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Reinvestigating the Spatiotemporal Differences and Driving Factors of Urban Carbon Emission in China

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This study analyzed the spatiotemporal differences and driving factors of carbon emission in China's prefecture-level cities for the period 2003–2019. In doing so, we investigated the spatiotemporal differences of carbon emission using spatial correlation analysis, standard deviation ellipse, and Dagum Gini coefficient and identified the main drivers using the geographical detector model. The results demonstrated that 1) on the whole, carbon emission between 2003 and 2019 was still high, with an average of 100.97 Mt. Temporally, carbon emission in national China increased by 12% and the western region enjoyed the fastest growth rate (15.50%), followed by the central (14.20%) and eastern region (12.17%), while the northeastern region was the slowest (11.10%). Spatially, the carbon emission was characterized by a spatial distribution of "higher in the east and lower in the midwest," spreading along the "northeast–southwest" direction. 2) The carbon emission portrayed a strong positive spatial correlation with an imbalance polarization trend of "east-hot and west-cold". 3) The overall differences of carbon emission appeared in a slow downward trend during the study period, and the interregional difference was the largest contributor. 4) Transportation infrastructure, economic development level, informatization level, population density, and trade openness were the dominant determinants affecting carbon emission, while the impacts significantly varied by region. In addition, interactions between any two factors exerted greater influence on carbon emission than any one alone. The findings from this study provide novel insights into the spatiotemporal differences of carbon emission in urban China, revealing the potential driving factors, and thus differentiated and targeted policies should be formulated to curb climate change.

Keywords: urban carbon emissions, spatiotemporal differences, driving factors, geographical detector model, interaction

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1 INTRODUCTION

Increased carbon emission is widely recognized as the primary cause responsible for global warming, greenhouse effects, and has led to extreme climate phenomena, such as glaciers melting, sea-level rising, storm surges, and floods, which represents a serious hazard to human health as well as economic development (Liu et al., 2019a; Wang and Jiang, 2019; Wei et al., 2019). Consequently, carbon emission reduction is not only of great necessity for human existence but also for the realization of green sustainable progress in an economic society. The Paris Climate Agreement in

2016 has announced the global mean temperature control goal of 1.5/2°C (Yang et al., 2022a). In light of that, more nations have pledged to curb carbon emission and established a raft of effective emission mitigation strategies to fulfill this challenging responsibility (Karmellos et al., 2021). As the world's largest developing country and carbon emitter, China has also actively participated in global carbon governance and promised to peak the carbon emission by 2030 and then become carbon neutral by 2060 (hereinafter named as "30.60" targets) at the 75th session of the United Nations General Assembly in 2020 (Gao et al., 2021; Zhang et al., 2022). However, it should be noted that following the continuously growing economy, the carbon emission in China, as contrary to the "30.60" targets, has rather increased (Zhou et al., 2019b; Wang et al., 2021). In addition, carbon emission varies remarkably across regions in China due to the significant differences in resource endowments, levels of economic development, and scientific and technological innovation (Liu et al., 2019c; Shen et al., 2021). Hence, investigating the spatiotemporal differences regionally and identifying the potential driving factors of carbon emission systematically in China are the major concerns of policymakers.

In the literature, a considerable number of studies have been concentrated on the measuring methods, spatiotemporal evolution, influencing factors, and mitigation strategies of carbon emission in China. For the measurements, the structural decomposition approach (SDA) and logarithmic mean Divisia index (LMDI) decomposition methods were the most frequently used worldwide (Huang et al., 2022; Ma et al., 2019). Studies on spatiotemporal characteristics have found that the carbon emission in China would continue to grow for a long time (Wang et al., 2021) and showed significant spatial correlations (Du et al., 2022; Zhao et al., 2020). In addition, some models have been employed to explore the time- and space-changing features of carbon emission, such as spatial correlation analysis (Wang and Zheng, 2021), exploratory spatial data analysis (Han et al., 2021; Zhang et al., 2021), spatial econometric model (Li and Li, 2020), and geographically weighted regression model (Xu and Lin, 2021; Yang et al., 2021). Regarding the driving factors, various natural and human factors of carbon emission have been researched systematically in the literature. Among the natural factors, the climatic condition was universally recognized as one of the most decisive factors affecting carbon emission (Xu et al., 2021). In addition, human factors including the economic development level (Cai et al., 2021; Dong et al., 2020), energy consumption structure (Xu and Lin, 2019; Yang et al., 2022b), urbanization and industry structure (Ali et al., 2019; Dong et al., 2019b), technology (Chen et al., 2020; Sun et al., 2021), transportation (Song et al., 2019), and trade openness (Pu et al., 2020) have also been identified to influence carbon emission, but their influences differed in diverse regions (Liu et al., 2021). These aforementioned findings corroborated the views of Huang and Matsumoto (2021), in which the authors found that the impacts of urbanization on carbon emission were significantly different between regions. In terms of the emission mitigation strategies, existing studies have mainly reached agreements upon transforming the economic development mode, optimizing industrial and energy structure, improving technology innovation capacity, and so on (Chuai and Feng, 2019; Wang et al., 2019; Wu et al., 2021). In summary, the aforementioned studies on carbon emission have given us much enlightenment. However, the existing literature was mainly conducted from the perspectives of countries, provinces, and industries, but studies, further exploring urban carbon emission, were still scarce. It has been reported that the energy consumption of major cities around the world shared 75% of world's total and more than 80% of global carbon emissions came from urban areas. In the case of China, people living in urban areas have reached over 902 million, comprising approximately 64% of the total population of China in 2020 (CSY, 2021). With cities as the biggest sources of carbon emission, urban carbon emission reduction should be set as the key issue for attaining China's "30.60" targets of reaching its peak by 2030 and turning carbon-neutral by 2060 (Dong et al., 2019a).

Although there have been an increasing number of research studies centering on carbon emission over Chinese cities, most of them have been conducted at the single city level (Shen et al., 2018; Wei et al., 2020) or typical urban areas (Liu et al., 2019b; Salvia et al., 2021); the studies on the urban carbon emission with a national coverage still remain insufficient. In addition, prior studies have demonstrated that the distribution of carbon emission was uneven in different regions but failed to reveal the sources of regional differences. Fortunately, the Gini coefficient improved by Dagum is capable of distinguishing the key contributor of the total difference, thus targeted policies can be formulated to alleviate carbon emission. Moreover, to date, studies usually focused on the separate effect of driving factors of carbon emission, and the interactive influences between these drivers tend to be neglected. In fact, the causes of carbon emission are associated, and the interaction between factors can indirectly affect carbon emission (Xu et al., 2021). The geographical detector model proposed by Wang et al. (2010) sheds light on the spatial relationships and interactive effects of variables, which is conducive to investigating important factors more comprehensively. To summarize, it is of great necessity to make an in-depth analysis of carbon emission with the aspect of city.

Compared with the existing literature combed previously, this study contributes to several aspects. 1). This study took 284 Chinese prefecture-level cities as the research unit and then investigated the spatiotemporal differences and driving factors of urban carbon emissions in China based on a series of diversified empirical frameworks. 2) ArcGIS techniques of Moran's *I*, cold and hot spots analysis, and standard deviation ellipse were adopted to intuitively portray the spatiotemporal evolution characteristics of urban carbon emission in China. 3) The Dagum Gini coefficient and its decomposition were further employed to reveal the leading sources of regional differences in carbon emission. 4) Using the geographical detector model to explore the main drivers of national and regional carbon emission, as well as their interactive effects, provided a basis for emission mitigation measures in cities with different regions.

The remainder of this article is organized as follows. **Section 2** introduces the related methodologies and describes the data sources. **Section 3** discusses the spatiotemporal differences and driving factors of carbon emission from national and regional perspectives. **Section 4** summarizes this study and puts forward policy implementations.

2 METHODOLOGY AND DATA

2.1 Methodology

2.1.1 Global Spatial Correlation Analysis

Global Moran's I is a commonly used statistics for testing spatial correlation (Moran, 1950). The formula can be set as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}}; \quad (1)$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2, \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i, \quad (2)$$

where y_i and y_j are the carbon emission of city i and j, respectively, n is the number of cities (284 in this study), S^2 refers to the variance, $\bar{y}$ represents the annual mean carbon emission, and W_{ij} is the spatial weight matrix using the nested weight matrix of spatial geography and economy. $I \in [-1, 1]$. If $I > 0$, it indicates positive spatial correlation; if $I < 0$, it means negative spatial correlation; and if $I = 0$, no spatial correlation exists.

The Z-value is used to evaluate the statistical significance of global Moran's I, whose formula can be set as follows:

$$Z = \frac{I - E(I)}{\sqrt{VAR(I)}}; \quad (3)$$

$$E(I) = -\frac{1}{n-1}, VAR(I) = E(I^2) - E(I)^2, \quad (4)$$

where $E(I)$ and $VAR\ (I)$ are the mathematical expectation and coefficient of variation of I.

Considering that the carbon emission may be affected by both geographical and economic factors. In this study, the nested weight matrix of spatial geography and economy is calculated by geographical distance and per capita GDP. The formula is shown as follows:

$$W_{1,ij} = \begin{cases} \frac{1}{(d_{ij})^2}, (i \neq j) \\ 0, (i = j) \end{cases}; \quad (5)$$

$$W_{2,ij} = \begin{cases} \left(\frac{PGDP_i}{PGDP_j}\right)^{½}, (i \neq j) \\ 0, (i = j) \end{cases}; \quad (6)$$

$$W_{ij} = (1 - \alpha)W_{1,ij} + \alpha W_{2,ij}, \quad (7)$$

where $W_{1,ij}$, $W_{2,ij}$, and W_{ij} are the geography, economy, and nested spatial weight matrix, respectively, d_{ij} is the distance between the centers of city i and j, $PGDP_i$ and $PGDP_j$ are the average values of per capita GDP of city i and j from 2003 to 2019. $\alpha \in [0, 1]$, it represents the proportion of economic weight. In this study, α is 0.50, implying that economy weight is equal to the geography weight.

2.1.2 Local Spatial Correlation Analysis

Compared with the global Moran's I, it only evaluates the spatial correlation of carbon emission from a global perspective, while the cold and hot spots analyses (Ord and Getis, 1995) can reflect the spatial agglomeration degree of individual units. In this study, the cold and hot spots analysis is also applied to identify significant spatial clustering of high- and low-carbon emission calculated by *Getis-Ord* G_i^*, which are represented as hot spots and cold spots, respectively. The formula for global G index is given as follows:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}X_iX_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} X_iX_j}. \quad (8)$$

The G_i^* index of sample i is set as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} W_{ij}X_i}{\sum_{j=1}^{n} X_j}. \quad (9)$$

Similar to Moran's I, the $Z(G_i^*)$ is used to assess the statistical significance of G_i^*. Its formula is as follows:

$$Z(G_i^*) = \frac{G_i^* - E(G_i^*)}{\sqrt{VAR(G_i^*)}}, \quad (10)$$

where X_i and X_j are the carbon emission of city i and city j, respectively; W_{ij} is the spatial weight matrix; $E(G_i^*)$ and $VAR(G_i^*)$ are the mathematical expectation and coefficient of variation of G_i^*; and $Z(G_i^*)$ is the standardized statistic of the G_i^* test, its significance can identify the spatial distribution of hot and cold spots in different areas.

2.1.3 Standard Deviation Ellipse

The standard deviation ellipse (SDE) proposed by Lefever (1926) quantitatively describes the spatial distribution characteristics of the research object through its center, long, and short axis, azimuth, and other basic parameters (Chen et al., 2021). The concrete calculating process can be reflected by the following equation:

$$SDE_x = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{X})}{n}}; \quad (11)$$

$$SDE_y = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{Y})}{n}}; \quad (12)$$

$$\tan_\alpha = \frac{A + B}{C} = \frac{\left(\sum_{i=1}^{n}\overline{x_i}^2 - \sum_{i=1}^{n}\overline{y_i}^2\right) + \sqrt{\left(\sum_{i=1}^{n}\overline{x_i}^2 - \sum_{i=1}^{n}\overline{y_i}^2\right)^2 + 4\left(\sum_{i=1}^{n}\overline{x_i}\,\overline{y_i}\right)^2}}{2\sum_{i=1}^{n}\overline{x_i}\,\overline{y_i}}; \quad (13)$$

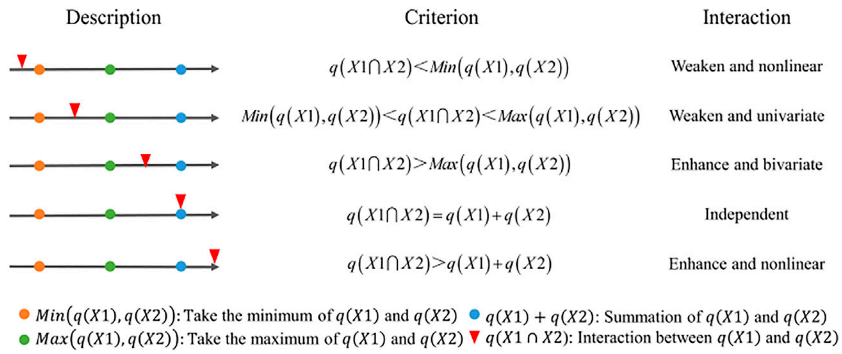

FIGURE 1 | Interaction relationships.

$$\sigma_x = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}\left(\overline{x_i}\cos\alpha - \overline{y_i}\sin\alpha\right)^2}{n}}; \tag{14}$$

$$\sigma_y = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}\left(\overline{x_i}\sin\alpha - \overline{y_i}\cos\alpha\right)^2}{n}}, \tag{15}$$

where (SDE_x, SDE_y) is the centroid of the ellipse, (x_i,y_i) is the geographic coordinates of the city i, $(\bar{X}, \bar{Y})$ is the weighted mean center, $(\bar{x}_i, \bar{y}_i)$ represents the D-value between the mean center and coordinates of XY, and the angle α is the ellipse directional orientation, meaning the clockwise rotation degree from north to the long axis of the ellipse. σ_x and σ_y are the length of the long and short axis of the ellipse, respectively.

2.1.4 Dagum Gini Coefficient and Its Decomposition

Dagum (1997) proposed a superior method for measuring inequity, which can describe the sources of overall regional difference and the distribution of subsamples remain unaffected by sample overlap (e.g., not all cities in the eastern region have a higher carbon emission than those in other regions; some cities in the center, western, and northeastern regions may also have higher carbon emission than individual cities in the eastern region, which calls as the sample overlap). This method has been widely employed in many fields, yet its applications in the environmental stewardship remain limited. Given this, we used Dagum's decomposition and Gini coefficient to explore the regional difference of the carbon emission in urban China. The following **Equation 16** can express it:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{nj}\sum_{r=1}^{nh}\left|y_{ji} - y_{hr}\right|}{2n^2\bar{y}}, \tag{16}$$

where y_{ji} (y_{hr}) is the carbon emission of city i (j) in the region j (h), $\bar{y}$ is national average carbon emission, n represents total number of cities, k denotes the number of regions, and n_j (n_h) is the number of cities in their respective region.

Before conducting Dagum's Gini coefficient decomposition, the regions under study must be classified by their average carbon emission using **Eq. 17**, as follows:

$$\overline{Y_h} \le \ldots \overline{Y_j} \le \ldots \overline{Y_k}. \tag{17}$$

Following Dagum (1997), the Gini coefficient can be decomposed into three terms, namely, contribution of intra-regional differences G_w, contribution of interregional differences G_{nb}, and contribution of the intensity of transvariation G_t, as illustrated in **Eqs 18–20**. Accordingly, the components meet $G = G_w + G_{nb} + G_t$. **Equation 21** denotes the Gini coefficient G_{jj} within the jth region, **Eq. 22** denotes the Gini coefficient G_{jh} between jth and hth region, and D_{jh} represents the relative difference of carbon emission between regions i and j, as shown in **Eq. 23**. Note that $p_j = n_j/n, s_j = n_j\overline{Y_j}/n\bar{Y}, j = 1, \cdots, k$.

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j; \tag{18}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right) D_{jh}; \tag{19}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right)\left(1 - D_{jh}\right); \tag{20}$$

$$G_{jj} = \frac{\frac{1}{2\mu_j}\sum_{i=1}^{nj}\sum_{r=1}^{nj}\left|y_{ji} - y_{jr}\right|}{n_j^2}; \tag{21}$$

$$G_{jh} = \sum_{i=1}^{nj}\sum_{r=1}^{nh}\left|y_{jr} - y_{hr}\right| \Big/ n_j n_h\left(\mu_j + \mu_h\right); \tag{22}$$

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}}. \tag{23}$$

Eqs 24, **25** show the detailed calculation process of d_{jh} and p_{jh}. Specifically, d_{jh} is the difference of the contribution rate of carbon emission between regions, which could be defined as aggregate expectation of all samples, satisfying $y_{ji} - y_{hr} \ge 0$, in regions j and h, whereas p_{jh} is the hypervariable first-order moment, and condition $y_{hr} - y_{ji} \ge 0$ is also satisfied, in regions j and h. $F_h(F_j)$ is the cumulative density distribution function of the hth (jth) region.

$$d_{jh} = \int_0^\infty dF_j(y)\int_0^y (y - x)dF_h(x); \tag{24}$$

TABLE 1 | Description of the driving factors.

Factor variable	Variable definition	Data description	Sources of original data
FDI (X_1)	Foreign direct investment level	Foreign direct investment to GDP/%	China City Statistical Yearbook; Statistical Bureau of each prefecture-level city
OPEN (X_2)	Trade openness	Total volume of imports and exports to GDP/%	
PGDP (X_3)	Economic development level	Per capita GDP in constant 2003 prices	China City Statistical Yearbook
TRA (X_4)	Transportation infrastructure	Number of public cars/car	
INV (X_5)	Investment scale	Per capita investment in fixed assets/Yuan	China City Statistical Yearbook; Statistical Bureau of each prefecture-level city
INF (X_6)	Informatization level	Internet comprehensive development index	China City Statistical Yearbook
ER (X_7)	Environmental regulation	Three waste treatment rates calculated by the entropy method	
PD (X_8)	Population density	Total population to areas/%	
IS (X_9)	Industrial structure	Tertiary GDP to GDP/Yuan	
FIN (X_{10})	Financial development level	Balance of deposits and loans of financial institutions to GDP/%	
RD (X_{11})	Research and development expense	Technology investment to local financial expenditure/%	
EI (X_{12})	Energy intensity	Electricity consumption for industrial to GDP/%	

Note: Three waste treatment rates refer to the ratios of industrial solid wastes, wastewater centralized treatment of sewage work comprehensively utilized, and consumption waste treatment.

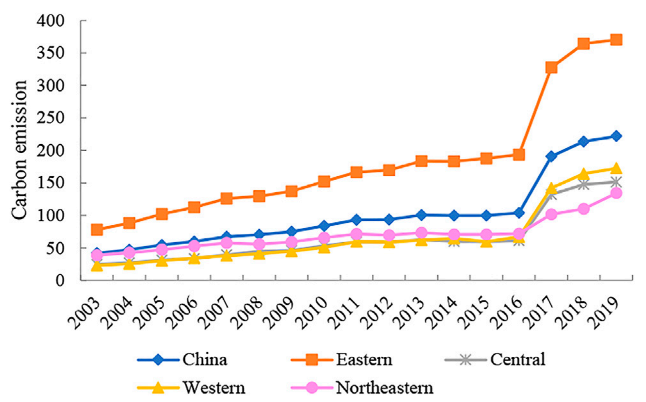

FIGURE 2 | Changing trends of carbon emission in China and four regions.

$$p_{jh} = \int_0^{\infty} dF_h(y) \int_0^{y} (y - x) dF_j(y). \tag{25}$$

2.1.5 Geographical Detector Model

The geographical detector model proposed by Wang et al. (2016) is an advanced statistical method, which can be used to detect spatial heterogeneity and reveal the key drivers behind that heterogeneity. The model mainly consists of four parts including the factor detector, interaction detector, ecological detector, and risk detector (Wang et al., 2010). To be specific, the factor detector, denoted by *PD* statistic, investigates the explanatory power of factor X on Y spatial heterogeneity; the interaction detector distinguishes whether there exist interactions between X_1 and X_2; the ecological detector compares the impact difference of X_1 and X_2 on Y; and the risk detector reveals potential risk areas of Y. In this study, based on the previous researches (Zhang and Zhao, 2018), we adopted the factor detector, interaction detector, and ecological detector to identify and extract the key contributors affecting carbon emission. The formula is given as follows:

$$PD = 1 - \frac{\sum_{h=1}^{L}\sum_{i=1}^{N_h}\left(y_{h1} - \overline{y_h}\right)^2}{\sum_{i=1}^{L}\left(y_i - \bar{y}\right)^2} = 1 - \frac{1}{n\sigma^2}\sum_{h=1}^{L} n_h\sigma_h^2, \tag{26}$$

where *PD* is the power of determinant on the carbon emission. $PD \in [0, 1]$, and the greater the value, the stronger the determinate power of this factor for carbon emission heterogeneity will be. The study area is divided into L layers, represented by $h = 0,1,2,3, L$. n and n_h refer to the total number of cities in China and layer h. σ^2 and σ_h^2 stand for the variance of carbon emission in the entire study region and layer h.

The fact is, however, that Y may be influenced by the interaction between two factors rather than a single one. With regard to this, the interaction detector can assist in significantly identifying the interaction between the two factors (Zhan et al., 2018). The interactive influence can be judged using **Figure 1**.

As shown in **Figure 1**, $q\ (X_1)$ and $q\ (X_2)$ refer to the separate impact of X_1 and X_2 on Y, and $q(X1 \cap X2)$ denotes the interactive impact of X_1 and X_2. To be specific, the weak and non-linear impact represents a smaller interactive impact of X_1 and X_2 than their separate impacts, while the enhanced and bivariate impact suggests a bigger interaction. In addition, the weak and univariate impact indicates that a moderate interaction impact exists in the separate impact of X_1 and X_2, whereas the independent effect shows that the interaction impact is equivalent to the sum of X_1 and X_2 separate impacts. Finally, the enhanced and non-linear impact stands for the interactive impact of X_1 and X_2 that is much stronger relative to the sum of their separate impact.

2.2 Data and Source

2.2.1 Data for the Carbon Emissions

Given the scarcity of official source on carbon emission data in cities and in accordance with Han and Xie (2017) and Ren et al. (2020),

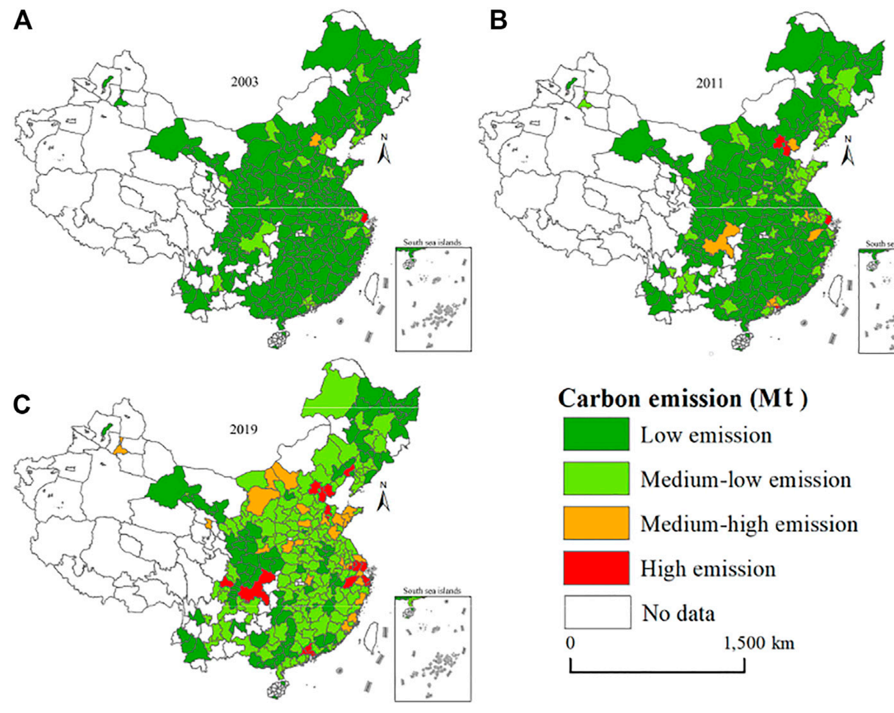

FIGURE 3 | Spatial distribution of carbon emission in 2003, 2011, and 2019.

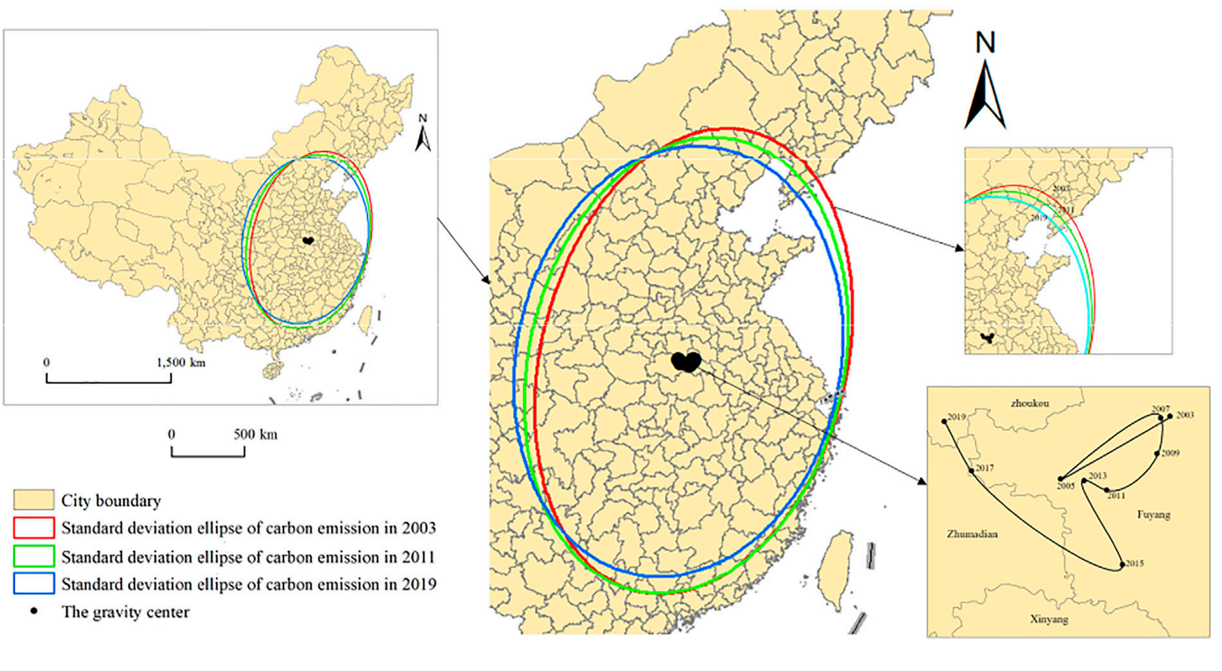

FIGURE 4 | Center of gravity migration of carbon emission in China from 2003 to 2019.

this study calculated carbon emission based on the consumption of liquefied petroleum gas, natural gas, and annual electricity in a concerned city by using a unified standard and scientific method proposed by IPCC (Eggleston et al., 2006). The formula for calculation is as follows:

$$CO_2 = C_1 + C_2 + C_3 = kE_1 + vE_2 + \varphi(\eta \times E_3), \quad (27)$$

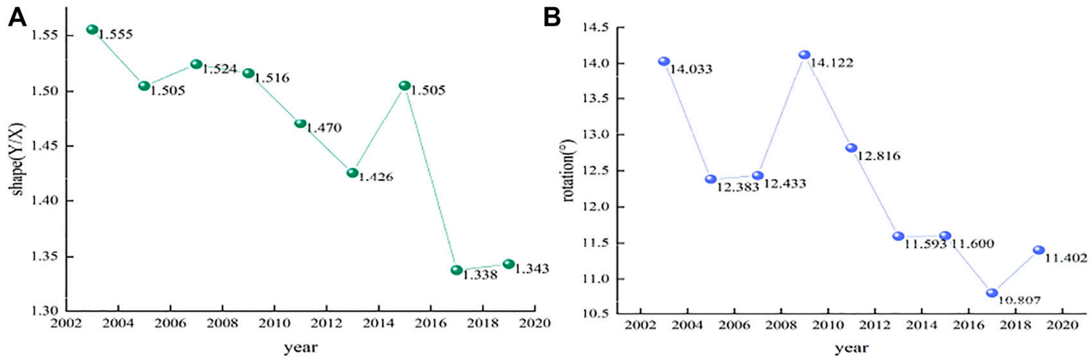

FIGURE 5 | Change of the rotation and shape of carbon emission in China from 2003 to 2019.

TABLE 2 | Global Moran's *I* of carbon emission for the year 2003, 2011, and 2019.

Year	Moran's *I*	Z-score	*p*-values
2003	0.037***	3.880	0.000
2011	0.043***	4.385	0.000
2019	0.064***	6.075	0.000

*Note: *** 1% significance level* (p < *0.01).*

where CO_2 is the carbon emission of cities; C_1, C_2, C_3 stand for the carbon emission caused by liquefied petroleum gas, natural gas, and annual electricity consumption; E_1, E_2, E_3 represent the consumption of liquefied petroleum gas, natural gas, and annual electricity, respectively; $k(v)$ is the converted coefficient of liquefied petroleum gas (natural gas); η denotes the proportion of coal power generation; and φ is the converted coefficient of coal power fuel chain, equivalent CO_2 is 1.320 3kg/(kwh) (Zhou et al., 2019a).

2.2.2 Data for the Driving Factors

Based on a previous study (Huang et al., 2019b; Essandoh et al., 2020; Zhang et al., 2020), 12 proxy indicators were selected as the potential driving factors for carbon emission. To be more specific, the foreign direct investment (*FDI*) level, trade openness (*OPEN*), economic development level (*PGDP*), transportation infrastructure (*TRA*), investment scale (*INV*), information level (*INF*), environmental regulation (*ER*), population density (*PD*), industrial structure (*IS*), financial development level (*FIN*), research and development expense (*RD*), and energy intensity (*EI*) were chosen in this study. All of the abovementioned variables have been classified using the natural breaks classification method, and the detailed description of these driving factors is displayed in **Table 1**.

2.2.3 Data Description

In view of data accessibility and consistency, the scope of our research was limited in 284 Chinese prefecture-level cities from 2003 to 2019. Since 9 January 2019, Jinan and Laiwu have amalgamated into one. With regard to this, we aggregated the original data of these two cities from 2003 to 2018.

In addition, taking into account the economic and geographical conditions of different areas in China, the carbon emission should be studied regionally. This study divided the study area into four regions, namely, eastern, central, western, and northeastern, to investigate regional differences in carbon emission.

3 RESULTS AND DISCUSSION

3.1 Temporal and Spatial Characteristics

The temporal changes in carbon emission in China and four regions during the same period are exhibited in **Figure 2**. As seen in the figure, the national annual average carbon emission took on an increasing trend for the period 2003–2019 and increased by 12% annually. More specifically, the annual average carbon emission maintained relatively steady growth between 2003 and 2016 from the minimum, 42.02 Mt, to the maximum, 104.09 Mt, but had a sharp increase since 2017 and hit an all-time high of 221.92 Mt in 2019. With regard to four regions, the carbon emission showed predominant regional differences with the annual average value sorted by a decreasing order as eastern region (180.65 Mt) > northeastern region (70.10 Mt) > western region (66.87 Mt) > central region (64.26 Mt), with the annual growth rates being 11%, 9%, 16% and 14%, respectively. Also, the carbon emission in those four regions presented a similar temporal behavior of increase to the whole country, indicating that carbon emissions have become a vital environmental issue to China's sustainable economic development.

The spatial distribution of carbon emission in 2003, 2011, and 2019 is presented in **Figure 3**. As shown in **Figure 3**, the carbon emission is divided into four types: "low emission" (0–100 Mt), "medium–low emission" (100–400 Mt), "medium–high emission" (400–700 Mt), and" high emission" (>700 Mt). Overall, the carbon emission from the 284 Chinese cities experienced a growing trend from 2003 to 2019, and the spatial diffusion breadth and scale expanded. Carbon emission in the studied cities was characterized by a spatial distribution of "higher in the east and lower in the midwest". Specifically, cities with higher emissions were distributed mainly over eastern

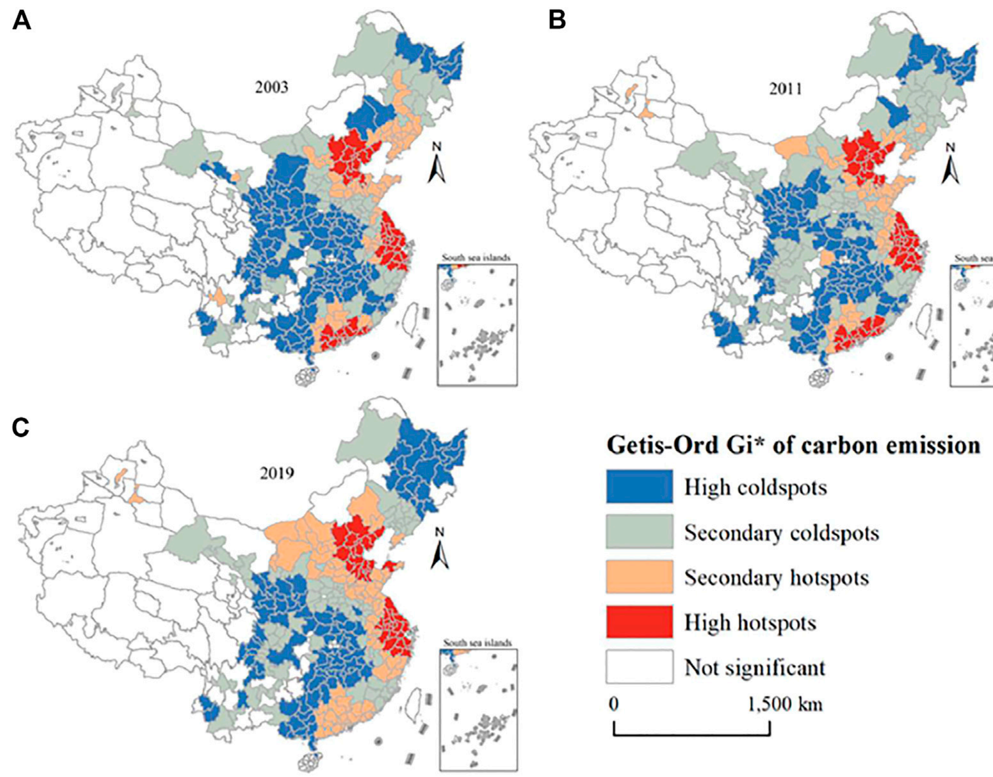

FIGURE 6 | Hot and cold spots of carbon emission in 2003, 2011, and 2019.

China, such as Shanghai (1,647.16 Mt), Beijing (1,490.28 Mt), Binzhou (1,078.21 Mt), and Shenzhen (984.27 Mt), which ranked in the top five, while cities in other areas had relatively lower emissions (apart from Chongqing, 1,173.34 Mt, and Chengdu, 718.40 Mt). In addition, it is to be noted that all municipalities were located in high carbon emission levels being concentrated above 700 Mt. As a result of rapid industrialization and urbanization, these developed cities were suffering more severe environmental pressure.

To further analyze the overall spatial pattern changes in carbon emission with time, in **Figure 4** and **Figure 5**, a series of distribution charts of carbon emission in Chinese cities from 2003 to 2019 were illustrated by using the SDE method. During the study period, the spatial distribution of carbon emission showed the "northeast-southwest" direction, and the gravity center moved northwest, from Fuyang to Zhumadian then to Zhoukou. As described in **Figure 5A**, the shape index (the ratio of long axis to short axis) varied from at most 1.56 in 2003 to a lower value of 1.34 in 2019, indicating that heterogenous spatial changes in carbon emission were happening over time. The closer the ratio was to 1, the more the ellipse looked like a circle, thus the smaller the carbon emission differences between regions tended to be. In addition to that the azimuth of the long axis was rotated counterclockwise from 14.03° to 11.40°, which suggested that "northeast-southwest" direction was the basic distribution pattern of urban carbon emissions in China (see **Figure 5B**). It has to do with the rapid increase of carbon emission in the northeast and western regions over recent years.

Table 2 showed the global Moran's *I* of carbon emission of 284 Chinese cities in 2003, 2011, and 2019. The results suggested that the Moran's *I* of carbon emissions were positive, and the *p*-values for all passed the significance test at the level of 1%. We, therefore, concluded that a spatial positive correlation of carbon emission existed between regions.

The cold and hot spots results of carbon emission in Chinese cities are illustrated in **Figure 6**. From the perspective of spatial distribution, the primary and secondary hot spots of carbon emission were located in eastern China, mainly in Beijing, Shanghai, Guangdong, and their surrounding cities, manifesting that the carbon emissions in these cities have not been effectively controlled. Most of the primary and secondary cold spots were mainly concentrated in central and western regions of China, which formed a contrast with the east. As for time trends, the hot spots of the Guangzhou-centered area have changed from primary to secondary, and the secondary hot spots have spread to most parts of central China. During the study period, new spatial and temporal changes did not appear significantly in primary and secondary cold spots (see **Figure 6**). In summary, the cold and hot spots of carbon emission showed obvious spatial clustering characteristics, featuring as a distribution pattern of "eastern hot spots gathering and western cold spots grouping".

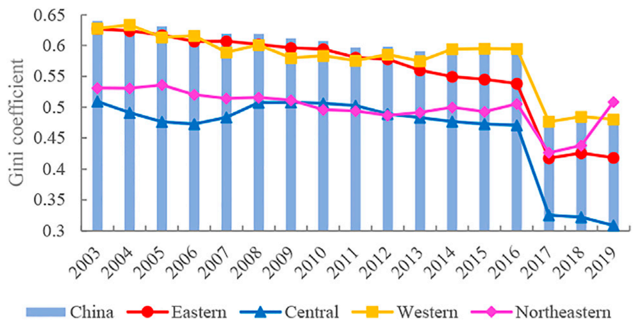

FIGURE 7 | Changing trends of the overall and intra-regional Gini coefficient of carbon emission.

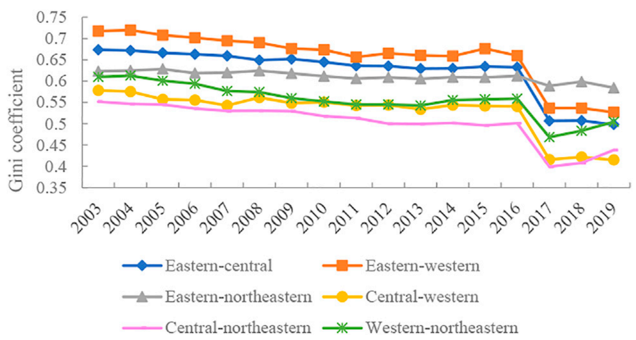

FIGURE 8 | Changing trends of the interregional Gini coefficient of carbon emission.

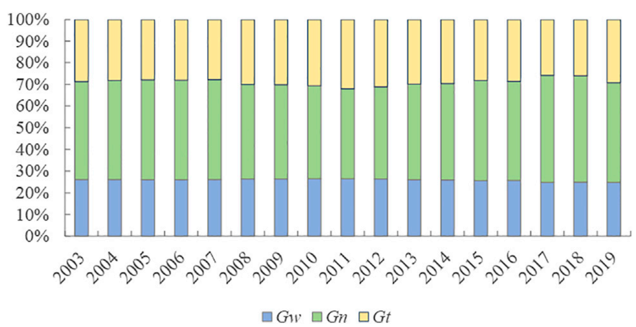

FIGURE 9 | Sources of the overall differences in carbon emission and the trends of their distributions.

3.2 Regional Differences and Its Decomposition

In this section, the Dagum Gini coefficient was used for the measurement and decomposition of regional differences in China's carbon emissions. **Figure 7** depicted the variation in overall and intra-regional Gini coefficient of carbon emission in China from 2003 to 2019, respectively. The overall Gini coefficient exhibited a downward and fluctuating trend, with the annual average decrease of 1.71%. The final Gini coefficient in 2019 (0.48) was lower than that in 2003 (0.64), indicating a narrowing regional difference in China's carbon emission in the research period.

For each specific region, **Figure 7** further showed that the average intra-regional Gini coefficients of the four regions, namely, eastern, central, western, and northeastern, were 0.59, 0.46, 0.58, and 0.50, respectively. The Gini coefficient of the northeastern region displayed a V-shaped trend of "decreased first and increased afterward", with the annual decrease being 0.10%. To be more specific, the Gini coefficient first declined slightly from 2003's 0.53 to 2017's 0.43, which was an annual decrease of 1.46%, followed by a strong increase until 2019, reaching the value of 0.51, and then increased by 9.43% annually. Compared with the northeastern region, the differences in eastern, western, and central regions all showed slowly declined trends from 2003 to 2019, decreasing by 2.33, 2.72, and 1.50% at annual rates, respectively. As analyzed before, the differences in carbon emission within regions were progressively alleviated, which is conductive to help China to become carbon-neutral quickly in the future.

The changing trends of the interregional Gini coefficient are illustrated in **Figure 8**. As described in **Figure 8**, the differences between regions were fairly clear, with the largest gap being between eastern and western regions at an annual average of 0.66, followed by eastern-central (0.62), eastern-northeastern (0.61), central-western (0.56), and western-northeastern (0.53), while the differences between central and northeastern regions was the lowest (0.50). In addition, the interregional Gini coefficient changing trends for the four regions were generally consistent and steadily decreasing, with the annual decline rates of 1.86, 1.79, 1%, 1.79%, 1.74%, 1.26%, 1.08% and 0.39% in central-western, eastern-western, eastern-central, central-northeastern, western-northeastern, and eastern-northeastern, respectively. These trends might be the results of resource endowment, technological innovation, and economic development level, which caused the differences in carbon emission between regions.

For further analysis of the regional differences in carbon emission, **Figure 9** presented the decomposition of the overall Gini coefficient of the carbon emission in China and the main sources for the differences. **Figure 9** shows that the intra-regional differences (G_w) contributed 25.91% on the total differences on average, the intensity of transvariation (G_t) contributed 28.99% during 2003–2019, and the contribution of inter-regional differences (G_n) was 45.10%, which meant the difference between regions was the greatest source. Regarding the changing processes, it was fairly obvious that the contributions of G_w and G_t remained relatively stable, while the contribution of G_n was increasing, as it varied gently within 41.48%–49.34%, with the annual increase rate being 0.20%. Therefore, it was concluded that the deterioration trend of carbon emissions in China was largely attributable to the differences between regions; thus, shrinking the gap of regions should be the key contributor to facilitate China's carbon-abatement agenda.

3.3 Driving Factors of Carbon Emission

The results in **Table 3** represented the selected 12 driving factors' influence on carbon emission using the factor detector model in 2003 and 2019. Furthermore, the ecological detector was utilized to

TABLE 3 | Power of the determinant value (*PD* value) for driving factors in China (2003 and 2019).

Driving factor	*PD*		Effect direction
	2003	2019	
FDI (X_1)	0.146***	0.073***	↓
OPEN (X_2)	0.376***	0.247***	↓
PGDP (X_3)	0.380***	0.561***	↑
TRA (X_4)	0.667***	0.586***	↓
INV (X_5)	0.030*	0.138***	↑
INF (X_6)	0.447***	0.365***	↓
ER (X_7)	0.095***	0.003	
PD (X_8)	0.215***	0.325***	↑
IS (X_9)	0.138***	0.158***	↑
FIN (X_{10})	0.298***	0.121***	↓
RD (X_{11})	0.160***	0.171***	↑
EI (X_{12})	0.135***	0.015	

*Note: *10% significance level (p < 0.1); ** 5% significance level (p < 0.05); *** 1% significance level (p < 0.01).*

test the distinct differences among these influencers regarding the spatial heterogeneity of regional carbon emission (see **Figure 10**, $p < 0.05$). To investigate the interactive effects between any two factors of carbon emission in China, the interaction detector was introduced, and the results are provided in **Figure 11**.

Based on **Table 3**, these drivers were found to differ in their impacts on carbon emission in China, with most drivers showing significant effects, among which *TRA* (0.586), *PGDP* (0.561), *INF* (0.365), *PD* (0.325), and *OPEN* (0.247) had the strongest determinative power. In detail, the influences of the twelve factors mentioned before on carbon emission in China are elaborated further:

(1) It can be seen that *TRA* was closely associated with carbon emissions in China, with the PD value changing from 0.667 in 2003 to 0.586 in 2019, which implied that the influence of *TRA* appeared to have weakened during the study period. The finding that transportation infrastructure expansion stimulated pollution comprising carbon emissions was not surprising, which was consistent with other studies (Xie et al., 2017; Huang et al., 2019a). This indicated that rapid economic growth and population expansion increased travel needs which further caused more traffic carbon emissions. Notably, with the appeal for sustainable economic development and green travel, *TRA* tended to form a more energy-saved and low-carbon style, as fossil energy was being replaced gradually by cleaner sources of energy such as solar in the transportation sector.

(2) The results showed that *AGDP* posed a huge environmental hazard to carbon reduction with the PD value up to 0.561 in 2019, while *AGDP* portrayed a smaller role that determined only 0.380 of the change of carbon emission in 2003. The reason for this result may be the extensive economic development mode characterized by high energy, high polluting, and high emission, which made the economy to become the second decisive and influential driver. As the economy grew faster, the number of resources and energy consumption increased rapidly, which in turn led to more carbon emissions (Ma et al., 2021). With this in mind, economic development must offset its environmental damage to a great extent, to simultaneously attain a win-win scenario with China's economic growth and carbon abatement.

(3) According to the estimated results, the explanatory power of *INF* has had a negative and an obstructive impact on carbon emission, with the PD value ranging from 0.447 in 2003 to 0.365 in 2019. Similar results include Anser et al. (2021); on the one hand, the widespread application of information technology has enhanced enterprise green knowledge and innovation capacity, and on the other hand, it brought about opportunities for socioeconomic cleaner production and low-carbon development. In addition, the *INF* can promote environmental information exchange and resource sharing and will serve as a technological foundation for the government to strengthen environmental supervision, which can lead to lower carbon emission.

(4) The decisive power of *PD* on carbon emission in 2003 was 0.215, while it increased to 0.325 in 2019, indicating that *PD* has added considerable pressure on carbon mitigation. Our findings also echoed the argument that the positive correlation between population density and environmental pollution existed in China (Sharma et al., 2021; Xu et al., 2021). The possible reason was that high *PD* levels accelerated urbanization, leading to an enormous increase in energy resource consumption, and thus the environment was seriously damaged. To sum up, the side-effects on the environment caused by *PD* must, these aforementioned results suggested, be properly arranged in the enactment and deployment of emission-inhibiting policies.

(5) Consistent with a previous study produced by Wang and Zhang (2020), *OPEN* showed a quite significant, adverse effect on carbon emission in the research period, with the PD value decreasing dramatically from 2003's 0.376 to 2019's 0.247. Along with the implementation of reform and opening up, China has been active in formulating various measures that yielded sound, long-term economic and environmental benefits, including expanding its import–export trade and attracting massive foreign investment. We can conclude that a higher openness level is greatly conducive for ceasing the growth of carbon emissions. Further deepening the internal–external opening should be recognized as an important impetus for the high-quality environment, and bringing into full play a promoting role of *OPEN* on carbon abatement was of great magnitude in China.

(6) It is noted that the PD values of the remaining seven factors all stayed low in the years 2003 and 2019, implying a relatively smaller decisive power on carbon emission. It can be found that *INV*, *IS*, and *RD* had exerted a positive, incentive influence on carbon emission. Conversely, *FDI* and *FIN* hindered the growth of carbon emission. Moreover, from a long-term perspective, *ER* and *EI*'s PD values exhibited a downward trend and were no longer significant in 2019.

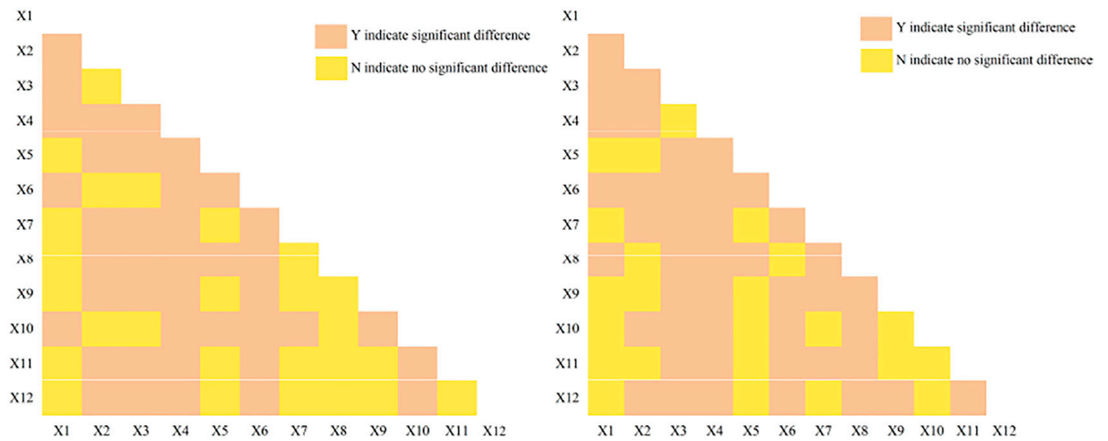

FIGURE 10 | Ecological detector results for driving factors on carbon emission in 2003 and 2019.

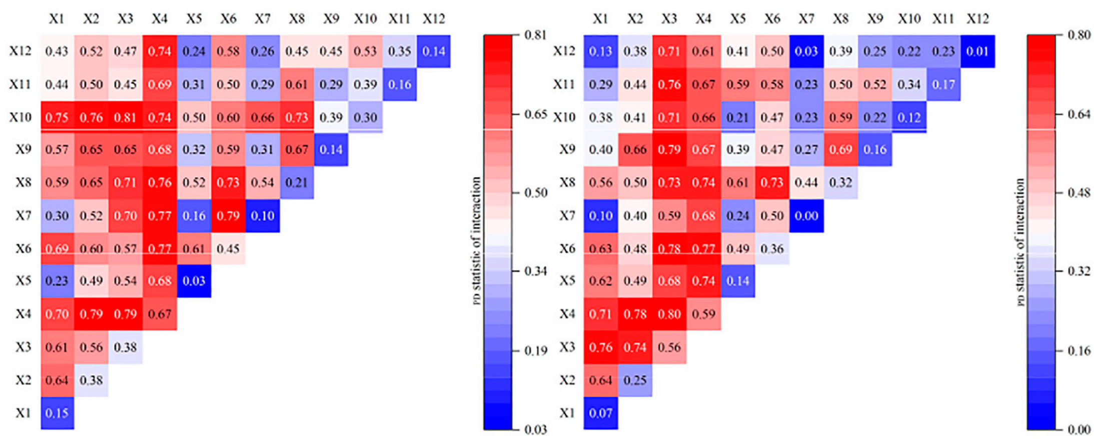

FIGURE 11 | Interaction detector results of driving factors on carbon emission in 2003 and 2019.

TABLE 4 | *PD* values for driving factors in four regions of China (2003 and 2019).

Driving factor	2003				2019			
	Eastern	Central	Western	Northeastern	Eastern	Central	Western	Northeastern
FDI (X_1)	0.100	0.066	0.030	0.341	0.189**(↑)	0.059	0.378**(↑)	0.086
OPEN (X_2)	0.408***	0.056	0.006	0.016	0.254**(↓)	0.131*(↑)	0.109	0.334*(↑)
PGDP (X_3)	0.362***	0.605***	0.185**	0.659***	0.692***(↑)	0.508*** (↓)	0.291***(↑)	0.615***(↓)
TRA (X_4)	0.695***	0.601***	0.707***	0.579**	0.732***(↑)	0.688***(↑)	0.704***(↓)	0.503***(↓)
INV (X_5)	0.075	0.026	0.085	0.010	0.370***(↑)	0.215* (↑)	0.025	0.142
INF (X_6)	0.415***	0.390***	0.265***	0.266	0.438***(↑)	0.321* (↓)	0.225***(↓)	0.323
ER (X_7)	0.058	0.258***	0.128*	0.551***	0.021	0.035	0.029	0.056
PD (X_8)	0.221**	0.139**	0.093	0.250	0.336***(↑)	0.164**(↑)	0.177	0.244
IS (X_9)	0.365***	0.123***	0.147**	0.192	0.323***(↓)	0.240***(↑)	0.207**(↑)	0.204
FIN (X_{10})	0.549***	0.460***	0.262***	0.188	0.153*(↓)	0.436** (↓)	0.178** (↓)	0.430
RD (X_{11})	0.334***	0.226***	0.253***	0.410**	0.153**(↓)	0.150	0.330***(↑)	0.353
EI (X_{12})	0.225***	0.327***	0.285***	0.168	0.070	0.010	0.040	0.029

Furthermore, this study used the ecological detector to examine the significant differences in the impacts of factors on carbon emission at the 0.05 significance level. As is indicated in **Figure 10**, a great majority of those drivers showed a rather remarkable difference. For instance, in 2003, the impacts of *TRA* (X_4) had a distinct difference as compared to those of *ER* (X_7) and *PD* (X_8). Results from the ecological detector showed that significant differences existed between *PGDP* (X_3) and any other factors on the spatial distribution of carbon emission except *TRA* (X_4) by 2019. The effects of *TRA* (X_4) and *INF*(X_6) on carbon emission were also significantly different, while the influences of *INV*(X_5) and *FIN*(X_{10}) were not significant (**Figure 10**).

The results of the interaction relationships between every two drivers in the years 2003 and 2019 are shown in **Figure 11**. The PD statistics on the diagonal represented the same separate effects of each driver, as listed in **Table 3**, while those distributed in the upper triangular matrix referred to the interactive effects. From the figure, it can be found, obviously, that interactions between most factors showed enhanced and non-linear effects on the carbon emission in China but some had an enhanced and bivariate effect. Taking *FDI* (X_1) and *OPEN* (X_2) for example, the relationship between X_1 and X_2 ($X_1 \cap X_2\,(0.64) > X_1\,(0.15) + X_2\,(0.38) = 0.53$) was non-linear in 2003, X_1 and X_2 enhanced each other, leading to a continuous increase in carbon emission. Likewise, the interaction between *OPEN* (X_2) and *TRA* (X_4) $[X_2 \cap X_4\,(0.79) > Max\,(X_2, X_4) = 0.667]$ was greater than the maximum of their separate effects, indicating an enhanced, bivariate impact on carbon emission. From **Figure 11**, in 2003, the interactive determinant powers of *TRA* (X_4) with other factors were significantly enhanced. This finding was also applicable to *OPEN* (X_3) in 2019. According to the aforementioned analysis, the improvement of each variable might not reduce and cease the carbon emission without paying enough attention to interactions between factors.

The factor detection model was applied to further reveal the main driving factors affecting carbon emission regionally. The whole China was divided into four regions based on its geographical location, as shown in **Table 4**. The results are outlined as follows: in the eastern region, *TRA* was the primary factor affecting carbon emission both in 2003 and 2019 (with PD value increased by 0.037). *PGDP* (0.692), *INF* (0.438), *INV* (0.370), and *PD* (0.336) were also the important factors for increasing carbon emission. In 2003, *PGDP* (0.605) had the strongest determinative power on carbon emission in the central region; *TRA* (0.601), *FIN* (0.460), *INF* (0.390), and *EI* (0.327) also exerted major impacts on carbon emission. By comparison, *TRA* (0.688) surpassed *PGDP* (0.508) and became the primary influencing factor in 2019. Obviously, the PD values of *FIN* (0.436) and *INF* (0.321) decreased during the study period, thus indicating that the financial development and information construction in central areas reduced their impacts on carbon emission. As for the western part of China, the influence of *TRA*, *FIN*, and *INF* on carbon emission decreased significantly from 2003 to 2019, whereas that of *FDI, PGDP, IS*, *and RD* increased, resulting in more carbon emission. That might be due to the fact that cities in the western region were relatively intensive in energy resources but lagged in technology, short in innovation and poor in research. The effects on *PGDP* and *TRA* was weakened (with PD values decreased by 0.044 and 0.076, respectively) in the northeastern region, whereas the *OPEN* showed a growing impact on carbon emission (with the PD value remarkably increased from 0.016, 2003 to 0.334, 2019), which signified that trade openness exacerbated carbon emission.

4. CONCLUSION AND POLICY IMPLICATIONS

4.1 Conclusion

This study investigated the spatiotemporal differences and driving factors of carbon emission in 284 Chinese cities for the period 2003–2019. Specifically, we used the spatial correlation analysis, standard deviation ellipse, and Dagum Gini coefficient methods to derive the spatiotemporal evolution pattern of carbon emission and revealed the main sources of regional differences. Moreover, the geographical detector model was introduced to identify the major drivers of carbon emission in China. We draw the following conclusions:

(1) From the spatiotemporal evolution, the annual average carbon emission in China was 100.974 Mt for the period 2003–2019 and exhibited a general upward trend over time. Among the four regions, carbon emission was the highest in the eastern region and then followed by northeastern and western regions, while the center region was the lowest. In addition, all the four regions presented a persistent increase in carbon emission, and the western region enjoyed the largest growth rate. In addition to that, the results showed that the carbon emission portrayed a "northeast–southwest" spatial distribution direction and represented a strong positive spatial correlation with an imbalance polarization trend of "east-hot and west-cold."

(2) The overall differences in carbon emission for cities showed a gradual downward trend during the research period from the Dagum Gini coefficient analysis, with higher Gini coefficients in eastern and central regions and lower Gini coefficients in western and northeastern regions, indicating that the regional differences in carbon emission were shrinking. Moreover, the contribution of interregional differences was obviously the largest and still increasing, thus narrowing the interregional differences should be set as the crucial point to reduce the overall carbon emission from a policy perspective.

(3) As for the driving factors of carbon emission, the results of the geographical detector model showed that transportation infrastructure, informatization level, and trade openness had the strongest determinative power in 2003, while transportation infrastructure, economic development level, and informatization level were the primary drivers affecting carbon emission in 2019. In the eastern, central, and

northeastern regions, transportation infrastructure and the economic development level exerted a greater effect on carbon emission; however, the explanatory powers of transportation infrastructure and the foreign direct investment level were larger than other factors in the western region. In addition, the interactions can be classified into two kinds: enhanced and nonlinear and enhanced and bivariate. Also, the interactive effects between any two factors showed greater influence on carbon emission than their separate effects.

4.2 Policy Implications

In line with the conclusions obtained, the following policy implications for carbon emission mitigation in China can be put forward:

First, and most importantly, China has to seek new ways to simultaneously guarantee sustained economic growth and carbon emission reduction. As the largest developing country, China still needs to spare no efforts to develop its economy, and the carbon emission may continue to increase at the same time. Over the long term, under such urgent circumstances of extreme climate change, degeneration of ecological conditions, and exhaustion of resources, the first task for the Chinese government should be looking for alternative ways to change the economic growth from high inputs, high consumption, and high discharge to green and low carbon. For example, the government should prioritize clean vehicle research, economic structure adjustment, information technology improvement, and increased trade openness to curb carbon emission. Meanwhile, the interactions between factors should also be given full play to achieve the steady progress of China's economy while reducing carbon emission, for example, considering the interactions with other factors during economic development, accelerating the development of new energy transportation, and improving the level of informatization, so as to achieve a win–win scenario with economic development and carbon mitigation.

Rather, the disparity between regions was the largest contributor to the total difference of carbon emission, so narrowing the gap between regional carbon emissions in urban areas should be treated as an effectual approach in mitigation policymaking. According to the aforementioned analysis results, the difference between eastern and western regions was the largest; thus, it is necessary for the local government to take the top priority for policies implementation about shrinking the gap across the cities belonging to eastern and western regions. For cities with higher emissions in the eastern region, the enactment of emission mitigation policies should be based on promoting green- and low-carbon economic transformation, so as to cease the growth of carbon emission. Strengthening the polluting industries and capital control and maintaining the current low-carbon development status, for lower cities in the western region, can assist in significantly curbing carbon emission. In addition, given that the carbon emission showed strong spatial positive correlation, the regional cooperation system should also be established to promote information exchange and cooperation, which can accelerate the emission-inhibiting process.

Last, in view of the distinguished decisive power of driving factors affecting regional carbon emission, it is pertinent for the Chinese government to formulate several flexible and targeted policies to facilitate its carbon-abatement agenda which are suitable for different parts of China. To be specific, the cities in all regions should stay devoted to modifying the traditional means of transportation into a cleaner way. In addition, to reduce carbon emission, the eastern region also has to put the main attention on economic progress and the enhancement of informatization level. Also, improving economic development quality and financial development level, increasing efforts to attract FDI, and accelerating research and development could serve as tools for carbon emission mitigation both in central and western regions. Regarding cities in the northeastern region, it is thus imperative for the local government to spur regional economic growth and expand the opening in trade during the carbon emission reduction.

However, there still exist some limitations that can be further improved in the future. First, carbon emission is an important catalyst for global warming, which could be triggered by various natural causes such as climatic types in different regions (Cai et al., 2018). Therefore, the analysis of impact factors on carbon emission should be considered into climatic types in future studies. Furthermore, the interactive influences in this study provided by the geographical detector model may not be comprehensive due to the complex relationships between variables (Zhu et al., 2020). With the improvement of the model, there is a need for future research to probe the interactive effects among three or more influencing factors on carbon emission in China. Finally, since December 2019, the global COVID-19 pandemic has been exerting profound impacts on human health and economic development. How will it affect carbon emission? With the extension of the study period and the update of data, this topic is worthy of further research.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors without undue reservation.

AUTHOR CONTRIBUTIONS

Conceptualization: K-LW; writing—original draft: R-YX; data curation: R-YX and F-QZ; supervision: K-LW and Y-HC.

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