(u_i, v_i)$ is the regression coefficient of the j-th variable of unit i, j denotes the uniform bandwidth of the regression coefficient, x_{ij} is the j-th influencing factor for unit i, and ε is the error term of i. When $\beta_j(u_i, v_i)$ is a constant, GWR is equal to the ordinary least squares (OLS) model.

However, the bandwidth of GWR is constant, and it cannot explain the phenomena, which involve numerous spatial processes with various [41]. Therefore, Fotheringham et al. (2017) proposed a multiscale geographically weighted regression (MGWR) model [42]. MGWR allows an optimal bandwidth for the explanatory variables based on local regression. MGWR is formulated as follows:

$$y_i = \beta_{bw0}(u_i, v_i) + \sum_{j=1}^{n} \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \tag{5}$$

where $bw0$ denotes the bandwidth used for the regression coefficient of the global variable, bwj denotes the bandwidth used for the regression coefficient of the j-th variable, and the other variables have the same meaning as in the GWR model.

3. Results

3.1. Spatiotemporal Variation of CO_2 Emissions

3.1.1. Temporal Variation of CO_2 Emissions

Figure 3 shows the CO_2 emissions of three urban agglomerations in YREB during 2008–2017. The CO_2 emissions of three urban agglomerations reached their peak around 2012–2013 and then began to decrease, with the lowest emissions of the three urban agglomerations in 2017. Moreover, the CO_2 emissions of YRD-UA were much higher than those of CY-UA and YRMR-UA, where 41.87% of the CO_2 emissions in YREB were contributed by YRD-UA. YRD-UA had entered the middle and late stages of urban agglomeration development with a higher level of regional integration and stronger comprehensive strength [43]. The CO_2 emissions of CY-UA were the lowest among the urban agglomerations since CY-UA was at the initial stage of urban agglomeration development with fewer megacities [44].

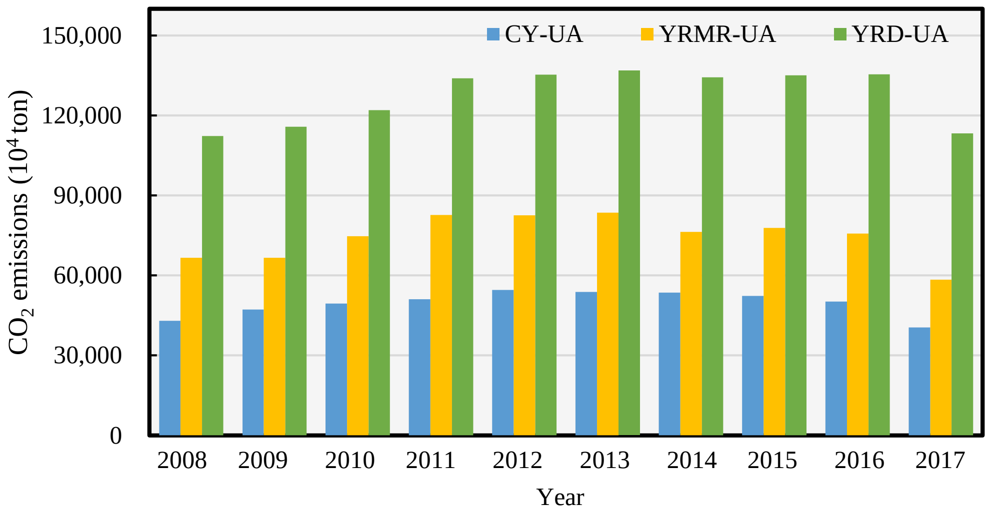

Figure 3. The CO_2 emissions of the three urban agglomerations from 2008 to 2017.

Since 2013, the CO_2 emissions of three YREB urban agglomerations have shown a decreasing trend; CY-UA reached its peak around 2012, while YRMR-UA and YRD-UA reached their peaks around 2013. Specifically, the CO_2 emissions in YRMR-UA declined most significantly, while the CO_2 emissions decline in YRD-UA was relatively stable. In 2016, a symposium on comprehensively advancing the development of the sustainable development of YREB was held for the first time, highlighting the importance of ecological conservation and environmental management [45]. The significant reduction of CO_2 emissions in 2017 illustrated the effectiveness of government policies.

3.1.2. Spatial Variation of CO_2 Emissions

Figure 4 shows the CO_2 emissions in 2008 and 2017. The 10-year average CO_2 emissions of CY-UA was 49,553 × 10^4 tons, with the low-value area distributed in the western mountainous area and northern mountainous areas, and the high-value area distributed in the urban areas around Chongqing and Chengdu. The 10-year average CO_2 emissions of YRMR-UA was 74,461 × 10^4 tons, with the low-value area distributed in the southern mountainous area and the border of Jiangxi and Hubei provinces, and the high-value area distributed in Wuhan, Changsha, and Nanchang. For YRD-UA, the 10-year average CO_2 emissions was 127,413 × 10^4 tons, with the low-value areas distributed in the southwestern mountains and western and northern plains, and the high-value areas distributed in Shanghai, Hangzhou, Nanjing, and the surrounding areas. Notably, the CO_2 emissions of several large cities, such as Chengdu in the CY-UA and Wuhan in the YRMR-UA, decreased in 2017 compared to 2008.

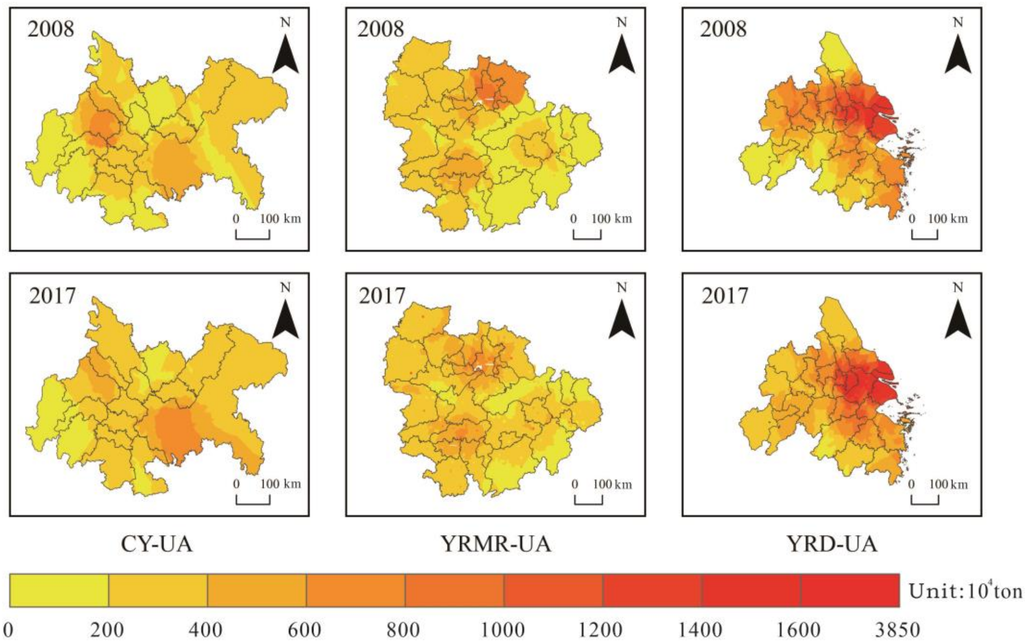

Figure 4. Spatial variation of CO_2 emissions in the three urban agglomerations in 2008 and 2017.

3.1.3. Spatial Aggregation of CO_2 Emissions

Table 3 shows the global autocorrelation performance. The *Z* score is a multiple of the standard deviation, and the *p* value indicates probability. *Z* is correlated with *p*, where $p < 0.05$ indicates that the confidence level is greater than 95% [46]. CY-UA and YRD-UA presented significant spatial aggregation characteristics. The Moran's *I* of CY-UA in 2008 and 2017 were 0.146 and 0.173, respectively, where the spatial autocorrelation of CO_2 emissions increased. The Moran's *I* of YRMR-UA in 2008 and 2017 was 0.034 and 0.045, respectively. As for YRD-UA, the Moran's *I* was 0.180 and 0.135 in 2008 and 2017, respectively.

Table 3. Global spatial autocorrelation of CO_2 emissions in three urban agglomerations.

2008	CY-UA	YRMR-UA	YRD-UA	2017	CY-UA	YRMR-UA	YRD-UA
Moran's *I*	0.146	0.034	0.180	Moran's *I*	0.173	0.045	0.135
Z score	4.260	0.969	3.257	*Z* score	5.463	1.105	2.427
p value	0.000	0.333	0.001	*p* value	0.000	0.269	0.015

Figure 5 shows the spatial aggregation characteristics of the CO_2 emissions of three urban agglomerations. For CY-UA, the H-H clusters and L-H clusters were distributed around Chongqing and Chengdu, and the L-L clusters were distributed in the western mountainous areas and scattered in the south and east. The cluster pattern of CO_2 emissions in CY-UA can be described as high in the middle and low around, and the overall pattern has not changed in the decade. For YRMR-UA, the H-H clusters mainly appeared in the north area, the L-H clusters mainly appeared around Wuhan, Changsha, and Nanchang, and the L-L clusters appeared in the southeast area. The cluster pattern of CO_2 emissions in YRMR-UA was high in the north and low in the south. For YRD-UA, the H-H clusters and L-H clusters were mainly distributed in the eastern coastal area, including Shanghai and Nanjing, while the L-L clusters were scattered in the south and southwest areas. The cluster pattern of CO_2 emissions in YRD-UA was high along the coast and low in the southwest.

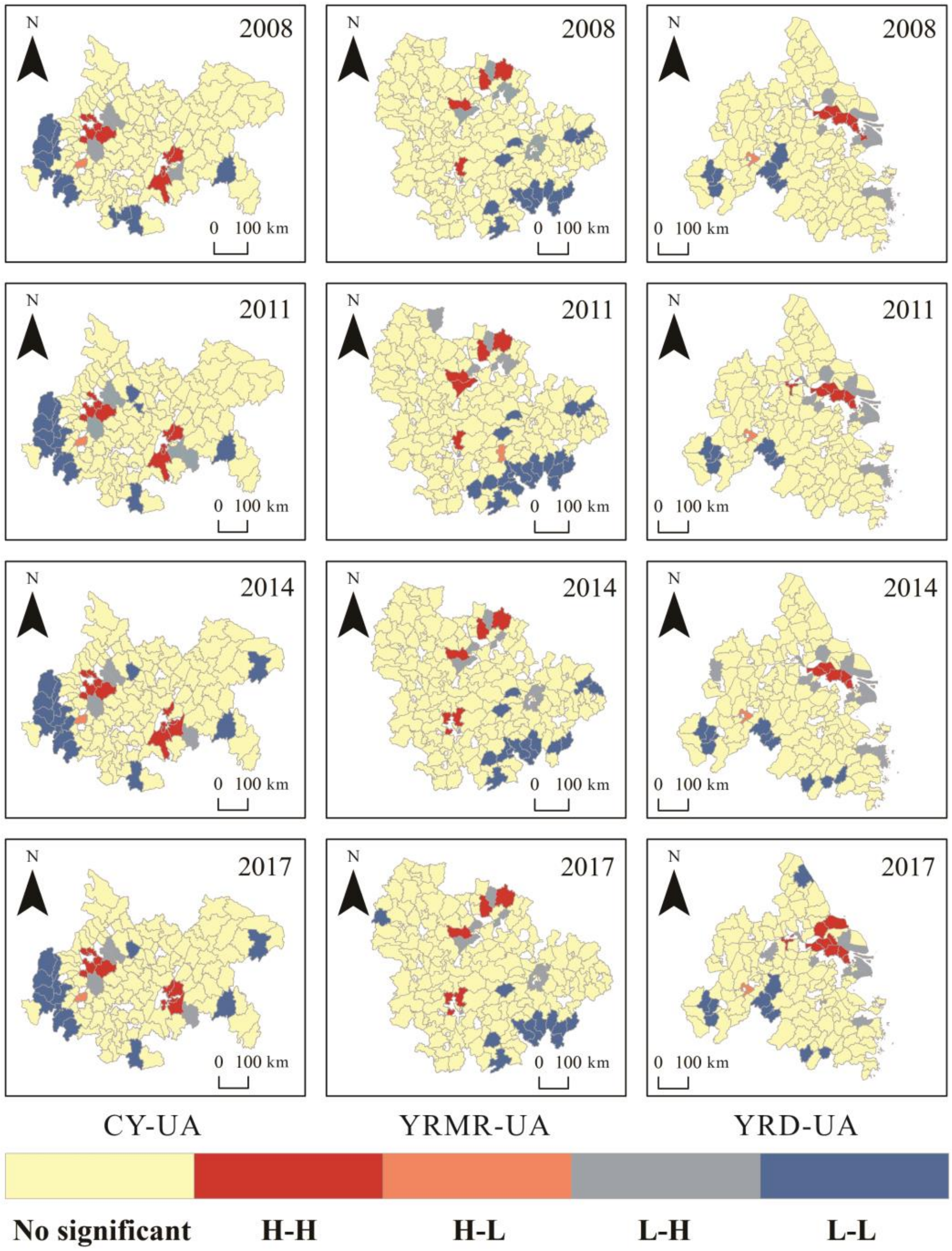

Figure 5. Spatial autocorrelation of CO_2 emissions in the three urban agglomerations.

3.2. Carbon Emission Development Stage Analysis

Figure 6 shows the relationship between carbon emissions and GDPPC for CY-UA. The carbon emission development stage of CY-UA could be divided into three stages: S_1 (–2005), S_2 (2005–2012), and S_4 (2012–). S_3 and S_4 of CY-UA largely overlapped and could be combined into one stage. The peak time of CO_2 emissions in CY-UA was around 2011, and CY-UA is at the low-carbon stage.

Figure 7 shows the relationship between carbon emissions and GDPPC for YRMR-UA. Similar to CY-UA, the S_3 and S_4 stages of YRMR-UA were combined. The YRMR-UA CO_2 emissions could be divided into three stages: S_1 (–2008), S_2 (2008–2011), and S_4 (2011–). The peak time of CO_2 emissions in YRMR-UA was around 2011, and YRMR-UA is at the low-carbon stage.

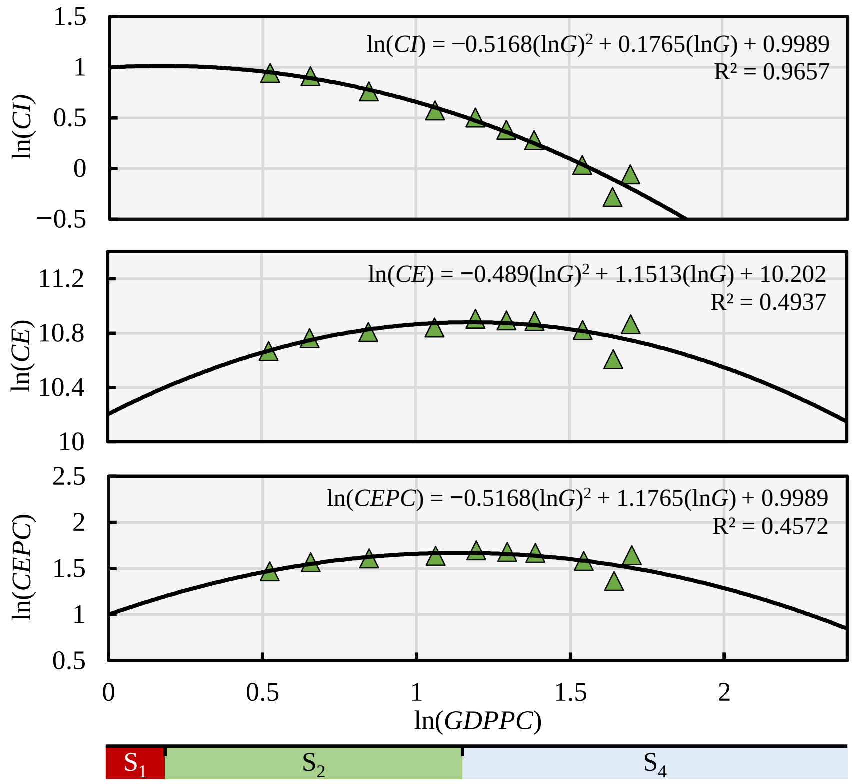

Figure 6. Carbon emission development stage of CY-UA.

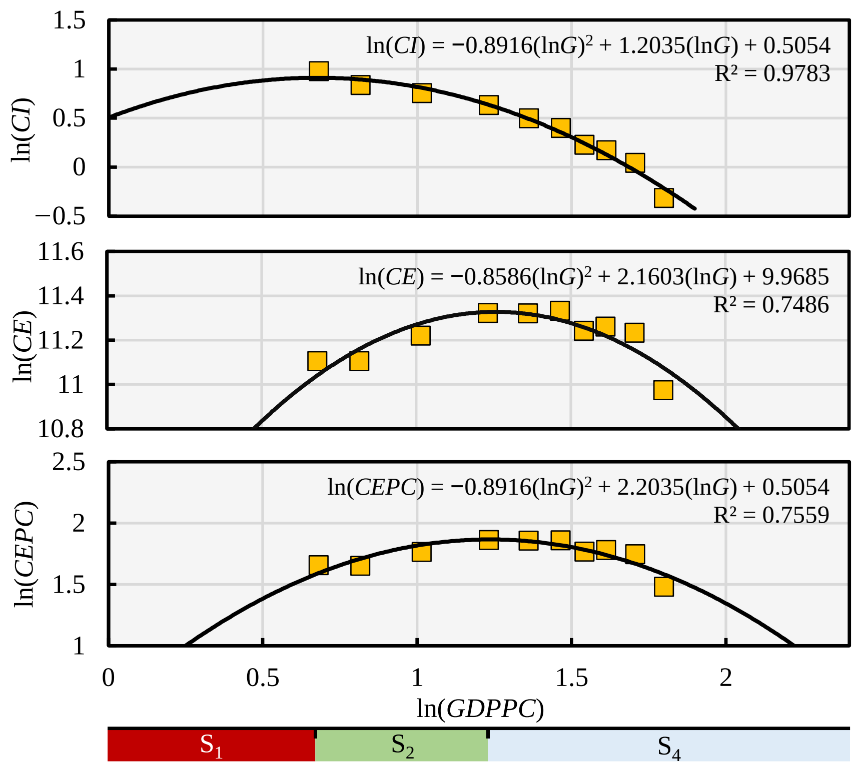

Figure 7. Carbon emission development stage of YRMR-UA.

Figure 8 shows the relationship between carbon emissions and GDPPC for YRD-UA. The emissions of YRD-UA could be divided into four stages: S_1 (–2005), S_2 (2005–2020), S_3 (2020–2022), and S_4 (2022–). The CO_2 emissions of YRD-UA reached the peak around 2020, and YRD-UA was at S_4 stage. Obviously, the actual CO_2 emissions peaked earlier than the carbon emission development stage. It could be concluded that the Yangtze River Delta integration policy strongly deepened the industrial division of labor and industrial transfer among cities, which contribute to the reduction of CO_2 emissions.

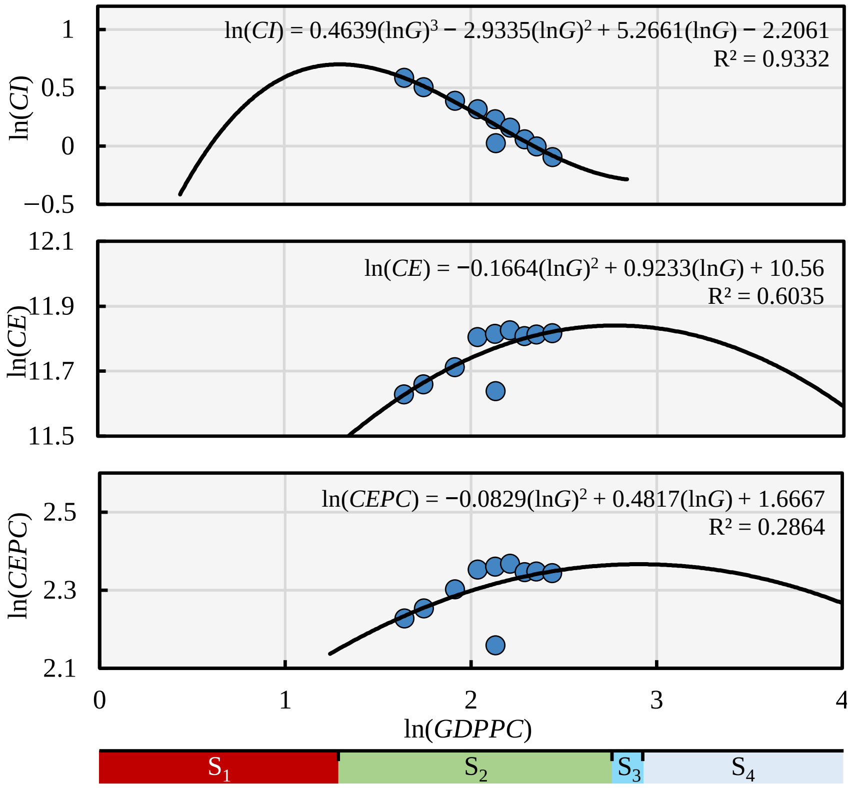

Figure 8. Carbon emission development stage of YRD-UA.

3.3. Model Comparison

3.3.1. Comparison of Model Performance

Table 4 shows the statistical results of OLS, GWR, and MGWR. R^2 is the coefficient of determination. Adjusted R^2 excludes the effect of the number of independent variables on R^2. AICc denotes the corrected Akaike information criterion, which is a relative measure of the goodness of fit [47]. RSS is the sum of squared errors. The effective number of parties (ENP) is a trade-off between the variance of the fitted values and the deviation of the coefficient estimates to measure the value of the equilibrium point.

Table 4. Comparison of OLS, GWR, and MGWR indicators from 2008–2017.

Year	**Model**	**R^2**	**Adjusted R^2**	**AICc**	**RSS**	**ENP**
2008	MGWR	0.96	0.95	5.38	2.85	11.42
	GWR	0.96	0.95	7.40	2.80	12.52
	OLS	0.93	0.92	1159.39	/	/
2011	MGWR	0.95	0.94	13.24	3.33	10.42
	GWR	0.95	0.94	17.48	3.81	8.61
	OLS	0.93	0.92	1177.63	/	/
2014	MGWR	0.95	0.94	12.45	3.35	10.01
	GWR	0.95	0.94	13.92	3.59	8.83
	OLS	0.93	0.93	1165.29	/	/
2017	MGWR	0.88	0.87	74.08	8.12	9.88
	GWR	0.87	0.86	75.64	8.80	8.43
	OLS	0.86	0.85	1204.20	/	/

As shown in Table 4, compared to GWR and OLS, MGWR gave higher R^2, adjusted R^2, and ENP, with lower AICc and RSS, indicating that MGWR had a better local fit and less information loss. Meanwhile, the spatial distribution of R^2 for GWR and MGWR is presented in Figure 9. CY-UA shows a higher R^2 than the other urban agglomerations.

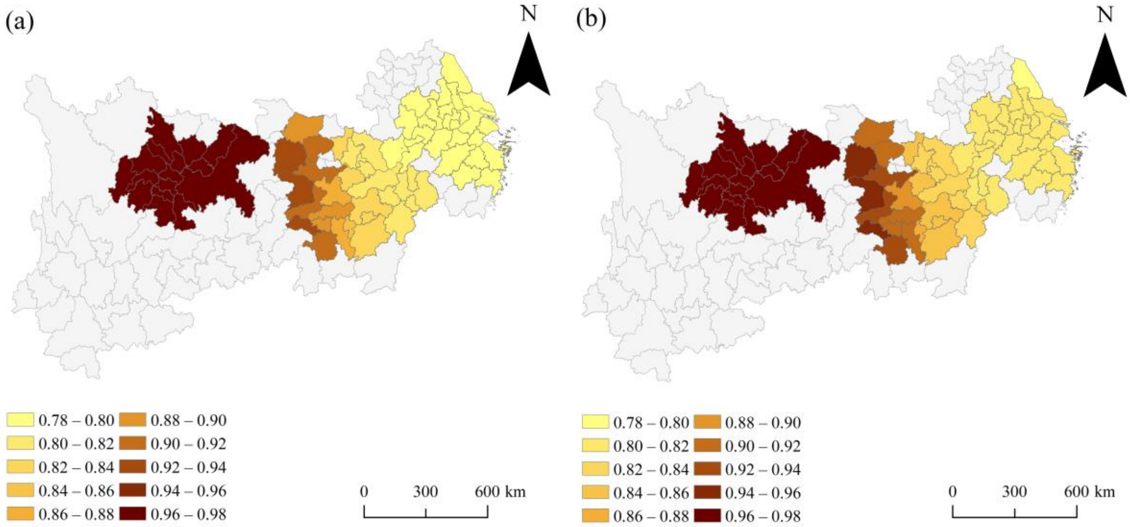

Figure 9. Distribution of the local R^2 for (**a**) GWR and (**b**) MGWR in 2017.

3.3.2. Comparison of Model Bandwidth

Table 5 presents the bandwidths of each influencing factor for GWR and MGWR in different years. In GWR, the factors shared the same bandwidth, while they were assigned to different bandwidths in MGWR. The different values of bandwidth demonstrated the spatial heterogeneity of factors, by which the diversity of influencing factors can be better represented [48].

Table 5. Bandwidths of different influencing factors in MGWR and GWR.

Factors	2008		2011		2014		2017	
	MGWR	GWR	MGWR	GWR	MGWR	GWR	MGWR	GWR
POP	66	51	68	67	68	66	68	69
GDPPC	48	51	59	67	53	66	68	69
SI	68	51	68	67	68	66	68	69
CI	44	51	48	67	68	66	52	69
UR	46	51	46	67	46	66	44	69

3.4. Influencing Factors for CO_2 Emissions

Table 6 shows the descriptive statistics of the regression coefficients of influencing factors in MGWR. It can be seen that the rank of the generated regression coefficients was POP > GDPPC > CI > UR > SI. Obviously, POP and GDPPC presented the highest regression coefficients. The coefficient of POP is positive, indicating that the rise of population will promote the CO_2 emissions of urban agglomerations in YREB. GDPPC presented the second highest regression coefficient, indicating that GDPPC had a facilitating effect on CO_2 emissions. The coefficients of UR and SI were much lower, and their impact on CO_2 emissions was not significant.

Table 6. Statistics of regression coefficients for different influencing factors in MGWR.

Factors	Year	Min	Median	Max	Mean	STD
POP	2008	0.637	0.818	0.992	0.814	0.134
	2011	0.664	0.814	0.89	0.79	0.089
	2014	0.705	0.805	0.961	0.821	0.102
	2017	0.719	0.732	0.743	0.733	0.007
GDPPC	2008	0.594	0.659	0.678	0.647	0.03
	2011	0.591	0.63	0.647	0.625	0.019
	2014	0.635	0.647	0.66	0.65	0.007
	2017	0.183	0.192	0.234	0.201	0.018
SI	2008	−0.034	−0.017	0.106	0.011	0.052
	2011	−0.035	−0.027	0.011	−0.019	0.017
	2014	0.016	0.022	0.047	0.028	0.012
	2017	0.037	0.065	0.083	0.063	0.015
CI	2008	0.098	0.184	0.285	0.202	0.066
	2011	0.105	0.171	0.3	0.195	0.066
	2014	0.082	0.16	0.269	0.177	0.063
	2017	0.157	0.236	0.509	0.262	0.091
UR	2008	−0.068	0.075	0.161	0.041	0.07
	2011	−0.038	0.038	0.111	0.027	0.038
	2014	−0.048	−0.044	−0.004	−0.033	0.017
	2017	0.132	0.214	0.408	0.255	0.108

Figure 10 shows the spatial distribution of the regression coefficients of POP. There was a significant positive correlation between POP and CE, where an increase in population will increase energy consumption and thus produce more CO_2 emissions [49]. The impact of POP on CE was significant in YRD-UA. YRD-UA was an important economic center in China, which provided sufficient jobs and attracted a large number of migrants [50]. Traffic congestion caused by population concentration was not conducive to adequate combustion of fuels [51], leading to an increase in transportation CO_2 emissions. The transportation CO_2 emissions in YRD-UA amounted to 9971.78×10^4 tons in 2017, which is approximately equal to the sum of CY-UA and YRMR-UA.

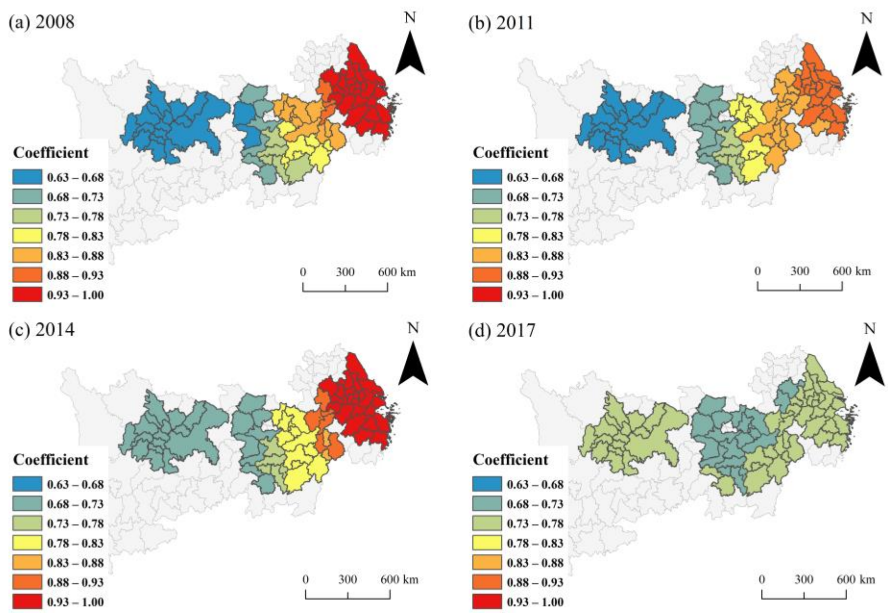

Figure 10. Spatial distribution of regression coefficients of POP.

Figure 11 shows the spatial distribution of regression coefficients for GDPPC. The positive correlation between GDPPC and CE indicates that the growth of GDPPC promoted CO_2 emissions in YREB urban agglomerations. The influence of GDPPC on CE was significant in YRD-UA, and the regression coefficient decreased from east to west in 2008, 2011, and 2014. Economically developed regions responded better to the policy. The government improves local competitiveness in response to economic conditions [52]. More attention should be paid to the change in people's awareness and environmental management caused by the economic improvement.

Figure 12 shows the spatial distribution of the regression coefficients of CI. The positive correlation between CI and CE indicates that the adoption of technological innovations and the improvement of energy use efficiency reduced CO_2 emissions [53]. The impact of CI on CE was significant in YRD-UA. Technological advances promoted the harmonization of economic and environmental development [54]. Companies were more inclined to use environmentally friendly technologies [55].

Figure 13 shows the spatial distribution of regression coefficients for UR. The impact of UR on CE was insignificant, and the value of the regression coefficient varied between -0.07 and 0.41. The reason was that urbanization led to an increase in people's demand for employment, housing, transportation, commodities, and energy dependence [56], and urban construction increased society's demand for high-emitting industries such as steel and cement [57].

Figure 14 shows the spatial distribution of regression coefficients for SI. SI presented a negative correlation with CE in 2008 and 2011, while SI positively correlated with CE in 2014 and 2017. The reason may be that some cities in YREB were at the stage of industrial start-up and development. YRD-UA was dominated by light industry and high-tech industry with low CO_2 emissions [58]. YRMR-UA was at the initial stage of the Rise of Central China Plan, and CY-UA was vital to China's western development [59]. The industrial layout and energy structure of YREB are gradually maturing.

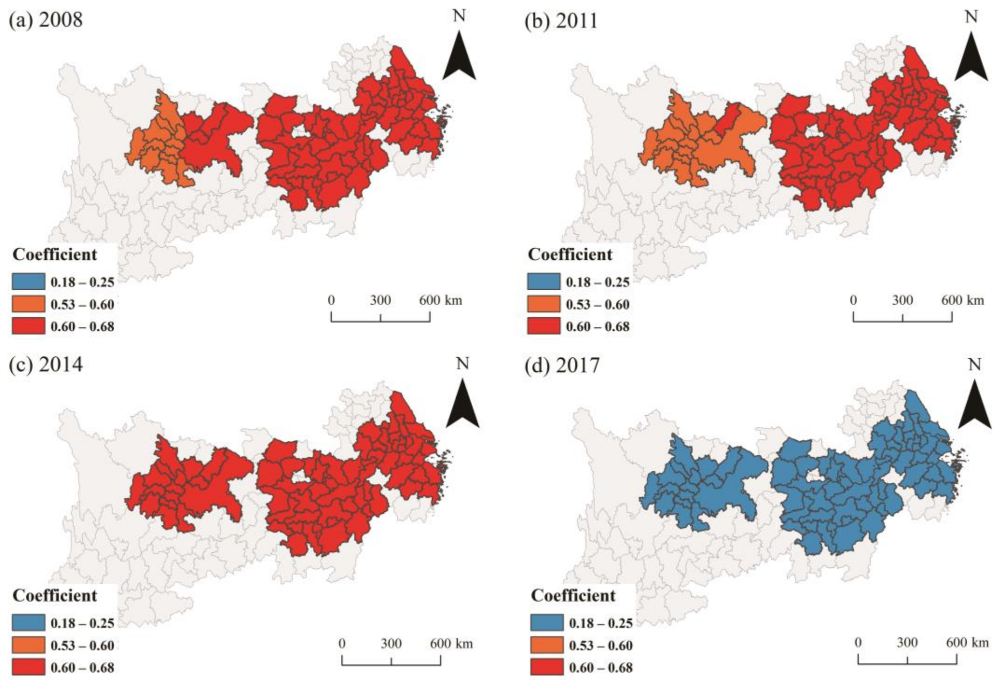

Figure 11. Spatial distribution of regression coefficients of GDPPC.

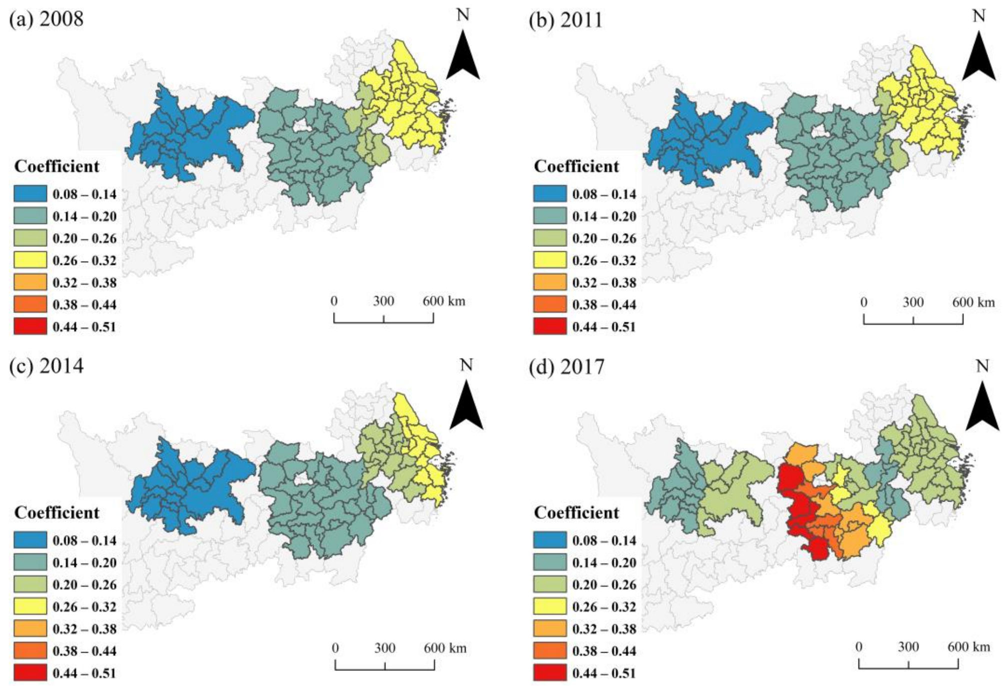

Figure 12. Spatial distribution of regression coefficients of CI.

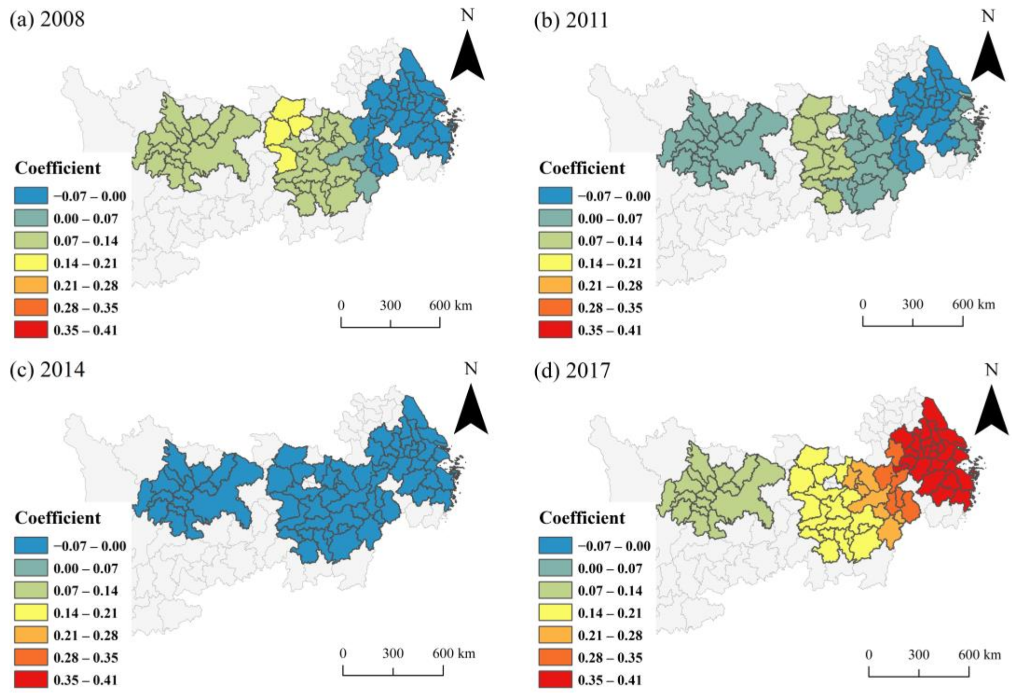

Figure 13. Spatial distribution of regression coefficients of UR.

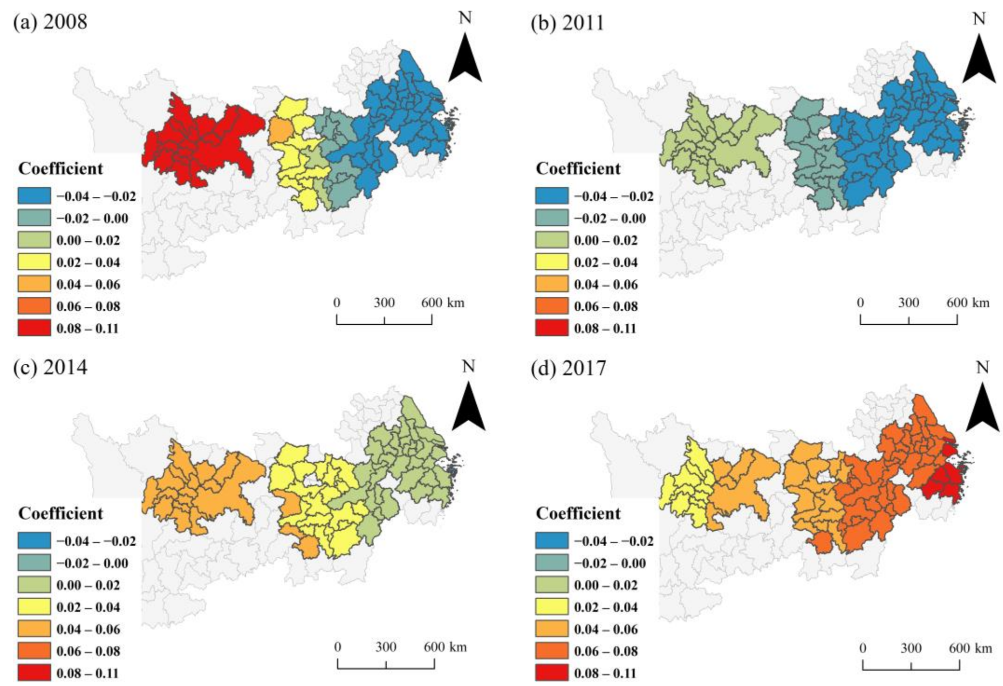

Figure 14. Spatial distribution of regression coefficients of SI.

It is noteworthy that the spatial distribution of five influencing factors changed significantly in 2017. The spatial heterogeneity of POP decreased, the impact of GDPPC decreased, the spatial heterogeneity of CI increased, and the spatial heterogeneity of UR increased. It may be due to the convening of the symposium on comprehensively advancing the development of sustainable development in YREB held in 2016. The difference in the sensitivities of inland and coastal cities to policies resulted in changes in the regression coefficients of the influencing factors in 2017.

4. Discussion

4.1. Insights into the CO_2 Emissions of YREB Urban Agglomerations

As a pioneer demonstration belt for the construction of ecological civilization in China, YREB is of great significance to China and the world in achieving emission reduction and sustainable development. Different urban agglomerations present different carbon emission characteristics at different stages of economic development, making it important to develop targeted emission reduction measures. China is in the process of rapid urbanization and industrialization [60]. In 2017, the proportion of tertiary industry in YRD-UA was 2.84% higher than the proportion of secondary industry [53]. Several cities in the southeast coastal region had already crossed the industrialization stage and entered the post-industrialization period [61], which was confirmed by the low proportion of industrial CO_2 emissions in YRD-UA and the significant growth of electricity CO_2 emissions. However, most cities in central and western China were in the process of industrialization, and the proportion of tertiary industry was lower than the proportion of secondary industry [62], which led to a higher proportion of industrial CO_2 emissions in CY-UA and YRMR-UA than that in YRD-UA.

The optimization and upgrading of industrial structures could promote carbon mitigation in CY-UA and YRMR-UA. Specifically, attention can be paid to industries such as electronic information, engineering machinery, rail transportation equipment, automobiles, aerospace, biomedicine, and new materials. In addition, CY-UA and YRMR-UA could undertake the transfer of high-tech industries from the developed coastal regions. With the deepening of the 14th Five-Year Plan and the vigorous development of wind, hydro, and photovoltaic power generation [63], renewable energy will be the mainstream of the future energy structure in YREB. The west-east gas pipeline project has provided cleaner energy and reduced fossil fuel consumption [64]. More attention should be paid to taking measures to reduce CO_2 emissions from production and life while increasing the share of the service industry in the regional economy. Meanwhile, YRD-UA should focus on reducing the facilitating effects of population on CO_2 emissions by considering human capital agglomeration in the process of urbanization [65]. The investigation of spatiotemporal variations in CO_2 emissions contributes to timely policy adjustments for carbon emission mitigation in YREB urban agglomerations. Meanwhile, EKCs revealed the relationship between CO_2 emissions and economic development, providing a strategy that can be applied to analyze the carbon emission development stage of more regions. Furthermore, the importance of different influencing factors for CO_2 emissions was generated and discussed, which can be conducive to promoting regional sustainable development.

4.2. Limitations

This study investigated the CO_2 emissions of YREB urban agglomerations, but there is still room for further research. The MEIC CO_2 emissions data is from 2008 to 2017, and the spatiotemporal patterns of CO_2 emissions after 2017 were not explored in this study. Therefore, expanded CO_2 emissions datasets with more recent years will be considered in the future. Meanwhile, five influencing factors that reveal economic and social characteristics were selected in this study, and future studies will focus on the selection of representative and comprehensive influencing factors of CO_2 emissions in urban agglomerations.

5. Conclusions

This paper revealed the spatial and temporal variations of CO_2 emissions in three urban agglomerations in YREB. Meanwhile, the carbon emission development stage of the YREB urban agglomerations was explored based on EKCs that take economic growth and carbon emissions into account. In addition, the influencing factors of CO_2 emissions were analyzed using MGWR. The main conclusions are as follows:

(1) The CO_2 emissions in the three urban agglomerations first increased and then decreased from 2008 to 2017. YRD-UA contributed 41.87% of the CO_2 emissions of YREB, with the highest CO_2 emissions among the three urban agglomerations. A symposium on comprehensively advancing the development of the sustainable development of YREB was held in 2016, and the CO_2 emissions in three urban agglomerations decreased significantly in 2017.

(2) The carbon emission development stage of urban agglomeration was analyzed based on the relationship between carbon emissions and economic growth. According to the EKCs, CY-UA, YRMR-UA, and YRD-UA reached the CO_2 emissions peaks around 2012, 2011, and 2020, respectively. Nowadays, the urban agglomerations in YREB are at the low-carbon stage.

(3) The CO_2 emissions of YREB urban agglomerations were significantly affected by POP and GDPPC, while the impacts of UR and SI were not significant. The spatial distribution of influencing factors changed significantly in 2017. To reduce CO_2 emissions, human capital agglomeration and clean energy should be considered in the process of urbanization.

Moreover, future work will focus on the long-term carbon emission development stage analysis of typical urban agglomerations, where more comprehensive CO_2 emissions data and influencing factors will be taken into account.

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