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RESEARCH ARTICLE

Identification of the driving factors' influences on regional energy-related carbon emissions in China based on geographical detector method

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Abstract

To investigate the influences of different factors on spatial heterogeneity of regional carbon emissions, we firstly studied the spatial-temporal dynamics of regional energy-related carbon emissions using global Moran's *I* and Getis-Ord *Gi* and applied geographical detector model to explain the spatial heterogeneity of regional carbon emissions. Some conclusions were drawn. Regional carbon emissions showed significant global and local spatial autocorrelation. The carbon emissions were greater in eastern and northern regions than in western and southern regions. Fixed assets investment and economic output had been the main contributing factors over the study period, and economic output had been decreasing its influence. Industrial structure's influence showed a decrease trend and became smaller in 2015. The results of the interaction detections in 2015 can be divided into two types: enhance and nonlinear, and enhance and bivariate. The interactive influences between technological level and fixed assets investment, economic output and technological level, population size and technological level, and economic output and economic development were greater than others. Some policy recommendations were proposed.

Keywords Carbon emissions · Spatial heterogeneity · Driving factors · Geographical detector model · Regions

Introduction

Due to the repaid economic growth, industrialization, and urbanization, China has become the largest carbon emitter (Qiu 2008; Zeng et al. 2008). Under such circumstances, international community had paid much attention to the carbon emissions in China (Wang et al. 2014; Wang et al. 2013). Chinese government promised that the carbon intensity would be declined by 40–50% by 2020 in comparison with the 2005 level (Qiu 2009). In a joint statement on climate changes issued by China and the USA, China made promises to stabilize its carbon emissions by 2030 (Malakoff 2014). In the "Thirteenth Five Year Plan" (2016–2020), the government supported the relatively developed regions to achieve the carbon emissions peak (Mi et al. 2017). It is one of the major problems to reduce or slow down the carbon emissions without negatively influencing the reasonable economic growth (Han et al. 2017).

In fact, current studies pay close attention to the calculation of carbon emissions (Guan et al. 2012; Johnson et al. 2007), driving factors (Fan et al. 2015; Wang et al. 2017; Zhang et al. 2017a), scenario analysis (Wang and Watson 2010; Zhao et al. 2017), policy simulation (Fragkos et al. 2017; Qi et al. 2014), etc. Analysis of the driving factors is necessary to make policies or conduct scenario analysis. According to the previous studies, the driving factors mainly includes economic growth and development (Salahuddin et al. 2015; Zhang and Da 2015), energy structure (Wang et al. 2016; Wu et al. 2017), industrial structure (Chen et al. 2016; Ji et al. 2014), urbanization (Ding and Li 2017; Li et al. 2016), population size

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(Ohlan 2015; Zhang and Tan 2016), technological progress (Irandoust 2016; Nduagu and Gates 2016), and fixed assets investment (Xu and Gao 2016).

A possible shortcoming is that the above studies were based on the temporal analysis. Although some studies were conducted from the perspectives of regional analysis, the regions were mainly treated as homogeneous individual or independent, and the significant spatial relationships among regions and interactive effects of driving factors tended to be ignored. Tobler's first law of geography indicates that there exist relationships among things, but the relationships among the near things are stronger than those of distant things (Tobler 1970). Anselin (1988) also pointed out that neighboring regions would affect a region's activities to some extent. Some scholars had also studied the neighboring regions' influences on regional carbon emissions. Cheng et al. (2014) used spatial panel econometric model to explain the factors' influence on the changes in spatial dynamics of China's carbon emissions; Long et al. (2016) used spatial panel data models to measure its main determinants of provincial industrial carbon productivity in China over 2005–2012; Ang et al. (2016) applied the spatial-temporal decomposition approach to analyze the contributing factors of energy and carbon emissions for eight economic regions from China. As a consequence, it is necessary to have a deeper understanding on the driving factors from the prospective of spatial interaction effects.

Overall, most studies have analyzed the influences of spatial relationships, but studies, further exploring the interactive influences between driving factors, are still scarce. Geographical detector model was proposed by Wang et al. (2010). Its principle is that the spatial distributions of two attribute values tend to be similar, if these two attribute values are associated with each other. Geographical detector model can reflect spatial relationships or interactive effects. As a relatively novel spatial analysis model, there are some significant advantages. First, no assumption or restriction was required with respect to dependent and independent variables. Second, it can examine the interactive influence of two independent variables on dependent variable. Thus, geographical detector model is excellent to analyze the influences of driving factors on spatial heterogeneity, and it has been applied the study in urbanization (Zhu et al. 2015), environment (Luo et al. 2015), and human health (Huang et al. 2014). Thus, we firstly studied the spatial-temporal dynamics of regional energy-related carbon emissions using global Moran's I and Getis-Ord Gi and then used the geographical detector model to analyze the driving factors' influences and interactive influences on spatial heterogeneity of regional carbon emissions. According to the analysis, we could know that whether two driving factors were independent in influencing carbon emissions, or whether they enhanced or weakened one another when taken together. So, the results made it clear that which two driving factors could be combined to reduce carbon emissions. In the end, some targeted policies would be proposed.

Methodology

Global Moran's *I*

The spatial relationships among neighboring regions can be examined by global Moran's I (Anselin 1988). The equation is expressed as follows:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\left(y_i-\overline{y}\right)\left(y_j-\overline{y}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\sum_{i=1}^{n}\left(y_i-\overline{y}\right)} \tag{1}$$

where y_i and y_j are the energy-related carbon emissions of region i and j, respectively; $\overline{y}$ is the average carbon emissions of all regions; w_{ij} represents the weights matrix; and n represents the number of regions. Moran's $I\in(-1,1)$. When $-1<$ Moran's $I<0$, provinces with different carbon emissions are grouped together; when Moran's $I=0$, no spatial correlation exists; when $0<$ Moran's $I<1$, provinces with the similar carbon emissions are grouped together (Xu and Lin 2017). GeoDa software has the function of spatial data analysis, which can be used to calculate the global Moran's I.

The results of Moran's I were statistically tested using the standardized statistic Z. The equation is shown as follows: $z=\frac{I-E(I)}{\sqrt{\mathrm{VAR}(I)}}$ (2)

When the z value is greater than 0 and statistically significant, it means that the significant agglomeration exists. When z value is smaller than 0 and statistically significant, it means that the significant spatial difference exists; when z value is equal to zero, there is no spatial correlation.

Getis-Ord *Gi*

In order to identify the local spatial autocorrelation, Getis-Ord Gi is introduced. The spatial agglomeration of high or low carbon emissions can be identified within the context of neighboring features (Getis and Ord 1992). It can be expressed as follows:

$$G(d)=\frac{\sum_{j=1}^{n}w_{ij}y_j-\overline{y}\sum_{j=1}^{n}w_{ij}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n}w_{ij}^2-\left(\sum_{j=1}^{n}w_{ij}\right)^2\right]}{n-1}}} \tag{3}$$

$$s=\sqrt{\frac{\sum_{j=1}^{n}y_j^2-\overline{y}^2}{n}} \tag{4}$$

where $G(d)$ is the value of Getis-Ord Gi. When the value of the $G(d)$ is positive and $Z(G)$ is statistically significant, the hot spot exists. When the value of the $G(d)$ is negative and $Z(G)$ is statistically significant, the cold spot exists (Xu and Lin 2017; Zhu et al. 2010).

Geographical detector model

On the basis of spatial variance analysis of geographical strata, Wang et al. (2010) proposed the geographical detector model to analyze the influences of different factors on spatial heterogeneity. The association between these two attribute values can be examined as follows:

$$\mathrm{PD} = 1-\frac{\sum_{h=1}^{L}\sum_{i=1}^{N_h}\left(y_{h1}-\overline{y}_h\right)^2}{\sum_{i=1}^{N}\left(y_i-\overline{y}\right)^2} = 1-\frac{\sum_{h=1}^{L} N_h\sigma_h^2}{N\sigma^2} \quad (5)$$

where PD is the power of determinate; based on the spatial heterogeneity of study object, the study is divided into L strata, denoted by $h = 1,\ldots, L$; σ^2 and $\sigma^2{}_h$ are the variances of whole units and h strata, respectively; and N and N_h are the numbers of the units in the study area and h strata, respectively. As shown in Fig. 1, the strata of Y was formed by laying Y over X which consists of strata. PD∈ [0, 1], and the PD can reflect the influence of X on the spatial heterogeneity of Y. The larger the PD is, the larger the influence of X is.

The spatial heterogeneity of Y is influenced by many factors. There may exist interaction between each two factors, and whether each two factors together enhance or weaken each other, or they are independent in influence the spatial heterogeneity of Y. The geographical detector model can examine the interaction between two factors. As shown in Fig. 2, powers of determinate of factor $X1$ and $X2$ to Y are firstly calculated; then, $X1$ and $X2$ are overlaid, and new strata are formed; at last, the power of determinate of interaction between $X1$ and $X2$ can be calculated. The interactive influence between two factors can be judged as Table 1. ArcGis 10.0 and GeoDetector software can help realize them. The GeoDetector software can be obtained at http://www.sssampling.org/Excel-GeoDetector/(Wang and Hu 2012).

Data management

Data resources, consisting of gross domestic product (GDP), added of secondary industrial, the population including urban population, and fixed assets investment in 2000, 2007, and 2015, were all collected from the *China Statistical Yearbook* (2001, 2008, and 2016). Energy data were collected from *China Energy Statistical Yearbook* (2001–2016).

Results and discussions

Temporal-spatial characters

As indicated in Fig. 3, China's energy-related carbon emissions were generally on the rise. In 2000, the total carbon emissions were only 1270.38 million tons and reached 4282.84 million tons in 2015, which increased by 3.37 times from 2000 to 2015. It also can be seen that energy-related carbon emissions declined in 2015, and it is the first time for China. In 2015, total coal consumption declined in comparison with 2014. Meanwhile, China has led the way on renewables such as solar power, wind, and hydropower (Wang and Wang 2017). Thus, energy-related carbon emissions were lower in 2015 than in 2014.

The global Moran's I of energy-related carbon emissions was calculated by means of the GeoDa software. Meanwhile, with the aid of random permutation, the normal distribution was also established to test the significance of annual global Moran's I. These results were shown in Fig. 3. During the period 2000–2015, the annual the Global Moran's I was positive, and the normal statistics z was statistically significant at the 5% level or 1% level (Table 2). Therefore, it illustrated that the regions with higher or lower energy-related carbon emissions tend to be adjacent, and regional carbon emissions showed significant spatial autocorrelation over the study period. The Moran's I increased with fluctuations from 0.171 in 2000 to 0.294 in 2011, with annual average concomitant probability of 0.02. Thus, the agglomeration degree of regional carbon emissions showed an increasing trend. After 2011, the Moran's I decrease from 0.294 to 0.243 over 2011–2015, with annual average concomitant probability of 0.01, which indicated that the agglomeration degree showed a slight

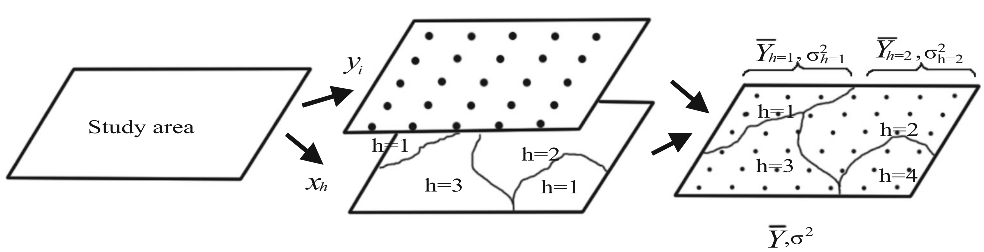

Fig. 1 The principle of geographical detector

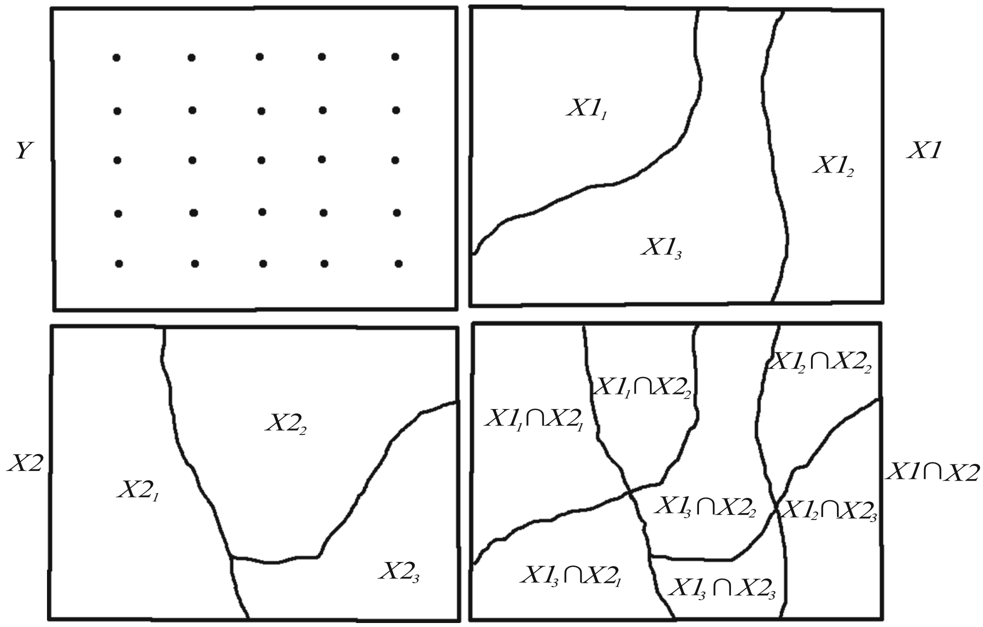

Fig. 2 Detection of interaction

decreasing trend. In general, the spatial agglomeration of energy-related carbon emissions was obvious over the study period, and the regions with similar carbon emissions were agglomerated in spatial distribution.

Getis-Ord *Gi* was used to analyze the local agglomeration patterns of regional carbon emissions in 2000, 2007, and 2015, and five types were divided using the Natural Breaks Classification method. According to Fig. 4, regional carbon emissions showed significant characteristic of local spatial autocorrelation. The regions with high z score, that being hot spots, were located in eastern and northern China in 2000, 2007, and 2015, and the regions with low z score, that being cold spots, were mainly located in western and southern China. It illustrated that the carbon emissions were greater in eastern and northern regions than in western and southern regions. Shandong, Henan, Hebei, and Shanxi had been the hot spots over the study period, indicating that their neighboring regions were mainly high carbon emitters. Xinjiang, Qinghai, Sichuan, and Guangdong had been the cold spots over the study period, indicating that their neighboring regions were low carbon emitters. These regions with similar carbon emissions were close to each other.

Driving factors' influences

Based on the analysis in above sections, regional carbon emissions showed obvious spatial autocorrelation. The agglomeration patterns of regional energy-related carbon emissions were influenced by many factors. Based on the previous studies (Wang et al. 2017; Zhang et al. 2017c; Zhang et al. 2011), some factors were selected to analyze their influence on the spatial heterogeneity of carbon emissions. We used economic output and economic development to explore the influences of regional economic differences on the environmental pressure. We used the proportion of urban population in total population to reflect the urbanization; thus, the influences of regional population structure changes on spatial heterogeneity could be analyzed combining urbanization with population size. We applied the proportion of the secondary industry to analyze the influences of regional industrial structure differences on spatial heterogeneity. Proportion of coal consumption in total energy consumption was applied to reflect the influence of regional energy structure differences on spatial heterogeneity. Energy consumption per unit GDP was applied to analyze the influences of regional technological level difference on

Table 1 Interaction relationships

Description	Interaction
PD ($X1 \cap X2$) < Min (PD($X1$), PD ($X2$))	Weaken and nonlinear
Min (PD($X1$), PD ($X2$)) < PD ($X1 \cap X2$) < Max (PD ($X1$)), PD ($X2$))	Weaken and univariate
PD ($X1 \cap X2$) > Max (PD($X1$), PD ($X2$))	Enhance and bivariate
PD ($X1 \cap X2$) = PD ($X1$) + PD ($X2$)	Independent
PD ($X1X2$) > PD ($X1$) + PD ($X2$)	Enhance and nonlinear

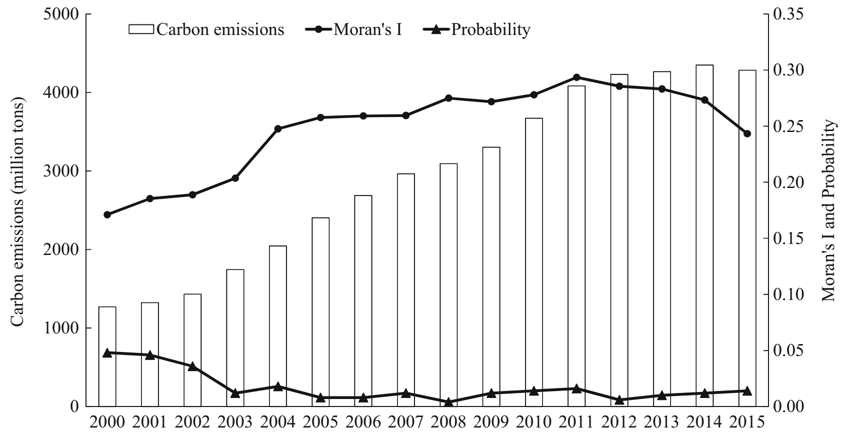

Fig. 3 Changes in carbon emissions and Moran's *I* index

spatial heterogeneity. Fixed assets investment could influence the economy, industrial structure, and energy structure, so we used regional fixed assets investment to analyze the influence on spatial heterogeneity. These factors and their explanations were listed in Table 3. ArcGIS 10.0 was applied to express the agglomeration patterns of these driving factors, and five types were divided using the Natural Breaks Classification method. Then, Eq. (5) was used to examining the driving factors' effect on the spatial heterogeneity of regional carbon emissions, and the results were shown in Fig. 5.

In 2000, based on the influencing degree on the spatial heterogeneity, the driving factors were ranked as follows: industrial structure > economic output > fixed assets investment > population size > technological level > urbanization > economic development > energy structure. China's secondary industry was characterized by high energy consumption, low energy efficiency, and secondary industry, especially industrial sector, consumed much more fossil energy than primary industry and tertiary industry. Thus, the difference of regional industrial structure contributed most to the spatial heterogeneity of regional carbon emissions in 2000. Many provinces with larger economic output were also the bigger emitters, such as Shandong and Jiangsu. Fossil energy was one of the most important input factors during the process of economic growth. Economic growth demanded massive energy; meanwhile, the regional economic output existed difference, making the economic be the second contributing factor. Power of determinant of fixed assets investment was also remarkable. It illustrated that they shared the spatial features, i.e., the fixed assets investment exhibited a spatial distribution similar to that of the regional carbon emissions. According to the theory of geographical detector model, the regional carbon emissions were also significantly influenced by fixed assets investment. In 2000, energy efficiency was very low, and the energy consumption per GDP of the relatively developed provinces, which also emitted more carbon, was much larger than that of some regions. This made technologic level be the fourth contributing factor in influencing the spatial heterogeneity of regional carbon emissions. Urbanization, economic development, and energy structure played relatively small role in the spatial heterogeneity.

In 2007, the driving factors were ranked as follows: fixed assets investment > industrial structure > economic output > economic development > population size > energy structure > urbanization > technological level. Since joining the WTO in 2001, China's economy gained new opportunities for development, and fixed assets investment grew very fast. In comparison with 2000, the total fixed assets investment increased by 12.04 times. The growth rate of fixed assets investment was much larger. Some regions, which had been the larger emitter such as Shandong, Jiangsu, and Guangdong, gained more fixed assets investment, and regional carbon emissions also increased. Thus, fixed assets investment had become the most influential factors for the spatial heterogeneity of regional carbon emissions in 2007. Proportion of secondary industry increased from 45.4% in 2000 to 46.7% in 2007. Meanwhile, the relatively undeveloped regions with less carbon emissions, such as Jiangxi, Guangxi, also increased the proportion of secondary industry output. These made the industrial structure be still one of the main contributors, but its influence also decreased. Economic output was the third contributing factor, but it was clear that its power of determinant decreased from 0.598 in 2000 to 0.437 in 2007. Economic development and population size also contributed much to the spatial heterogeneity. The

Table 2 Normal statistics z

Year	z	Year	z	Year	z	Year	z
2000	−2.034**	2004	−2.224**	2008	2.504**	2012	2.510**
2001	−2.011**	2005	−2.547**	2009	2.334**	2013	8.951***
2002	−2.266**	2006	−2.065**	2010	2.478**	2014	−2.377**
2003	−2.175**	2007	−2.447**	2011	2.166**	2015	−2.266**

** and *** indicate that the variable is statistically significant at the 5% significance level and 10% significance level, respectively

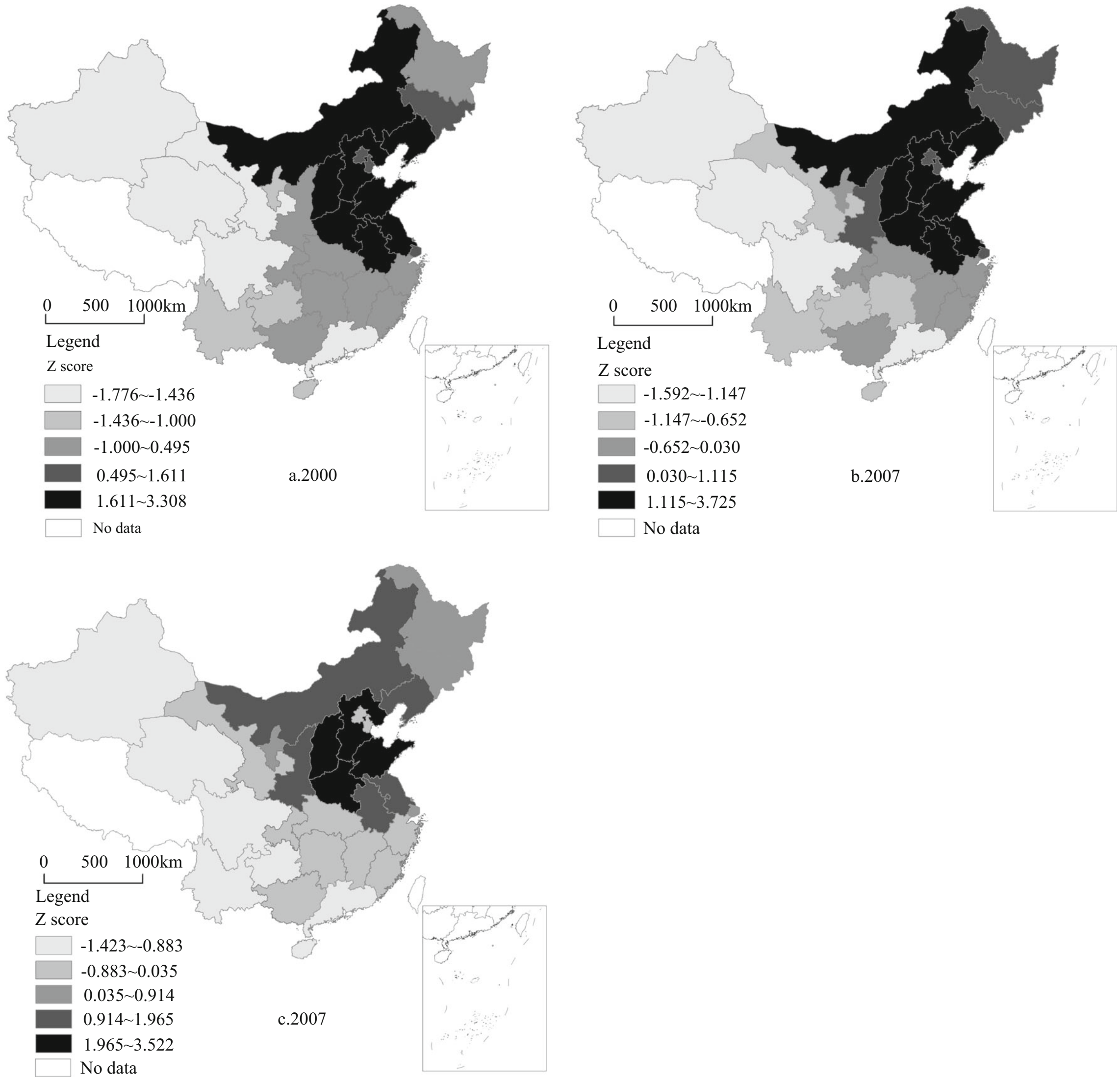

Fig. 4 The agglomeration patterns of regional carbon emissions in 2000, 2007, and 2015

influences of energy structure, urbanization, and technological level were much smaller than other driving factors.

In 2015, based on the influencing degree on the spatial heterogeneity, the driving factors were ranked as follows: fixed assets investment > economic output > technological level > population size > energy structure > urbanization > industrial structure > economic development. Fixed assets investment contributed most to the spatial heterogeneity; nevertheless, its power of determinant decreased from 0.521 in 2007 to 0.453 in 2015. Economic output was also the main

Table 3 Factors and their explanations used in the analysis

Factors	Symbols	Definition measuring methods
Economic output	EO	Gross domestic product (GDP)
Economic development	ED	Per capita GDP
Urbanization	U	Proportion of urban population in total population
Population size	P	Regional total population
Industrial structure	IS	Proportion of the secondary industry
Energy structure	ES	Proportion of coal consumption in total energy consumption
Technological level	T	Energy consumption per unit GDP
Fixed assets investment	F	Total fixed assets investment

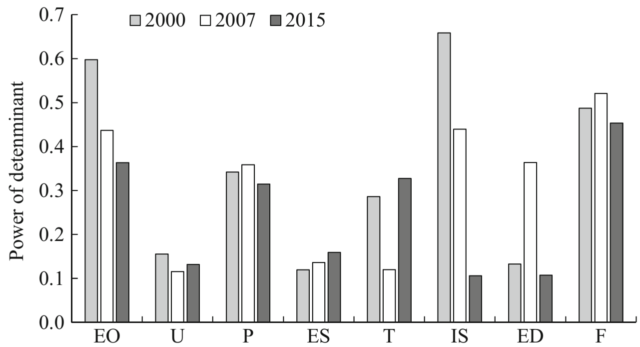

Fig. 5 The influences of driving factors on spatial heterogeneity in 2000, 2007, and 2015

contributing factor, but its power of determinant showed a decrease trend during the study period. It indicated that the spatial distribution of economic output became different gradually to the spatial distribution of regional carbon emissions, and economic output had been decreasing its influence on spatial heterogeneity of regional carbon emissions. Technological level became the third contributing factor. Nevertheless, the driving mechanism in 2015 was different than that in 2000 and 2007. In 2000, the technological level was relatively backward, and energy efficiency was also low, these making the spatial distribution of poor technological level be similar to that of high carbon emissions. In 2015, advanced technology had already been introduced, and energy consumption per unit GDP decreased, these making the spatial distribution of high technological level be similar to that of high carbon emissions. It belonged to transition period in 2007; thus, the power of determinant of technological level was the smallest. It illustrated that improvement of technological level did not decrease the regional carbon emissions. Population size also played an important role in the spatial heterogeneity. Energy structure, urbanization, economic development, and industrial structure played relatively small role in the spatial heterogeneity. Over the study period, the influences of urbanization and energy structure were much smaller than other factors, indicating that their influences on spatial heterogeneity of regional carbon emissions were not significant.

Wang et al. 2017 and Xu and Lin 2017 deemed that fixed assets investment and economic output were the main influential driving factors, which was consistent with our conclusion. The increase in fixed assets investment drove growth in industries and then increased the carbon emissions, but the influence of industrial structure varied considerably in different years, and this conclusion was consistent with Wang and Feng 2017. Cheng et al. 2014 and Jiang et al. 2016 also thought that urbanization and energy structure had smaller influence on spatial heterogeneity. Our conclusions on the influence of population size and technological level were also consistent with the studies of Wang et al. 2017 and Zhang et al. 2017b.

Interaction detections between driving factors

Do each two driving factors enhance or weaken each another when they were taken together, or are they independent in influencing the spatial heterogeneity of regional carbon emissions? In order to reveal the interactive influence between each two driving factors, the interaction detector was applied. This paper only analyzes the interaction influences in 2015, and the results were shown in Table 4. The results of the interaction detections in 2015 can be divided into two types: enhance and nonlinear, and enhance and bivariate. It indicated that the power of determinant of each two driving factors was bigger than that of each one driving factor, and each driving factor enhanced other factors' influences when they were taken together. That is, the interactive influence on spatial heterogeneity was greater. As shown in Table 4, the interactive influences between technological level and fixed assets investment, economic output and technological level, population size and technological level, and economic output and economic development were greater than others. The interactive influences between economic output and technological level, population size and technological level, and economic output and economic development were greater than the sum of each

Table 4 Results of the interaction detections in 2015

q	EO	U	P	ES	T	IS	ED	Types	EO	U	P	ES	T	IS	ED
U	0.61							U	EN						
P	0.43	0.66						P	EB	EN					
ES	0.69	0.52	0.53					ES	EN	EN	EN				
T	0.93	0.46	0.92	0.43				T	EN	EB	EN	EB			
IS	0.51	0.41	0.45	0.37	0.69			IS	EB	EN	EB	EN	EN		
ED	0.89	0.53	0.50	0.44	0.45	0.37		ED	EN	EN	EN	EN	EN	EN	
F	0.56	0.68	0.48	0.72	0.95	0.60	0.65	F	EB	EN	EB	EN	EB	EB	EN

EN denotes "enhance and nonlinear;" EB denotes "enhance and bivariate" two factors' influence. The interactive influence between technological level and fixed assets investment was greater than the maximum of their separate influences. It was obvious that the interactive influences between technological level and other factors were significant. As analysis in "Interaction detections between driving factors" section, the spatial distribution of high technological level and high carbon emissions was similar in 2015. These regions with high technological level always had larger population, economic output, and fixed assets investment. This meant that improvement of technological level could not decrease or slow down regional carbon emissions if no attention was paid to other factors.

Conclusions and policy recommendations

We firstly studied the spatial-temporal dynamics of regional energy-related carbon emissions using global Moran's I and Getis-Ord Gi and applied geographical detector model to explain the spatial heterogeneity of regional carbon emissions. We draw some conclusions:

(1) Energy-related carbon emissions showed an overall increasing trend in China. Regional carbon emissions revealed significant global and local spatial autocorrelation. The carbon emissions were greater in eastern and northern regions than in western and southern regions. Shandong, Henan, Hebei, and Anhui had been the hot spots over the study period, and Xinjiang, Qinghai, Sichuan, and Guangdong had been the cold spots over the same period.

(2) The influences of each factor were different in 2000, 2007, and 2015. Fixed assets investment and economic output had always been the main contributing factors over the study period, and economic output had been decreasing its influence. Industrial structure played an important role in 2000 and 2007, but its influence showed a decrease trend and became smaller in 2015. Technological level became the third contributing factor in 2015, and its driving mechanism was different than that in 2000 and 2007. The influence of population size was in relatively stable condition. The influences of urbanization and energy structure were much smaller than other factors.

(3) The results of the interaction detections in 2015 can be divided into two types: enhance and nonlinear, and enhance and bivariate. Each driving factor enhanced other factors' influences when they were taken together. The interactive influences between technological level and fixed assets investment, economic output and technological level, population size and technological level, and economic output and economic development were greater than others.

Based on the above findings, we proposed some policy recommendations as follows. Regional fixed assets investment and economic output have become the first two contributing factors. Along with the rapid increases of economic output in different regions, the total fixed assets investment would also increase additionally. In 2015, industrial sectors accounted for about 40% of the total fixed assets investment. Industrial sectors emitted most of the energy-related carbon emissions. Thus, reasonable fixed assets investment was very important for regional carbon emissions. For the regions with large fixed assets investment, energy-saving assessments should be implemented for the new projects of fixed assets investment, and new fixed assets investment for energy-intensive sectors should be controlled. Although industrial structure's influence became relatively smaller in 2015, it needed also to pay enough attention to the industrial restructuring. As mentioned above, improvement of technological level could not decrease or slow down regional carbon emissions if no attention was paid to other factors. It is important for the regions with low fixed assets investment. In 2015, the distribution of the low technological level was similar to that of regional carbon emissions. But it is hard for these regions, such as Xinjiang, to inhibit the investment in industrial sectors. New technological level is necessary for these regions, and these regions need to apply the clean technology or new technology to improve the production capacity of cleaner production. Urbanization and energy structure played relatively minor role, but their influences cannot be ignored. In the foreseeable future, the level of urbanization in China will continue to increase. Its spatial influence was not significant, but urbanization can promote the regional carbon emissions by industrial restructuring, influencing economic growth, changes in residents' consumption, and various other factors (Donglan et al. 2010). Thus, the quality of the development of regional urbanization should be paid enough attention. Most region's coal proportions were still high, and the disparity of regions was relatively small. So it is necessary to decrease the coal proportion for every region.

Geographical detector model is excellent to explore the interactive influences between driving factors. But it can only probe the interactive influences between two driving factors. In fact, energy-related carbon emissions are influenced by many factors. So, the GeoDetector software needs to be improved to probe the interactive influences among three or more driving factors in the future studies. Thus, more targeted policies will be proposed.

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