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Original Research

Temporal-Spatial Evolution Characteristics and Influencing Factors of Urban Carbon Emissions in China

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Abstract

Based on the natural discontinuity method, kernel density estimation, Dagum Gini coefficient, exploratory spatial data analysis and other methods, this paper explores the temporal-spatial characteristics of China's urban carbon emissions from 2000 to 2017, and investigate the influencing factors of China's urban carbon emissions by using the decomposition model of the spatial Dubin model. The main conclusions are as follows: (1) China's urban carbon emissions are steadily rising, but the growth rate of carbon emissions is slowing down gradually; The two-level differentiation of carbon emission distribution in the eastern and central regions are obvious, while that in the western and northeastern regions are not obvious. (2) There is a significant spatial autocorrelation of China's urban carbon emissions, and the local agglomeration features are obvious, which are mainly "high-high agglomeration" and "low-low agglomeration". (3) In terms of carbon emission factors, technological innovation, foreign investment, and government intervention can reduce carbon emissions in the eastern region; Government intervention has a mitigation effect on carbon emissions in the central region; Infrastructure construction and technological innovation can reduce carbon emissions in the western region; The industrial structure has a mitigation effect on carbon emissions in the northeastern region. The main research values are as follows: It is helpful to comprehensively understand the dynamic distribution, regional differences and spatial agglomeration characteristics of China's urban carbon emissions, and then investigate the driving factors of carbon emissions in different regions, so as to provide a scientific basis for each region to further implement the "double carbon" strategy, promote the coordinated emission reduction of cities, and jointly build a green development path.

Keywords: urban carbon emissions, temporal-spatial evolution, spatial autocorrelation, influencing factors

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Introduction

During the 40 years of reform and opening up, China's economy has achieved leapfrog development, while its carbon emissions have also maintained rapid growth. Since 2005, China's carbon emissions have been ranked first in the world. According to the Statistical Review of World Energy released by BP, the total carbon emissions in 2020 account for 30.7% of the global total. In the face of a series of environmental crises and international political and economic problems caused by global climate change, the United Nations has been urging countries around the world to take effective actions in recent years to reduce greenhouse gas emissions and strengthen their defenses against climate change. In order to actively assume international responsibility for climate change and promote the building of a community with a shared future for mankind, China formally proposed the goals of "carbon peaking" and "carbon neutrality" at the United Nations General Assembly in September 2020. In October 2021, policy documents such as "Opinions on Completely Accurately Implementing the New Development Concept and Doing a Good Job in Carbon Neutralization" were issued, making a systematic planning and overall deployment for carbon peaking in 2030 and carbon neutrality in 2060. The road to "double carbon" is imperative. In order to accelerate the promotion of green and low-carbon development, the outline of the 14th Five-Year Plan proposes to reduce the intensity of carbon emissions and support regions with conditions to take the lead in reaching the peak carbon emissions. At present, the economic foundation, industrial structure and resource endowment of different regions in China are different, and the carbon emissions are significantly different. Therefore, it is of great significance to carry out research on the spatio-temporal evolution characteristics and influencing factors of carbon emissions at the city level, and then to clarify the regional differences, spatial agglomeration characteristics and influencing factors of carbon emissions, which can promote the coordinated governance of regional carbon emissions and accelerate the realization of the "double carbon" goal.

In this context, carbon emissions have become a hot research topic in academia, however, the research on the temporal and spatial evolution characteristics of carbon emissions mainly focuses on the national and provincial scales [1-2], and the existing municipal carbon emissions research is mostly concentrated in a specific region, urban agglomeration [3] or city [4]. Among them, there is no unified measurement method for carbon emissions. Scholars mainly adopt entropy weight method [5], stochastic frontier method SFA [6] and other methods to explore carbon emissions. Some scholars directly use the carbon dioxide emissions retrieved from night light data to carry out research [7]. In terms of spatial differences, scholars mainly use Dagum Gini coefficient and its decomposition [8], Moran's I index [9], three-stage nested decomposition of Theil index [10] and other methods to reveal regional differences in carbon emissions. In terms of temporal and spatial dynamic evolution, the mainstream method is to use kernel density estimation method to describe the dynamic evolution characteristics of carbon emissions in different regions [11]. In addition, a large number of scholars have investigated the influencing factors of carbon emissions and found that foreign investment [12], environmental regulation [13], urbanization level [14], scientific and technological innovation [15], industrial structure [16] and other factors are important factors affecting carbon emissions in Chinese cities.

Although academia has carried out systematic research on carbon emissions, which provides important experience for this paper, there are still the following deficiencies: Firstly, the limitations of energy statistics lead to relatively insufficient research on China's carbon emissions based on prefecture level cities. Secondly, many studies only reveal the linear relationship between various socio-economic factors and carbon emissions, but lack systematic research on the driving factors of the spatial differentiation model of carbon emissions. Compared with existing research, the innovations of this paper are as follows: Firstly, this paper selects the carbon emission data of 284 prefecture-level cities measured by particle swarm optimization-back propagation (PSO-BP) algorithm, focusing on a comprehensive investigation of the spatio-temporal pattern and evolution trend of China's urban carbon emissions from the municipal level. Secondly, this paper uses the Dagum Gini coefficient and its decomposition to analyze the characteristics of regional differences in China's urban carbon emissions, and clarify the sources of regional differences in China's urban carbon emissions; and then uses kernel density estimation, spatial autocorrelation analysis and other methods to analyze the evolution characteristics of China's urban carbon emissions from two dimensions of space and time. Finally, this paper establishes a decomposition model of the spatial Dubin model to comprehensively analyzes the core influencing factors of urban carbon emissions in China and the four regions, providing scientific reference for all regions to scientifically promote the "double carbon" goal and accelerate the realization of green, low-carbon and high-quality development.

Material and Methods

Variable Selection

Explanatory variable: Carbon emissions (CO_2). This paper refers to the county-level carbon emission data measured by Chen et al. (2020) [17], and summarizes the carbon emission data of prefecture-level cities.

Explanatory variable: Industrial structure (*cy*) is measured by the proportion of the output value of the secondary industry in GDP. Foreign investment (*fdi*) is measured by the proportion of foreign direct investment in GDP. Financial development (*fin*) is measured by the proportion of various loan balances of financial institutions in GDP. Population density (*pop*) is measured by dividing the population by the administrative area. Government intervention (*gov*) is measured by the proportion of fiscal expenditure in GDP. Infrastructure construction (*instra*) is measured by highway mileage. Technological innovation (*zlf*) is measured by the number of patent invention applications. Economic growth (*pgdp*) is measured by per capita GDP.

Data Source

This paper excludes some cities with more missing data, such as Lhasa, and takes 284 cities at prefecture level and above in China from 2000 to 2017 as the research object. The relevant data are mainly from the China City Statistical Yearbook, EPS database, etc., and the interpolation method is used to supplement some cities with serious data missing. Meanwhile, in order to more comprehensively reveal the regional evolution trend of carbon emissions during the observation period, this paper divides the city level into four regions: eastern, central, western and northeastern.

Methods

Kernel Density Estimation Method

As a non-parametric estimation method, kernel density estimation usually fits sample data through a smooth peak function, and uses a continuous density curve to describe the distribution of random variables. In this paper, the kernel density estimation method is used to investigate the dynamic evolution process of China's urban carbon emissions distribution, which can well observe the distribution location, trend, ductility and polarization trend of carbon emissions. This paper assumes that the density function of the random variable Y is $f(y)$:

$$f(y)=\frac{1}{Nh}\sum_{i}^{N}K\left(\frac{Y_i-\overline{y}}{h}\right) \tag{1}$$

In the formula, N represents the number of observations; Y_i represents the independent and identically distributed observation value; $\bar{y}$ represents the average value of carbon emissions; h refers to bandwidth; $K(\cdot)$ is nuclear density.

Dagum Gini Coefficient Decomposition Method

This paper uses the Gini coefficient decomposition proposed by Dagum (1997) [18] to dynamically interpret the regional and spatial differences and sources of carbon emissions in Chinese cities. This method can decompose them into intraregional differences, interregional differences and hypervariable density, effectively solving the problem of overlapping sample data and the source of regional differences. The value range of Gini coefficient is 0~1. This paper refers to the relevant provisions of the United Nations and takes 0.4 as the "warning line" of the gap [19].

$$G=\frac{1}{2n^2\overline{y}}\sum_{i=1}^{k}\sum_{j=1}^{k}\sum_{h=1}^{n_i}\sum_{r=1}^{n_j}\left|y_{ih}-y_{jr}\right| \tag{2}$$

In the formula, the whole is divided into four groups according to the eastern, northeastern, central and western regions, y_{ih} and y_{jr} indicates the carbon emission of cities within the region $i(j)$; n is the number of cities; $\bar{y}$ is the average value of carbon emissions; k is the number of areas; n_i and n_j is the number of regions in group $i(j)$. Dagum Gini coefficient can be decomposed into intra-regional difference contribution G_w, inter regional difference contribution G_{nb} and inter group hypervariable density G_t.

Spatial Autocorrelation Analysis Method

In order to study whether there is spatial dependence or spatial heterogeneity in China's urban carbon emissions, this paper calculates the Global Moran's I. If Global Moran's I is closer to 1, the positive correlation degree is stronger; if it is closer to -1, the negative correlation degree is stronger. Meanwhile, in order to reflect the local regional spatial characteristics of China's urban carbon emissions, this paper introduces the Local Moran's I. The greater the absolute value of the Local Moran's I, the higher the degree of concentration.

Decomposition Model of Spatial Dubin Model

This paper adopts the spatial Dubin model processed by the spatial autoregressive partial differential method to explore the spillover effect of carbon emission agglomeration. Referring to the proposed theory of the spatial Dubin model proposed by LeSage and Pace (2009) [20], the model is transformed into:

$$Y=(I-\sigma w)^{-1}\alpha+(I-\sigma w)^{-1}(X'\beta+wX'\theta)+(I-\sigma w)^{-1}\varepsilon \tag{3}$$

Based on the above analysis, this paper constructs a static spatiotemporal bidirectional fixed SDM model for estimation. The specific formula is as follows:

$$LnCO_{2it}=\rho W_i LnCO_{2t}+\beta x_{it}+\delta W_i X_t+\mu_i+\gamma_t+\varepsilon_{it} \tag{4}$$

$LnCO_{2it}$ represents the carbon emission of the explained variable, W is the spatial weight matrix, x_{it} is the explanatory variable, X_t is the spatial lag term of the explanatory variable, μ_i is the regional fixed effect, γ_t is the time fixed effect, ε_{it} is the random error term, ρ and δ are the coefficients of the explained variable and the spatial lag term of the explanatory variable respectively.

Results and Discussion

Temporal Evolution Characteristics

This paper plots the time series evolution trend of carbon emissions in the country as a whole and in the four major regions from 2000 to 2017, Fig. 1 shows that China's urban carbon emissions show the pattern of East>Northeast>Central>West. With the deepening of reform and opening up, the eastern region has achieved rapid economic development by virtue of its natural geographical advantages, with a high degree of industrialization, and carbon emissions have remained at a high level. However, the northeast region relies heavily on heavy industry, and has maintained an extensive development model for a long time. The industrial transformation and upgrading are slow, resulting in low carbon emission efficiency. The central region has actively undertaken the industrial transfer in the eastern region in recent years, but the overall industrial structure is relatively low-end, and the carbon emissions are relatively high; In the western region, due to the constraints of backward economic development and weak development of the tertiary industry, carbon emissions have increased significantly. From the perspective of the specific evolution process, before 2011, the carbon emissions of the four major regions maintained a steady increase in general, and after 2011, the carbon emissions of the four major regions remained basically stable. Moreover, the evolution trends of carbon emissions growth rates in the four regions were relatively similar, showing an inverted "V"-shaped evolution trend. Specifically, the growth rate of carbon emissions began to show a fluctuating downward trend after reaching its peak in 2005. Although it rose around 2008, it failed to change the overall evolution trend, and even experienced a negative growth in 2015.

Spatial Distribution Characteristics

In order to reflect the spatial dynamic distribution characteristics of China's urban carbon emissions, this paper selects 2000, 2005, 2010 and 2017 as representative years to draw the spatial distribution map of carbon emissions. Based on the natural discontinuity method in Arcgis10.5 software, this paper divides the average carbon emissions into 8 intervals to more intuitively reveal the clustering characteristics and spatial distribution rules of the China's urban carbon emissions. Fig. 2 shows that China's urban carbon emissions show obvious spatial imbalances. With the rapid development of China's industrial economy and the rapid increase of energy consumption, the imbalance of regional economy has become increasingly obvious, leading to an increasing absolute difference of carbon emissions between regions. Compared with 2000, the spatial imbalance of carbon emissions in 2010 and 2017 increased significantly. Specifically, the eastern

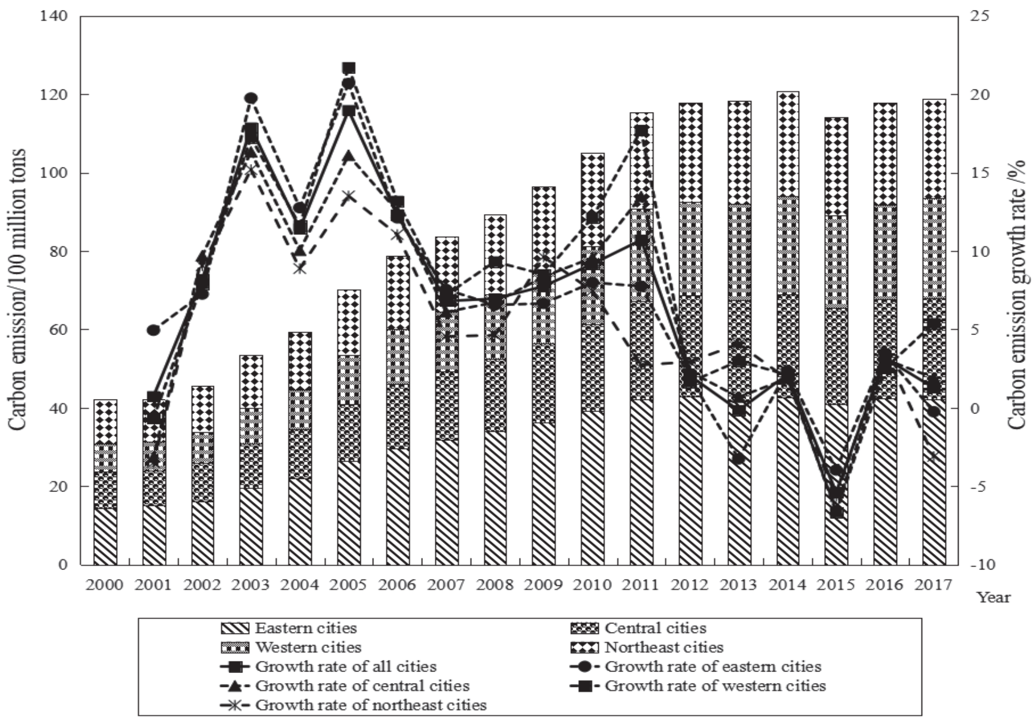

Fig. 1. Time distribution characteristics of carbon emissions.

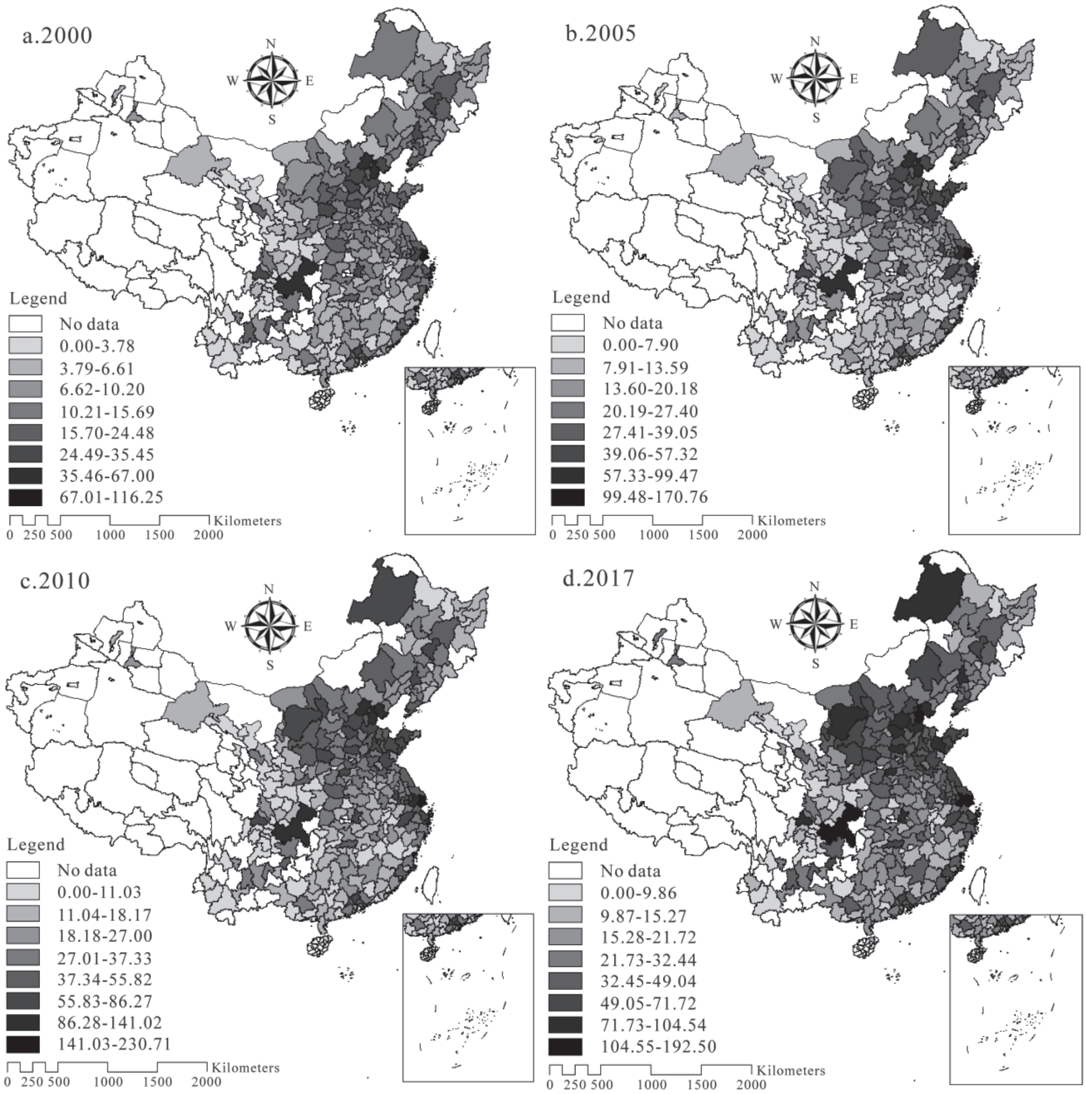

Fig. 2. Spatial distribution characteristics of carbon emissions.

region has relatively large carbon emissions, especially in Jiangsu, Zhejiang, Shanghai and other provinces and cities. Followed by the northeast and central regions, where Changchun, Harbin, Shenyang and Beijing-Hebei-Shanxi and other cities have been high carbon emissions, meanwhile, cities such as Hulunbuir and Chifeng have seen significant growth in carbon emissions in recent years. The carbon emissions in the western region are relatively low, but the carbon emissions in cities such as Chongqing and Chengdu have been maintained at a high level.

Regional Differences Characteristics

In order to further analyze the overall regional differences in China's urban carbon emissions and their sources, this paper will use Dagum Gini coefficient and decomposition method to calculate and decompose them. The results are shown in Fig. 3 and Fig. 4.

Overall Spatial Differences and Their Evolution Trends

Fig. 3 shows that, the overall Gini coefficient of China's urban carbon emissions shows an inverted "V"-shaped evolution trend, and the overall regional differences in carbon emissions show a fluctuating downward trend. In terms of its specific evolution process, the Gini coefficient kept a fluctuating upward trend from 2000 to 2007, rising from 0.416 to 0.425, and the overall regional differences in carbon emissions had been increasing; It then showed a rapid downward trend in 2007-2017. Although there was a slight rebound in 2014, it was far lower than the previous level, and continued the original downward trend in 2017. On the whole, compared with 2000, the overall regional differences of carbon emissions in 2017 narrowed slightly, and the overall Gini coefficient decreased by 4.47%. In the past 10 years after 2007, the overall regional differences of carbon emissions in Chinese

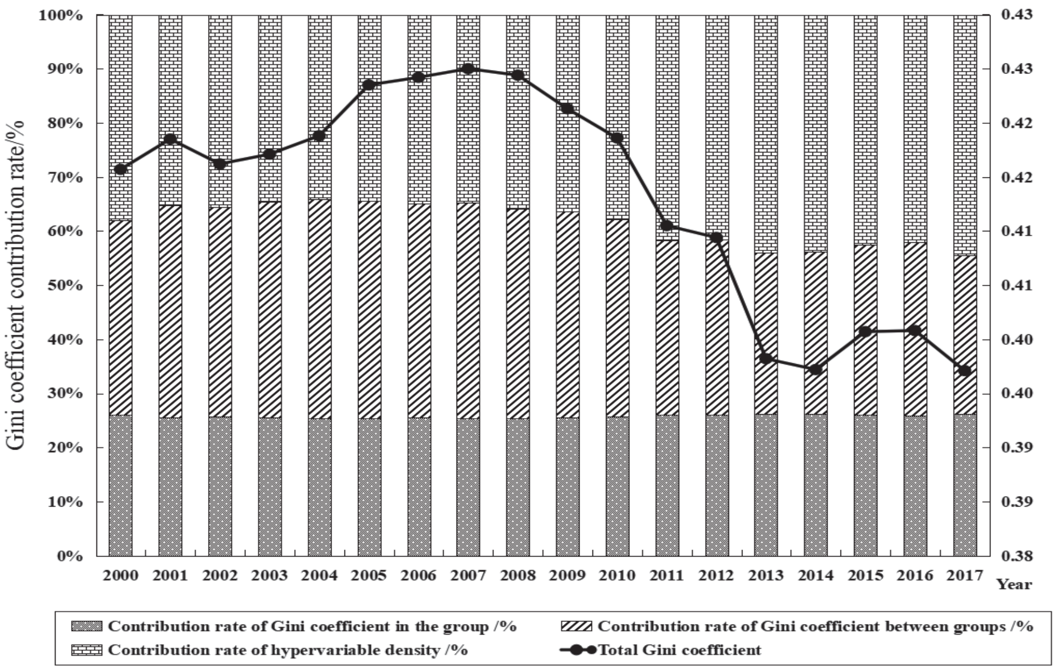

Fig. 3. Dagum Gini coefficient and decomposition.

cities tended to shrink rapidly, with a decrease of 6.56%, but the overall Gini coefficient was still relatively high, with an average of 0.4132 in the sample period. This shows that although the ecological and environmental protection strategies put forward before have achieved certain results and narrowed the carbon emission gap within the country to a certain extent, but the overall level of urban carbon emissions imbalance in China is still high.

Intraregional Differences and Their Evolution Trends

Fig. 4 shows that, from the average value of the Gini coefficient in the four regions, the northeastern (0.4629) > western (0.3877) > central (0.3152) > eastern (0.3105), which shows that during the observation period, the difference in carbon emissions in the northeast region is the largest and higher than the national average level, followed by the western and central regions, and the difference in carbon emissions in the east region is the smallest. From the evolution trend of intra-regional differences, the Gini coefficient in the eastern and central regions shows a fluctuating downward trend, and the intra-regional differences in carbon emissions are gradually narrowing; The Gini coefficient in the western region shows an inverted "V"-shaped downward evolution trend, reaching a peak of 0.4738 in 2008. Specifically, it decreased slightly from 2000 to 2003, increased from 2003 to 2008, and then fluctuated to 0.4542 in 2017, and the intra-regional difference in carbon emissions narrowed slightly. In addition, different from the other three regions, the Gini coefficient in the northeastern region increased slightly during the investigation period, showing a "W"-shaped evolution trend, specifically, it fell to the first trough of 0.3071 in 2009, then rose to the peak of 0.3255 in 2011, and then fell to the second trough of 0.3005 in 2013, and then showed an upward trend.

Interregional Differences and Their Evolution Trends

Fig. 4 shows that, from 2000 to 2017, the position of the Gini coefficient curve between the eastern and western regions was the highest, and the position of the Gini coefficient curve between the central and northeastern regions was the lowest; From 2000 to 2010, the Gini coefficient curve between the East-Northeast region was below the East-Central, Central-Western and West-Northeast regions, After 2010, the Gini coefficient positions between East-Northeast, East-Central, Central-Western and West-Northeast regions were basically the same. This shows that, during the whole survey period, the largest interregional difference in China's urban carbon emissions is in the East-Western region, and the smallest difference is in the Central-Northeast region, while the interregional differences in carbon emissions in the East-Northeast, East-Central, Central-Western and West-Northeast regions gradually converged after 2010.

From the perspective of the specific evolution process, the interregional differences in the East-Central and East-Western regions all showed an inverted "V"-shaped downward trend, with the Gini coefficient peak of 0.4317 and 0.5162 respectively in 2007, and then decreased to 0.3914 and 0.4577 respectively in 2017. The interregional differences in the west-northeast showed a downward trend of "steady decline-relative slowdown", and the Gini coefficient between regions decreased from 0.4321 in 2000 to 0.40 in 2017. The interregional differences in the East-Northeast showed a fluctuating upward trend, rising from 0.3775 in 2000 to 0.4062 in 2017. The interregional differences in the Central-Western showed a fluctuating downward trend of "down-up-down-up-down", from 0.4161 in 2000 to 0.3944 in 2017. The interregional differences in the Central-Northeast showed an evolution process of "down-up-down-up", and the interregional Gini coefficient decreased slightly from 0.3252 in 2000 to 0.3164 in 2017. In general, the interregional differences of carbon emissions in the East-Northeast show an increasing trend, and the interregional differences of carbon emissions in the East-Central, East-Western, West-Northeast, Central-Western, and Central-Northeast have all narrowed to varying degrees.

Difference Sources and Their Contributions

This paper decomposes the overall spatial differences of carbon emissions into three parts: inter-regional differences, intra-regional differences and hyper-variable density, and calculates their respective contribution rates. The data shows that during the observation period, the average annual contribution rates of intra-regional differences, inter-regional differences and hyper-variable density to the overall spatial differences in China's urban carbon emissions were 25.75%, 35.81%, and 38.44%, which indicates that the sources of the overall spatial differences in China's urban carbon emissions are hyper-variable density, inter-regional differences and intra-regional differences in order. In terms of the evolution trend of difference sources shown in Fig. 3, the intra-regional differences contribution rate showed a "V"-shaped upward trend, reaching a trough of 25.39% in 2007, and then rose to 26.14% in a small fluctuation. The contribution rate of inter-regional differences showed an inverted "V"-shaped downward trend, reaching a peak of 40.49% in 2004, and then decreased to 29.44% in 2017, with an average annual decrease of 0.61%. The contribution rate of hyper-variable density showed a fluctuating upward trend, rising from 38.06% in 2015 to 44.42% in 2017. On the whole, the influence of hyper-variable density and intra-regional differences on the overall differences in China's urban carbon emissions is gradually increasing, and the influence of inter-regional differences on the overall differences in China's urban carbon emissions is gradually shrinking.

Dynamic Evolution Characteristics

In order to capture the dynamic information of absolute difference in carbon emissions in more detail, this paper uses the kernel density estimation method to analyze the distribution dynamic characteristics of carbon emissions in four regions, including location, situation, ductility and polarization trend (Fig. 5). Firstly, from the perspective of distribution position, the center of the carbon emissions distribution curves in the four major regions show a right-shifting trend as a whole, which indicates that the carbon emissions in the four major regions generally show an upward trend. Secondly, from the perspective of distribution form, the peak heights of the carbon emissions distribution curves in the four regions have all experienced

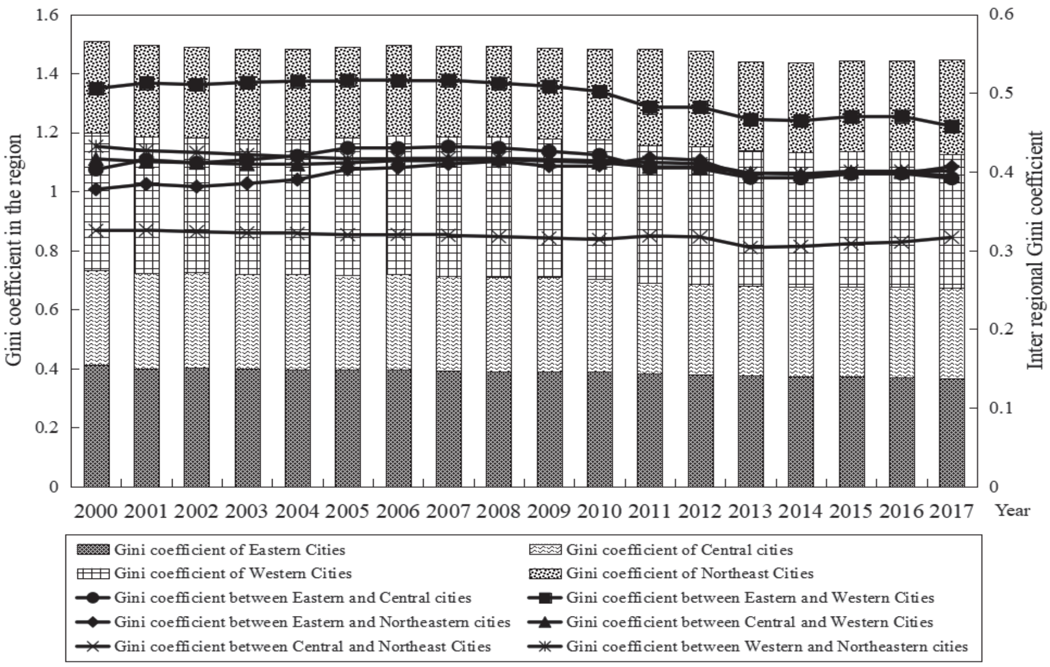

Fig. 4. Dagum Gini coefficients within and between regions.

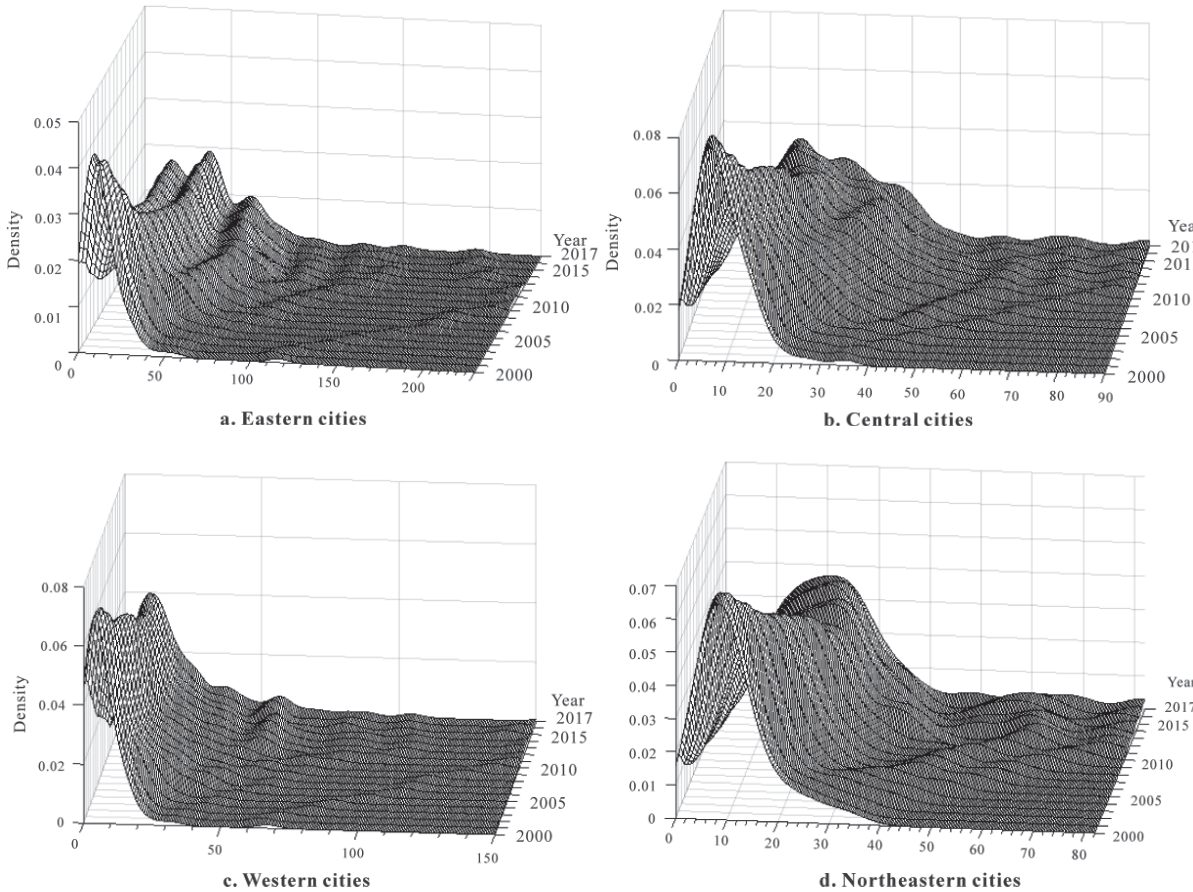

Fig. 5. 3D Kernel Density Estimation Map.

a downward evolution process of "decline-rise", and the peak widths have gradually increased, which means that the absolute differences in carbon emissions in the four major regions have generally tended to rise. Thirdly, from the perspective of distribution ductility, the distribution curves of carbon emissions in the four major regions have obvious right tailing phenomenon, and the distribution ductility shows a trend of widening to the right, which indicates that the carbon emissions of some cities have grown rapidly, and the regional differences of carbon emissions in the four major regions have increased. Finally, from the perspective of polarization, the distribution curves of carbon emissions in the eastern and central regions have gradually changed from the initial "single peak" to a "double-peak" or even "multi-peak" state, which indicates that there is a multi-polar phenomenon of carbon emissions in the eastern and central regions; The western and northeastern regions show an obvious "single peak" state. Although a double peak form of "one main side" appeared in the evolution process, the side peak is far lower than the main peak, which indicates that although the carbon emissions in the western and northeastern regions have a certain gradient effect, the polarization is not obvious.

Spatial Correlation Characteristics

Global Autocorrelation Analysis

With the help of Stata15.1 software, this paper measures the Global Moran's I index of China's urban carbon emissions from 2000 to 2017 (Table 1). The results show that the Moran's I index of China's urban carbon emissions are all positive, ranging from 0.127 to 0.2. The Z value of the normal statistic are all greater than 4.908, which have passed the 1% significance level test each year. It shows that China's urban carbon emissions have obvious positive global spatial autocorrelation, and urban carbon emissions may be affected by the development and carbon emissions of surrounding cities.

Local Autocorrelation Analysis

Here, 2000, 2005, 2010 and 2017 are selected as the representative years to study the local agglomeration characteristics of China's urban carbon emissions. Fig. 6 shows that the characteristics of the local spatial pattern of China's urban carbon emissions can be divided into four categories:

Table 1. Global Moran Indeex.

Year	Moran's *I*	*Z*	*P*	Year	Moran's *I*	*Z*	*P*
2000	0.127	4.908	0	2009	0.191	7.044	0
2001	0.143	5.443	0	2010	0.192	7.049	0
2002	0.144	5.491	0	2011	0.197	7.135	0
2003	0.154	5.827	0	2012	0.196	7.094	0
2004	0.161	6.074	0	2013	0.186	6.702	0
2005	0.178	6.616	0	2014	0.183	6.612	0
2006	0.181	6.738	0	2015	0.192	6.911	0
2007	0.193	7.121	0	2016	0.191	6.884	0
2008	0.2	7.334	0	2017	0.177	6.39	0

The first type of "high-low" agglomeration area, in the representative year, Chongqing, Chengdu and Wuhan have always been in the "high-low agglomeration area". With the passage of time, Changsha has also entered the "high-low agglomeration area". The main reason is that these cities have high economic scale, high energy consumption, and continuous inflow of labor capital and funds, which results in a large difference in carbon emissions levels with surrounding cities.

The second type of "low-low" agglomeration area, in 2000, only Lincang, Pu'er, Zhangye, Hezhou, Cangzhou and Langfang were located in the "low-low concentration area", and they were relatively scattered.

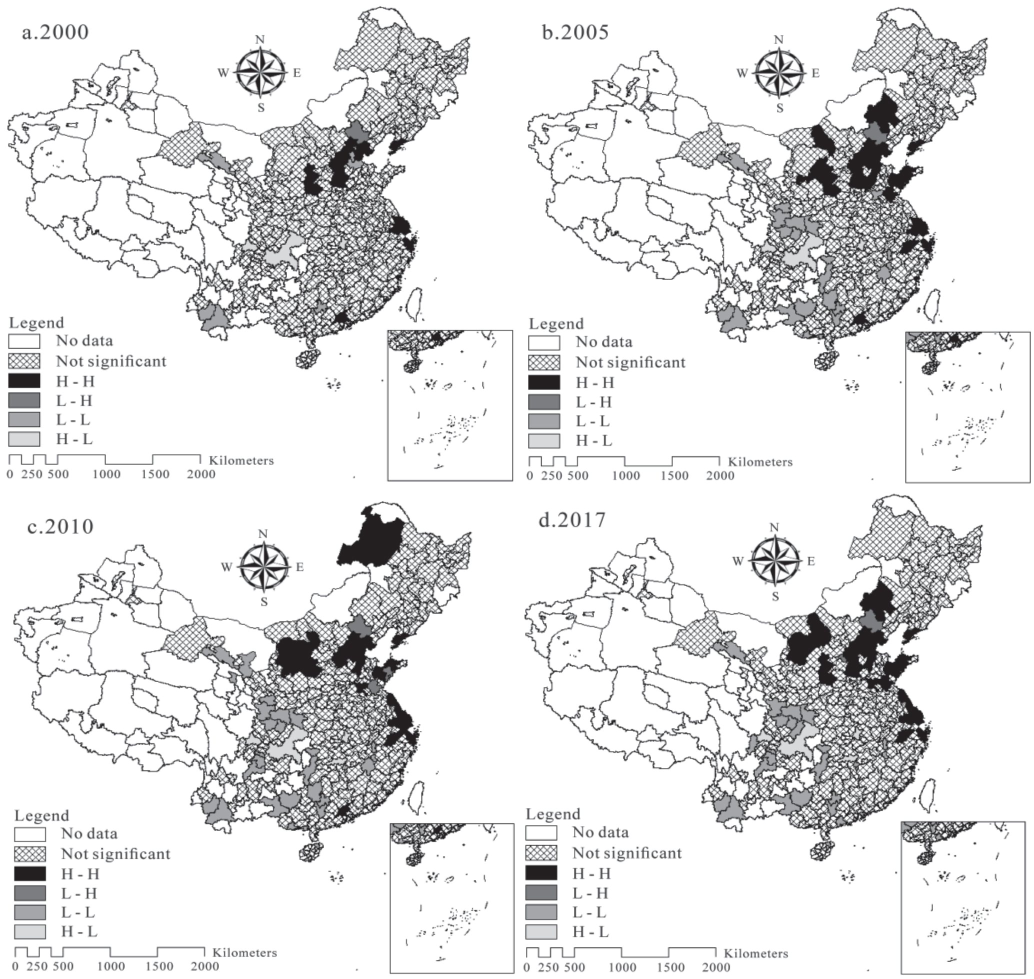

Fig. 6. Local Moran index LISA diagram.

With the passage of time, Bazhong, Yibin and other cities have entered "low-low agglomeration areas". In 2017, "low-low agglomeration area" were mainly distributed in Southwest China. These cities are restricted by resource endowment and other factors, and their carbon emissions have been at a low level.

The third type of "low-high" agglomeration area, Yongde has been in a "low-high agglomeration area" in the representative year. The carbon emissions of the city are low, but the carbon emissions of its surrounding cities are high.

The fourth type of "high-high" agglomeration areas are mainly concentrated in the eastern coastal and northeastern regions. These cities have a relatively high level of economic development, rapid industrialization, large energy consumption and high carbon emissions. In addition, the high level of coordinated urban development in the "high-high agglomeration area" has further promoted the increase of regional carbon emissions. In 2000, Beijing, Shanghai, Suzhou, Guangzhou and other cities were all located in "high-high agglomeration areas", they were mainly concentrated in Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta and other strategic economic circles. With the advancement of environmental protection, the carbon emissions of the Pearl River Delta urban agglomeration have gradually decreased, and then they have withdrawn from the "high-high agglomeration area", while the carbon emissions of the Beijing-Hebei-Shanxi and Yangtze River Delta urban agglomerations have increased significantly, and more and more cities have entered the "High-high agglomeration area".

In addition, from the perspective of the number of agglomeration types, the carbon emissions of Chinese cities in the representative year are dominated by high-high agglomeration and low-low agglomeration, supplemented by high-low agglomeration, and low-high agglomeration areas are the least. Meanwhile, due to the spatial spillover effect of urban carbon emissions, coupled with the coordinated development of regional industries and other reasons, it is difficult to change various agglomeration patterns, and finally form a spatial pattern of "the low is always low, and the high is always high".

Analysis of Influencing Factors

Based on the decomposition model of the spatial Dubin model, this paper explores the influencing factors of carbon emissions in China's overall cities and four major regions. The specific results are shown in Table 2 and Table 3.

The full sample regression results show: The estimated results of the direct effects of industrial structure, financial development, population density, infrastructure construction, and economic growth are significantly positive, which can promote carbon emissions. The reason is that the proportion of the secondary industry is increasing, which is accompanied by high energy consumption and high carbon emissions [21]. In addition, the current financial development system in China is still not perfect, in the initial stage, it mainly promotes economic growth and expands energy consumption by improving the level of industrialization and promoting the process of urbanization, thereby increasing carbon emissions [22]. In addition, cities with large population density have high demand for consumption, large energy consumption and high carbon emissions [23]. Meanwhile, the improvement of transportation infrastructure has also promoted the coordinated development among cities, thereby increasing the overall carbon emissions [24]. It is worth noting that although the long-term extensive mode of economic growth will lead to an increase in energy consumption and carbon emissions, there is an inverted "U" relationship between economic growth and carbon emissions, which shows that when the economy develops to a certain level, the environmental quality will be effectively improved [25]. The estimated results of the direct effects of foreign investment, technological innovation and government intervention are significantly negative, indicating that they can curb carbon emissions. This is mainly because improving technological innovation capability can improve energy efficiency [26]. Through the technology spillover effect of foreign investment, it can speed up the introduction of clean and environmental protection production technology, promote the green transformation of enterprises [27]. Meanwhile, in recent years, China has actively responded to global climate change and continuously increased financial investment in ecological environment protection and governance, which has also curbed carbon emissions to a certain extent [28-29].

The regional regression results show that: the main influencing factors of urban carbon emissions in the four regions are different, and the impact effects are also quite different. Among them, due to the high proportion of the secondary industry, imperfect financial development, large population density, perfect infrastructure and extensive economic growth in the eastern region, carbon emissions have been maintained at a high level. Meanwhile, the high level of foreign investment, large government financial investment in environmental protection and strong ability of technological innovation have played a positive role in energy conservation and emission reduction. In addition, the financial development, infrastructure construction, economic growth and other factors in the eastern region will aggravate the carbon emissions of neighboring cities, while the government intervention, technological innovation and other factors can alleviate the carbon emissions of neighboring cities. As far as the northeast region is concerned, the industrial structure has a certain inhibitory effect on carbon emissions, which may be due to the rapid industrial transformation and upgrading in this region, which promotes "carbon emission reduction". The improvement of transportation infrastructure has accelerated the coordinated development of industries in the region, and also promoted the carbon emissions of neighboring cities. Technological innovation capability also plays a weak role in promoting carbon emissions, which may be because technological progress causes a "rebound effect" while promoting local economic growth, leading to increased energy consumption, thereby promoting carbon emissions [30]. The development speed of the central region is not as fast as that of the west, and its strength is not as strong as that of the East. The large population density has attracted foreign businessmen to develop labor-intensive industries in central region, and finally formed an extensive economic growth mode of "high consumption, low efficiency, high emissions". In addition, the industrial structure, population density, financial development, infrastructure construction and other factors have also exacerbated the carbon emissions of neighboring cities. However, the central region has increasingly attached importance to the strategic position of

Table 2. Spatial decomposition models of full samples and eastern city samples.

Variables	Full sample		Eastern Region	
	Direct effect	Indirecteffect	Direct effect	Indirect effect
	(1)	(2)	(3)	(4)
$lncy_2$	0.178***	-0.0220	0.187***	-0.0791
	(0.0121)	(0.0386)	(0.0250)	(0.0836)
lnfdi	-0.0136***	-0.0108	-0.0215***	-0.00759
	(0.00338)	(0.00994)	(0.00587)	(0.0178)
lnfin	0.0663***	0.0808***	0.118***	0.0741*
	(0.00602)	(0.0215)	(0.0119)	(0.0442)
lnpop	0.110***	0.246***	0.0637***	-0.0295
	(0.0162)	(0.0533)	(0.0170)	(0.0561)
lngov	-0.0116***	-0.0689***	-0.0285***	-0.142***
	(0.00417)	(0.0150)	(0.00881)	(0.0331)
lninstra	0.0130**	0.0563***	0.0668***	0.113***
	(0.00629)	(0.0192)	(0.0109)	(0.0310)
lnzlf	-0.00616**	0.00236	-0.0166***	-0.0691***
	(0.00258)	(0.00761)	(0.00476)	(0.0176)
lpgdp	0.508***	0.203	0.558***	0.603*
	(0.0579)	(0.156)	(0.103)	(0.330)
$lpgdp^2$	-0.0155***	-0.00172	-0.0177***	-0.00420
	(0.00276)	(0.00746)	(0.00493)	(0.0158)
rho	0.594***		0.602***	
	(0.0121)		(0.0211)	
sigma2_e	0.00620***		0.00421***	
	(0.000126)		(0.000156)	
Urban fixed	YES		YES	
Fixed time	YES		YES	
Obs	5,112		1,566	
R-squared	0.326		0.249	
Number of id	284		87	

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.

Table 3. Spatial decomposition model of urban samples in central, Western and northeastern.

Variables	Central Region		Western Region		Northeast Region	
	Direct effect	Indirect effect	Direct effect	Indirect effect	Direct effect	Indirect effect
	(5)	(6)	(7)	(8)	(9)	(10)
$lncy_2$	0.0814***	0.265***	0.184***	-0.124**	-0.0389***	-0.0951**
	(0.0188)	(0.0581)	(0.0238)	(0.0544)	(0.0133)	(0.0479)
lnfdi	0.0225***	-0.0134	-0.00982	-0.0436*	-0.00231	0.0248
	(0.00515)	(0.0163)	(0.00882)	(0.0229)	(0.00435)	(0.0152)
lnfin	0.0118	0.0721**	0.0580***	-0.0743**	-0.00465	0.0441
	(0.00805)	(0.0341)	(0.0131)	(0.0318)	(0.00963)	(0.0386)
lnpop	0.209***	0.445***	0.120**	0.241	0.0482	0.301
	(0.0410)	(0.143)	(0.0528)	(0.149)	(0.0981)	(0.360)
lngov	-0.0135**	0.0114	0.00587	-0.0120	-0.00853	0.00545
	(0.00628)	(0.0238)	(0.00832)	(0.0217)	(0.00569)	(0.0194)
lninstra	0.00232	0.0947***	-0.0401***	-0.0205	0.0203***	0.0861***
	(0.00959)	(0.0322)	(0.0135)	(0.0282)	(0.00687)	(0.0253)
lnzlf	0.00406	-0.00620	-0.0219***	-0.0269**	0.00760*	0.0245
	(0.00346)	(0.0114)	(0.00580)	(0.0130)	(0.00454)	(0.0179)
lpgdp	0.392***	0.175	0.197*	-1.157***	-0.106	-0.603
	(0.104)	(0.360)	(0.112)	(0.245)	(0.111)	(0.395)
$lpgdp^2$	-0.0210***	-0.00657	-0.00803	0.0606***	-0.0107***	0.0550***
	(0.00496)	(0.0164)	(0.00535)	(0.0116)	(0.00398)	(0.0143)
rho	0.552***		0.462***		0.565***	
	(0.0243)		(0.0236)		(0.0357)	
sigma2_e	0.00272***		0.00925***		0.00123***	
	(0.000104)		(0.000347)		(7.22e-05)	
Urban fixed	YES		YES		YES	
Fixed time	YES		YES		YES	
Obs	1,440		1,494		612	
R-squared	0.138		0.011		0.086	
Number of id	80		83		34	

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.

ecological protection in high-quality development, actively promoted the implementation of environmental protection policies, and alleviated carbon emissions to a certain extent. The development of the western region has been lagging behind other regions, with the implementation of the western development strategy, the industrialization degree, financial development level, population density, per capita GDP are all improving, and the rapid economic development leads to increased energy consumption and carbon emissions. However, with the improvement of transportation infrastructure and technological innovation ability, the regional coordinated development of the western region has been strengthened, and carbon emissions have been restrained to a certain extent. Meanwhile, the industrial structure, foreign investment, financial development, technological innovation, economic growth and other factors have played a mitigating role in the carbon emissions of neighboring cities.

Government Policy Suggestion

Promote Regional Coordinated Carbon Emission Reduction

The government should accelerate the vertical and horizontal linkage of various regions in the East, West, North and South, and give play to the collaborative governance role of urban energy conservation and emission reduction within and between regions, and coordinate the orderly realization of carbon peaking in all localities. For example, when coordinating the carbon emission control targets of various regions, the government should fully consider the regional objective facts, for western cities with small total carbon emissions and low intensity, the government can reduce the carbon emission intensity reduction targets, and promote the development of nuclear, wind, light and other new energy with the help of their ecological advantages.

Accelerate the Transformation and Upgrading of Industries Structure

The government should accelerate the adjustment of the industrial structure, gradually reduce the proportion of industries with high pollution, high energy consumption, high carbon emissions and high carbon containing industries in the economy, and focus on the development of high-quality manufacturing, green and low-carbon manufacturing, modern service industries. Meanwhile, the government should rely on regional resource endowments and existing industrial structures to vigorously develop a green and low-carbon economy and accelerate the realization of green and low-carbon economic transformation.

Promote Green and Low-Carbon Transformation of Energy Structure

The government should promote the carbon emission reduction of the energy industry chain, and accelerate the development of wind power, solar power and nuclear power, and develop hydropower and other renewable energy according to local conditions, and enhance the supply capacity of clean energy. Meanwhile, the government should promote the substitution and transformation and upgrading of coal consumption, rationally regulate oil and gas consumption, and accelerate the construction of new power systems.

Conclusions

Based on panel data of 284 cities at prefecture level and above in China from 2000 to 2017, this paper studies the spatio-temporal evolution characteristics of urban carbon emissions in China, and discusses the influencing factors of urban carbon emissions in China. The main conclusions are as follows: (1) From the perspective of temporal-spatial distribution and evolution characteristics: The carbon emissions in the four regions showed a steady upward trend, and the growth rate of carbon emissions began to slow down after 2005. There was an obvious spatial imbalance in carbon emissions, of which the eastern region had the highest carbon emissions. Meanwhile, the distribution of carbon emissions in the eastern and central regions has obvious two-level differentiation. (2) From the sources of spatial-temporal differences and the characteristics of spatial agglomeration: The overall regional differences of China's urban carbon emissions show a fluctuating downward trend. Meanwhile, the local agglomeration characteristics of China's urban carbon emissions are obvious, mainly high-high agglomeration and low-low agglomeration, of which high-high agglomeration is mainly distributed in the East and northeast, and low-low agglomeration is mainly distributed in the southwest. (3) From the perspective of the influencing factors of carbon emissions: The influencing factors in different regions are quite different. Among them, factors such as industrial structure, financial development, population density, infrastructure construction, and economic growth have an aggravating effect on carbon emissions in the eastern region, while technological innovation, foreign investment and government intervention can alleviate carbon emissions in the eastern region. Factors such as industrial structure, foreign investment, population density, and economic growth have aggravating effects on carbon emissions in the central region, while government intervention can alleviate carbon emissions in the central region. Factors such as industrial structure, financial development, population density, and economic growth have aggravating effects on carbon emissions in the western region, while infrastructure construction, technological innovation can alleviate carbon emissions in the western region. Factors such as infrastructure construction and technological innovation have an aggravating effect on carbon emissions in the Northeast, while the industrial structure can alleviate carbon emissions in the Northeast.

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Conflict of Interest

The author declares no conflict of interest.

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