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Original Research

What Affects Carbon Emission Performance? An Empirical Study From China

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Abstract

In the context of global warming, low-carbon economy with low energy consumption, low pollution and low emissions as the main characteristics has become the focus of attention. The paper takes 30 provincial-level units in China as the basic research object, uses DEA model to measure China's carbon emission performance in 2005, 2010, 2015 and 2019, and uses spatial visualization and trend surface analysis method to analyze its spatial-temporal rule. On this basis, geographical detector is used to analyze the influencing factors and the results show that: (1) China's carbon emission performance is at a relatively low level, except for that of provinces such as Beijing, Shanghai, Hainan and Qinghai while other provinces still need more efforts to perform better. In addition, the carbon emission performance fluctuates during the research period. Specifically, the change trend of east-west direction is greater than that of north-south direction. (2) The spatial difference of the performance is significant. In general, areas of high performance are mainly distributed in the eastern and southern regions while areas at low performance level mainly in the western and northern parts. There is an evident spatial trend of mixed distribution, initially forming the development trend of „overall mixed distribution and partial aggregation". (3) Government intervention has the greatest influence on carbon emission performance, followed by ownership structure, foreign investment, energy structure, technological progress, industrial structure, and degree of opening to the outside world. In addition, interaction factors have a greater impact on performance than single factors, and show nonlinear enhancement characteristics.

Keywords: carbon emission performance, geographical detector, spatial-temporal differentiation, influencing factors

Introduction

Nowadays, climate change has become a major global challenge for mankind [1]. It is figured out in the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) that climate warming is mainly caused by greenhouse gas emission produced by human activities. Thus, carbon dioxide, as one of the most important greenhouse gases, is closely related to climate change. In order to achieve sustainable development, and in the context of "low-carbon", various countries have proposed corresponding low-carbon action plans, such as the British low-carbon

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action plan and Japanese low-carbon social action plan, etc. And China, as the world's largest emitter of carbon dioxide, has long been focusing on energy conservation and emission reduction for the national development strategy. During the 13th Five-Year Plan period, the goal of archiving green and low carbon development was continuously strengthened and the carbon emission intensity decreased by 18% in 2020 when compared with 2015. Besides, within the 14th Five-Year Plan period, in order to achieve the target for the 2030 nationally determined contribution on climate change, an action plan for peaking carbon dioxide emissions by 2030 was formulated. Therefore, it is easy to figure out that achieving carbon peak and carbon neutrality is both an inherent requirement for China to achieve high-quality economic development and the country's commitment to the international community. Hence, measuring the performance level of carbon emission in China, finding its spatial evolution rule from spatial-temporal dimension, and exploring its relationships with economic development, technological progress, energy consumption structure and other factors can help provide practical and feasible policy suggestions for the country to determine the regional responsibility of carbon emission reduction and to deploy carbon emission reduction actions.

On the basis of the discussed background, „emission reduction" and „low carbon" quicky become research hotspots in academic domain, whereinto, carbon emission performance, as the significant substance of environmental performance evaluation, has attracted the attention of scholars from all over the world. In terms of theory, some scholars keep presenting new evaluation methods starting with model construction on the one hand while on the other hand, they interpret the concept, connotation and compensation mechanism of low-carbon economic development from theoretical analysis, which are represented by the scenario development model of long-term low-carbon society at the urban scale [2-3], the regional social-economic development model designed by Shimada [4] and the regional development model considering climate factors by Truepenny [5]. Empirically, Song et.al. [6] utilized RAM model to measure the carbon emission efficiency of prefectural and municipal cities in Shandong province, finding out that the carbon emission efficiency of 17 cities in Shandong province was spatially aggregated. Besides, Xie et.al. [7] used DEA model and Malmquist total factor productivity index to analyze the performance and influencing factors of low-carbon economic development in China. The results showed that the development level of static performance of low-carbon economy in China was not high, but there were significant differences among provinces. The green coverage rate and total carbon emission of built-up areas were the main reasons affecting the performance of low-carbon economic development. Meanwhile, Wang et. al. [8] used the super-efficiency SBM model to explore the spatial-temporal dynamic evolution characteristics of China's carbon emission performance, revealing that the carbon emission performance of China's cities showed a trend of fluctuation and rise, and the overall level was low. Ma et al. [9] used DEA-BCC model and DEA-Malmquist model to measure the carbon emission performance and driving factors of China's logistics industry, finding that the overall carbon emission performance of China's logistics industry was at a medium level. Lin et al. [10] used the Comparative Study on Urban Transport and the Environment (CUTE) framework to identify the driving factors of China's logistics carbon emissions showed that technical intensity and transport structure promoted carbon emissions, while technical efficiency and agglomeration curbed carbon emissions. Chen et al. [11] employed the Tapio decoupling analysis method and the environmental Kuznets curve (EKC) model to represent speed decoupling and quantity decoupling and examined the decoupling relationship between Zhejiang Province's carbon dioxide (CO_2) emissions and economic growth. Zeng et al. [12] utilized STIRPAT model to study the influencing factors of CO_2 emissions in Chengdu-Chongqing urban agglomeration, finding that population, GDP, natural gas and electricity consumption and industrial structure were the main reasons affecting carbon emissions. And Liu et al. [13] used the non-angular mixed directional distance function model to study the carbon emission performance of the Yangtze River Delta region, revealing that the carbon emission performance of central cities was better than that of non-central cities, and technological progress and efficiency deterioration affected their carbon emission performance to varying degrees. Xie et al. [14] used DEA model to measure the carbon emission performance of manufacturing industry in 11 provinces and cities in western China, believing that the carbon emission performance of manufacturing industry in western China showed a trend of decreasing fluctuation and was generally at a low level. Lin et al. [15] used two-stage Super SBM model, spatial analysis and spatial econometric model to analyze the temporal and spatial evolution characteristics and influencing factors of industrial carbon emission efficiency in the Beijing-Tianjin-Hebei region, finding that the industrial carbon emission efficiency kept improving during the research period, the productivity level, industrial R&D investment and the level of opening-up have a positive effect on industrial carbon emission efficiency, and energy consumption intensity is always negatively correlated with industrial carbon emission efficiency. Yamaji [16] defined the ratio of total CO_2 emissions to GDP as CO_2 productivity to study the level of carbon emissions in Japan. Zhang et al. [17] in the system on the basis of combing the strengths and weaknesses of the existing carbon dioxide emissions targets, think that industrialization and cumulative emissions and per capita emissions per unit of GDP per capita the new evaluation index reflects the more scientific, fair and reasonable principle, and in a typical developed countries and developing countries as a representative for the calculation and comparison.

By reason of the foregoing, in terms of carbon emission performance and its influencing factors, domestic and foreign scholars have done a lot of researches and achieved a series of valuable research results, but there is still some room for improvement. In terms of research topics, scholars mainly study the estimation methods, influencing factors, intensity and performance of CO_2 emissions. From the perspective of the research scale, most scholars take a certain region as the research object, which mainly reflects the inter-regional carbon emission performance level, while the national carbon emission performance research is insufficient. In terms of research perspective, scholars mainly take carbon index energy intensity and carbon emission intensity as indicators to measure carbon emission performance, instead of fully considering the technology and scale efficiency of relevant input factors, and fail to take economy, energy and environment as a unified whole, resulting in different degrees of deviation in the evaluation results. In the aspect of research methods, current studies mostly use panel data regression model to analyze the impact of different factors on carbon emissions performance. traditional panel regression usually assumes that the impact of each factor on carbon emissions is independent of each other, which obviously deviates from the reality. But the geographical detector method can make up for this deficiency better, because it can detect both numerical data and qualitative data, thus offsetting the intense subjectivity shortcoming caused by the current evaluation indicators being mostly processed by assigning values. Furthermore, with its interactive detection function, the relationship between the influence factors can be analyzed from a deeper level. In view of this, this paper selects four time node, 2005, 2010, 2015 and 2019 and uses DEA model to measure China's carbon emissions performance and spatial visualization and trend surface analysis method to explore its space-time evolution law, on the basis of using the geographic detector to explore China's carbon emissions performance influence factors, so as to provide decision-making reference for promoting carbon performance, developing low-carbon economy and achieving carbon peak and carbon neutrality in China.

Data and Methods

Data Sources

This paper takes 30 provinces and regions in China as the research objects (except Hong Kong, Macao and Taiwan, and Tibet Autonomous Region is not included in the research object due to the lack of some data). The data is obtained from China Statistical Yearbook and national statistical website in 2006, 2011, 2016 and 2020. For a few missing data, the method of supplement value is used. Carbon emission data are obtained by multiplying the total consumption of various energy sources by the average low calorific and carbon dioxide emissions. Since the total carbon emission is unexpected output index, the total carbon emission is handled by reciprocal transformation.

On the basis of referring to related research [18], this paper selects car ownership, green coverage rate of built-up area, urban built-up area, number of employees at the end of the year, total investment in fixed assets and power consumption as input indicators, and total carbon emission and GROSS national product as output indicators. The carbon emission performance evaluation indicator system constructed is shown in Table 1.

Methods

DEA Model

Data Envelopment Analysis is performed by input and output to estimate the production frontier [19-20]. Now it's provided that the carbon emission performances of K provinces shall be evaluated, and the evaluation indexes are assumed as type L input index and type M output index. It is assumed that xij represents the input amount of resource i for low-carbon

Table 1. Evaluation index system of carbon emission performance.

Index attribute	Index selection	Index description
Input index	The number of car ownership / 10,000 vehicles	Transportation input
	Green coverage rate of built-up area/%	Afforesting input
	Urban built-up area /km^2	Land input
	Number of employees at year-end/ten thousand people	Labor input
	Total investment in fixed assets / 100 million yuan	Capital input
	Electricity consumption amount/gigawatt hours	Energy input
Output index	Total carbon emission amount / 10,000 tons	Environment load
	GNP / 100 million yuan	Economic benefit

economic development of Province J and yjm stands for the output amount of resource m for low-carbon economic development of Province J. Then, for the n-th (n = 1, 2, 3..., k) province, there is the following DEA application model in the following form [4]:

$$\begin{cases} min(\theta - \varepsilon(e_1^T s^- + e_2^T s^+)) \\ s.t. \sum_{j=1}^{k} x_{jl}\lambda_j + s^- = \theta x_l^n \quad \text{l=1,2,…,L} \\ \sum_{j=1}^{k} y_{jm}\lambda_j - s^+ = y_m^n \quad \text{m=1,2,…,M} \\ \lambda \geq 0 \quad \text{n=1,2,…,K} \end{cases} \tag{1}$$

In the formulas: In Equation (1): θ(0<θ≤1) denotes the technical efficiency index; λj(λj≥0) represents the weight variable; s-(s-≥0) Represents the slack variable; s+(s+≥0) represents the remaining variables; εstands non-archimedean infinitesimally small; eT1 = (1, 1,…, 1)∈Em; eT2 = (1, 1,…, 1)∈Ek are m and k-dimensional unit vector Spaces, respectively. The closer θ is to 1, the higher is the carbon emission performance of the NTH province; otherwise, the lower is the carbon emission performance. If θ = 1, it indicates that the carbon emission performance of the province runs on the optimal production frontier, and the output of the low-carbon economic development of the province is optimal relative to the input.

Trend Surface Analysis

Trend surface analysis is a mathematical method to simulate the spatial distribution and variation trend of geographical system elements by using mathematical surface [21-22]. Through trend surface analysis, the spatial distribution rule of geographical elements is simulated to show the variation trend of geographical elements in regional space. Trend surface analysis takes the coordinate points x and y in the 3 D coordinate system as the independent variable, and the value of point z as the dependent variable to investigate the change trend of this z value in space, so as to reveal the trend and law of the spatial distribution of geographical elements. If it is assumed that the actual observed value of carbon emission performance in a certain region is $z_i(x_i, y_i)$ (i = 1, 2, 3... N) and the fitted value of the trend is $\hat{z}_i(x_i, y_i)$, then the equation is shown as:

$$z_i(x_i, y_i) = \hat{z}_i(x_i, y_i) + \varepsilon_i \tag{2}$$

In the formula, ε_i is the residual value and it is apparent that when (x_i, y_i) is changing in space, the above equation describes the interaction between the actual distribution surface, trend surface and residual surface of carbon emission performance.

The core of trend surface analysis: the trend surface is calculated from the actual observed values, and the regression analysis method is generally adopted to minimize the sum of squares of residuals, namely:

$$Q = \sum_{i=1}^{n} \varepsilon^2 = \sum_{i=1}^{n} [z_i(x_i, y_i) - \hat{z}_i(x_i, y_i)]^2 \to \min \tag{3}$$

That is, the trend surface fitting in the least squares sense. Generally speaking, polynomials are usually used as the trend surface equation. This is because any function can always be approximated by polynomials within a certain range, and the degree of polynomials can be adjusted to meet the needs of trend surface analysis. In general, the higher the number of polynomials, the trend value is closer to the observed value, while the smaller the remaining value. Therefore, in practical work, the number of trendlines must be appropriately selected, which is rarely more than 5 or 6 times.

Geographical Detector

Geographical detector is a method used to detect spatial differentiation and explore its influencing factors [23-24]. This method can detect not only numerical data but also qualitative data, and can detect the interaction between two factors, and overcome the traditional regression model to judge the interaction between two factors simply by the multiplication relationship. The model is shown as follows [25]:

$$q = 1 - \frac{\sum_{i=1}^{l} N_i \delta_i^2}{N\delta^2} = 1 - \frac{SSW}{SST} \tag{4}$$

$$SSW = \sum_{i=1}^{l} N_i \delta_i^2 \qquad SST = N\delta^2 \tag{5}$$

In Equations (4) and (5): i =1,2... ,l, is the stratification of independent variable X and dependent variable Y, N and Ni, are the number of units and layer i in the whole region respectively; δ^2 and δ_i^2 are the variances of Y value and layer i of the whole region respectively. Meanwhile, what q value measures is the explanatory power with a range of 0 to 1. The larger q value is, the stronger the explanatory power of independent variable X to dependent variable Y is; otherwise, the weaker it is.

Results and Discussion

Measurement and Descriptive Statistics of China's Carbon Emission Performance

Based on DEA-SOLVER Pro software, this study obtains the carbon emission performance of 30 provincial units in 2005, 2010, 2015 and 2019, and the carbon emission performance (crste) as well as its decomposition items (pure technical efficiency (vrste) and scale efficiency (scale) scores in 4 years (Table 2).

According to Table 2, the performance characteristics of China's carbon emissions can be concluded as follows:

Firstly, in general, China's carbon emission performance is not high and most provinces and cities' performances remain below the optimal level. China's carbon emission technology efficiency in 2005, 2010, 2015 and 2019 only reached 87%, 89%, 80%, and 85%, and the score was 0.87,0.89,0.80 and 0.85 respectively. The four-year average was 0.85, which shows that China's carbon emission performance has only played 85% of the optimal level, with large development potential and improvement space. According to provincial analysis, in 2005, 2010, 2015 and 2019, there were 8, 12, 5 and 7 provinces in China whose carbon emission performance technical efficiency score was 1, respectively. The technical efficiency score of Beijing, Shanghai, Hainan and Qinghai provinces had always been 1 during the study period, indicating that these provinces and regions have a high level of low-carbon economic development. The reason may be that Beijing

Table 2. Performance scores of China's carbon emissions in 2005, 2010, 2015 and 2019.

DUM	2005			2010			2015			2019		
	Crste	Vrste	Scale	Crste	Vrste	Scale	Crste	Vrste	Scale	Crste	Vrste	Scale
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Tianjin	0.95	1.00	0.95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hebei	0.88	0.95	0.92	0.90	0.93	0.96	0.79	0.86	0.93	0.77	0.77	1.00
Shanxi	0.83	0.85	0.97	0.80	0.81	0.99	0.61	0.63	0.96	0.81	0.84	0.95
Inner Mongolia	0.62	0.68	0.92	0.93	0.93	1.00	0.75	0.75	1.00	0.87	0.88	0.99
Liaoning	0.72	0.72	1.00	0.83	0.89	0.94	0.78	0.85	0.92	0.89	0.90	0.99
Jilin	0.90	0.90	1.00	1.00	1.00	1.00	0.95	0.99	0.96	0.58	0.68	0.86
Heilongjiang	1.00	1.00	1.00	0.94	0.94	1.00	0.80	0.83	0.97	0.68	0.72	0.95
Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jiangsu	0.99	1.00	0.99	0.90	1.00	0.90	0.81	1.00	0.81	0.99	1.00	0.99
Zhejiang	0.81	1.00	0.81	1.00	1.00	1.00	0.86	1.00	0.86	0.86	0.95	0.90
Anhui	0.89	0.90	0.99	0.82	0.82	1.00	0.67	0.68	0.99	0.79	0.79	1.00
Fujian	1.00	1.00	1.00	1.00	1.00	1.00	0.94	1.00	0.94	1.00	1.00	1.00
Jiangxi	1.00	1.00	1.00	0.97	0.99	0.98	0.77	0.77	0.99	0.77	0.78	0.99
Shandong	0.95	1.00	0.95	0.89	1.00	0.89	0.74	1.00	0.74	0.71	0.77	0.91
Henan	0.90	1.00	0.90	0.88	1.00	0.88	0.78	1.00	0.78	0.88	1.00	0.88
Hubei	0.87	0.88	1.00	0.99	0.99	1.00	0.91	0.99	0.92	0.96	1.00	0.96
Hunan	0.96	0.96	1.00	1.00	1.00	1.00	0.97	1.00	0.97	1.00	1.00	1.00
Guangdong	1.00	1.00	1.00	0.88	1.00	0.88	0.73	1.00	0.73	0.79	1.00	0.79
Guangxi	0.85	0.86	0.99	0.76	0.81	0.95	0.66	0.67	0.98	0.66	0.68	0.98
Hainan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Chongqing	0.86	0.86	1.00	0.92	1.00	0.92	0.89	0.90	0.99	0.84	0.87	0.96
Sichuan	0.77	0.77	1.00	0.78	0.84	0.94	0.74	0.87	0.85	0.93	0.97	0.95
Guizhou	0.68	0.75	0.90	0.69	0.73	0.95	0.69	0.71	0.96	0.69	0.72	0.96
Yunnan	0.73	0.77	0.95	0.72	0.74	0.97	0.68	0.70	0.97	0.87	0.89	0.98
Shaanxi	0.78	0.84	0.93	0.97	0.98	1.00	0.84	0.84	1.00	0.81	0.83	0.98
Gansu	0.79	0.85	0.92	0.77	0.79	0.96	0.57	0.63	0.90	0.70	0.78	0.89
Qinghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ningxia	0.55	0.90	0.61	0.71	0.93	0.76	0.67	0.94	0.72	0.87	1.00	0.87
Xinjiang	0.79	0.79	1.00	0.70	0.82	0.86	0.46	0.52	0.89	0.78	0.80	0.97
Mean	0.87	0.91	0.96	0.89	0.93	0.96	0.80	0.87	0.92	0.85	0.89	0.96

and Shanghai have developed economies, more high-tech industries and high utilization rate of resources. Hainan province is located in the southernmost part of China, with sufficient light and heat and high vegetation coverage rate. Moreover, Hainan province has vigorously developed green industries, making its superior environment and a high level of low-carbon economic development. Qinghai province is located in a plateau, with its unique geographical location and climate conditions contributing to its optimal carbon emission performance. But other provinces' technical efficiency scores were not optimal and fluctuated differently, meaning that their performance is unstable and have great development potential.

Secondly, pure technical efficiency is the main factor affecting carbon emission performance. In 2005, 2010, 2015 and 2019, pure technical efficiency was 0.91, 0.93, 0.87 and 0.89 respectively, and the average was 0.90, indicating that the pure technical efficiency reached 90% of the optimal value, which also proves that the technical efficiency of China's low carbon economy has been fully developed in the process of development. In terms of provinces and regions, in 2005, 2010, 2015 and 2019, the number of provinces with the best pure technical efficiency in China was 13, 14, 12 and 12, respectively, more than the provinces with the best technical efficiency in the same period. Among them, Beijing, Tianjin, Shanghai, Jiangsu, Fujian, Hainan and Qinghai provinces always had the best pure technical efficiency during the research period. It can be concluded from Figure 1 that during the research period, China's low-carbon economy development was mainly affected by pure technical efficiency, and the change trend of carbon emission performance was almost consistent with the trend of pure technical efficiency. Therefore, pure technical efficiency is the main factor affecting the development of low-carbon economy.

Thirdly, there are also more provinces with the best scale efficiency than the provinces with the best technical efficiency. Scale efficiency is an effective way to improve the development of low-carbon economy. In 2005, 2010, 2015, and 2019, China's carbon emission scale efficiency scores were 0.96, 0.96, 0.92, and 0.96, respectively, with an average of 0.95, reaching 95% of the optimal level. It shows that with the social development and national policy support, the level of resource allocation in China's low-carbon economic

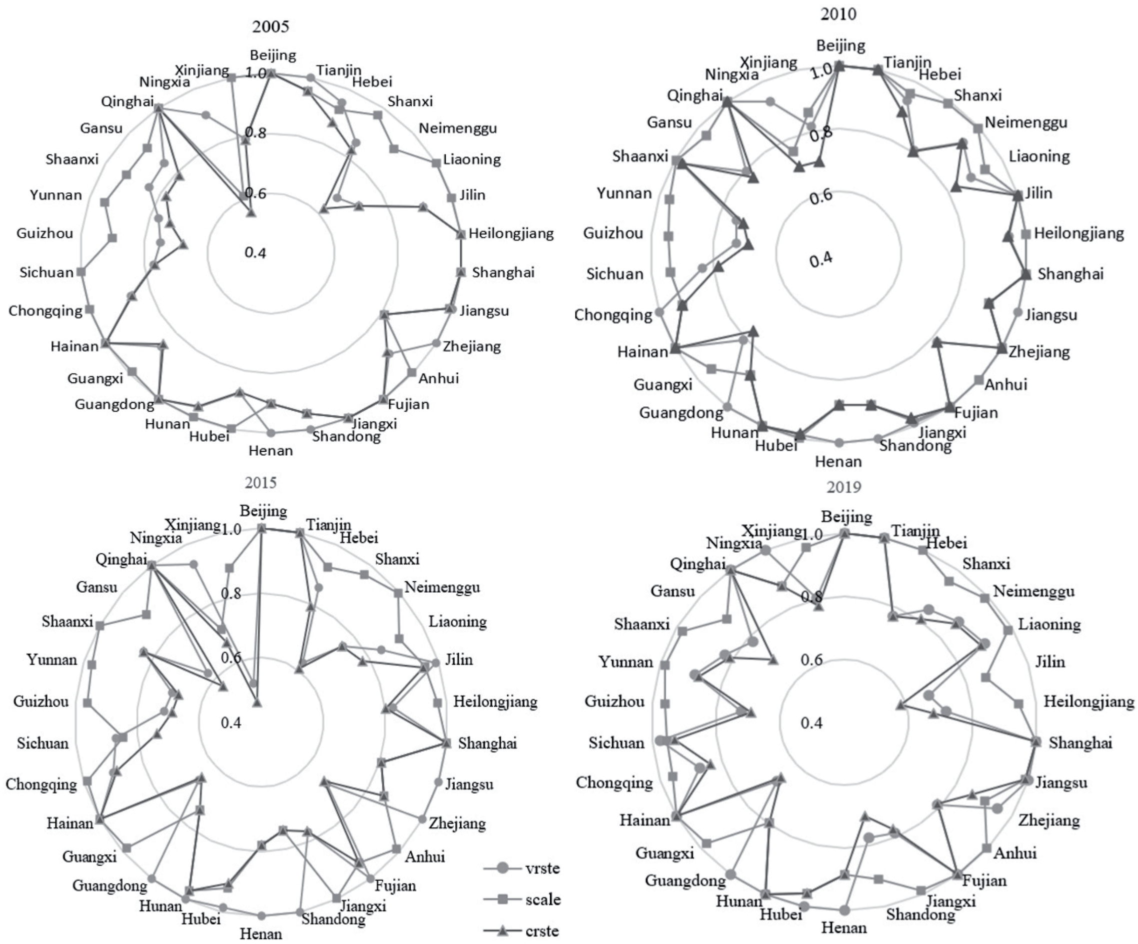

Fig. 1. Radar map of China's carbon emission performance in 2005, 2010, 2015 and 2019.

development is relatively reasonable. In terms of provinces and regions, in 2005, 2010, 2015 and 2019, the number of provinces with the best scale and efficiency of low-carbon economy development in China was 15, 14, 7 and 9 respectively, more than the provinces with the best technical efficiency in the same period.

Spatial Differentiation and Evolution Rule of China's Carbon Emission Performance

Based on the calculated cross-section sample of the mean values of the four typical years 2005, 2010, 2015 and 2019 in China, the spatial distribution map of China‘s carbon emission performance is drawn with the help of ArcGIS software, and the carbon emission performance of China is divided into four categories using the natural discontinuity point method: areas of high performance level, higher performance level, medium performance level and low performance level (Fig. 2).

It can be seen from the figure that the spatial variation characteristics of China‘s carbon emission performance from 2005 to 2019 are as follows:

Firstly, the space difference ofcarbon emission performance is significant. In 2005, 2010, 2015 and 2019, China had the highest carbon emission performance score of 1, while the lowest provinces were slightly different and distributed in Guizhou and Ningxia. The average carbon performance level of the two provinces was 0.69 and 0.70, respectively, indicating that the low-carbon economic development efficiency of the two provinces only reached 69% and 70% of the optimal level. It shows that the gap of low-carbon economic development level between different provinces and regions in China is slightly larger. In terms of various types of carbon performance regions, there were 12, 12, 8 and 9 provinces in high performance levels in 2005, 2010, 2015 and 2019, respectively, while the number of provinces in relatively high and medium performance levels remained basically unchanged, fluctuating between 14 and 15. The number of provinces in low-performance areas was 3, 4, 8 and 6, respectively. This also reflects the declining development level of carbon performance in China.

Secondly, the provinces of different performance types have a large change trend, presenting a pattern of „overall mixed distribution and partial aggregation“ among different performance types. For the years, 2005-2010, carbon emission performance type zone changed in 12 provinces, namely, Heilongjiang, Jilin, Inner Mongolia, Shandong, Jiangsu, Zhejiang, Guangdong, Guangxi, Yunnan, Xinjiang, Shaanxi, Shanxi and from 2010 to 2015, changes involved provinces such as Heilongjiang, Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Guangdong, Guangxi, Jiangxi, Anhui, Henan, Inner Mongolia, Shaanxi, Shanxi and Gansu while in 2015-2019, 15 provinces, including Xinjiang, Inner Mongolia, Heilongjiang, Jilin, Liaoning, Hebei, Shandong, Jiangsu, Yunnan, Hubei, Sichuan, Shaanxi, Shanxi, Henan and Ningxia were included, showing that the carbon emission performance level of Chinese provinces and regions fluctuates greatly, and the carbon emission performance has not formed a stable spatial pattern yet. From 2005 to 2010, carbon emission performance showed a trend of contiguous distribution, but seen from the change trend of 2015 to 2019, there existed an obvious trend of decentralized distribution. Generally speaking, the national carbon emission performance witnesses the central and eastern regions being higher than that

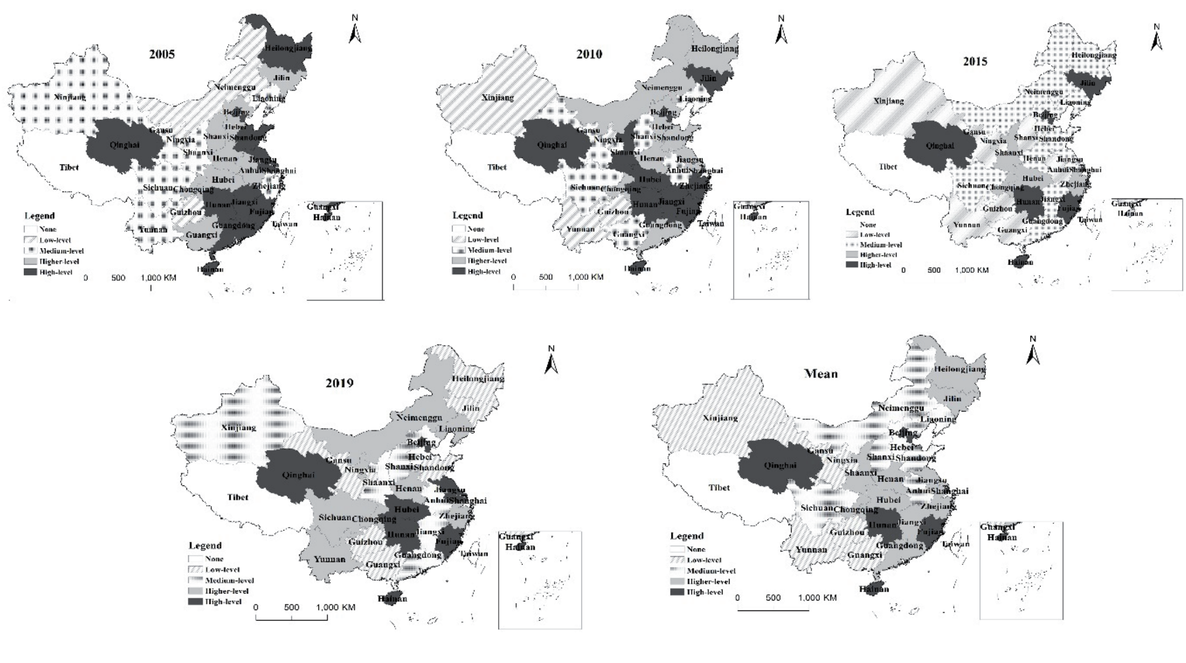

Fig. 2. Spatial distribution characteristics of China's carbon emission performance.

of the western regions, while that of the southern regions being higher than that of the northern regions.

In order to further explore the spatial distribution characteristics of China's carbon emission performance and identify the spatial data structure of carbon emission performance, this paper uses the trend analysis tool for data mining in ArcGIS, selects 2005, 2010, 2010 and 2019 as samples, and forms a three-dimensional trend chart (Fig. 3) with the X, Y and Z axes representing the due east direction, the due north direction and the vertical direction respectively, visualizing the agglomeration effect and spatial interaction mechanism of China‘s carbon emission performance.

In the trend analysis chart, each vertical bar stands for the carbon emission performance and geographical location of a data point, which is projected onto an east-west and a north-south orthogonal plane. Through the projected points, a line of best fit can be drawn, which can be used to simulate an existing trend in a particular direction. From what is shown in Fig. 3, it can be figured out that in the east-west direction, China‘s emissions performance trend during 2005-2019 showed an obvious reversed „U“ type relationship, showing that the western Xinjiang, Gansu, Guizhou, Yunnan and other provinces had slightly low carbon emission performance and were in low performance level areas, the central Shaanxi, Hubei, Henan, Jiangxi and other provinces were generally in high level areas, while Shandong and Hebei in the east were generally in medium performance level areas, suggesting that there was a large spatial difference between east and west, which was consistent with the spatial distribution characteristics of China‘s carbon emissions. In the north-south direction, the curve was smooth, indicating the difference between the north and south was insignificant and the southern change trend was slightly lower than the north. For example, Hunan, Fujian and Hainan had high carbon emission performance in the research period, while Sichuan remained medium for three consecutive years. The carbon emission performance of Inner Mongolia in the north had changed from „low-high-medium-high“, and Shaanxi had experienced the trend of „medium-high-high-medium“. On the whole, China‘s carbon emission performance was relatively high in 2005 and 2010, declined slightly in 2015, and was high in 2019 again, demonstrating that China‘s low-carbon economic development level is generally good, with slight fluctuations in stable development. From 2005 to 2010, the penetration rate of motor vehicles in China was low, and the number of cars was small. Most people used green travel, and the urban built-up area was small, resulting in high carbon emission performance. and more haze days in China during 2013-2015 might be the reason for the slightly declined performance in 2015. With the high-quality development of China‘s economy, the construction of ecological civilization and the proposal of dual carbon goal, China‘s low-carbon economic level has been continuously improved since 2019.

Influencing Factors Analysis of Carbon Emission Performance

Factors influencing carbon emission performance mainly include the degree of opening-up, energy structure, industrial structure, government intervention, technology progress and economic development, foreign investment and ownership structure, which involve numerous statistical indicators. Since many indicators are connecting significantly, excessively complicated index design may generate uncertain results. Therefore, this paper selects the most representative indicators

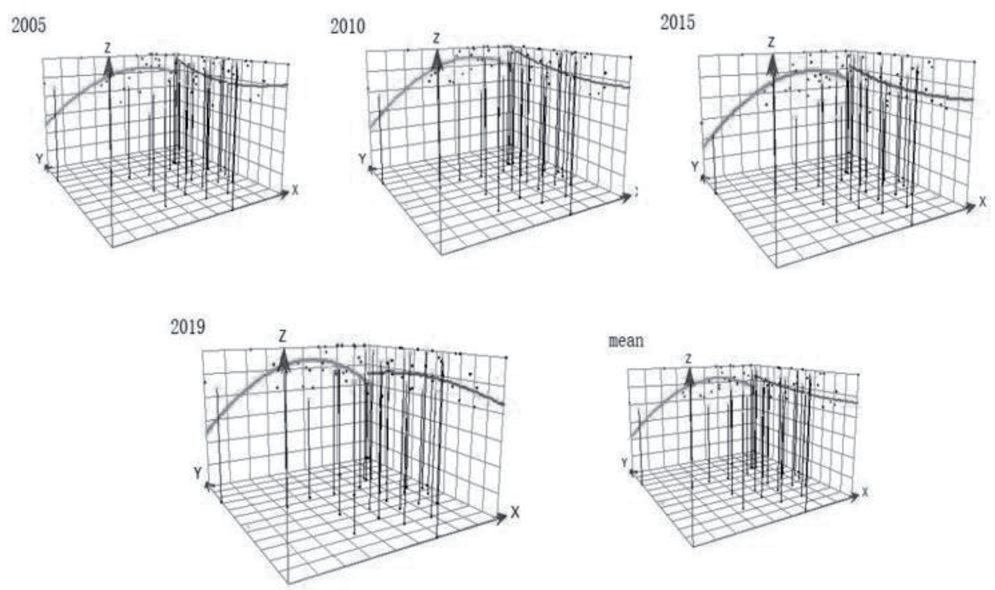

Fig. 3. Trend line of spatial pattern change of China‘s carbon emission performance.

Table 3. Index system of influencing factors of China's carbon emission performance.

Target layer	Index layer
Degree of opening-up	X_1: Proportion of total import and Export trade in GDP of each region
Energy structure	X_2: Proportion of coal consumption in total energy consumption
Industrial structure	X_3: Proportion of added value of tertiary industry in GDP
Degree of government intervention	X_4: Proportion of fiscal expenditure of local governments in GDP
Technological progress	X_5: Proportion of internal expenditure on research and development in GDP by region
Economic development	X_6: Total GDP/total population
Ownership structure	X_7: Number of employees of State-owned enterprises/Total number of employed persons
Foreign investment	X_8: Proportion of total industrial output value of foreign-invested (including Hong Kong, Macao and Taiwan) enterprises

(Table 3) to reflect the main influencing factors listed above respectively through comparing and screening multiple indicators and reviewing existing literature in accordance with the principle of scientific data and availability [26-27].

This paper expresses the degree of opening-up by the proportion of total import, uses the export trade in GDP and the proportion of coal consumption in the energy structure of each province as the energy evaluation index, so as to measure the carbon emission performance of each city, takes the proportion of the added value of the tertiary industry in GDP as the index for the industrial structure measurement, represents the degree of government intervention with the proportion of fiscal expenditure of each local government in GDP, displays technological progress by the proportion of internal expenditure of research and development expenditure in GDP of each region and economic development by the ratio of total GDP to total population while employing the proportion of the number of employees of state-owned enterprises in the total number of employed persons to show the ownership structure and the proportion of total industrial output value of foreign-invested enterprises (including Hong Kong, Macao and Taiwan) to present foreign investment.

This paper uses Arcgis10.2 to create a vector grid in China's administrative region map of 3.5 km×3.5 km, grid center point to extract the data of dependent variable carbon emission performance and 8 independent variables, and Geodetector software to conduct factor detection and interactive detection analysis on the influencing factors of China's carbon emission performance.

Analysis of Detection Results of Influencing Factors

This study uses factor detectors to obtain q values of 2005, 2010, 2015 and 2019, and as what has been shown in Table 4, the explanatory power of each factor passes the significance level test of 1%.

During the study period, as time went by, each factor showed a changing trend of fluctuation. Firstly, the q value of the degree of opening-up had a relatively large change, with a small increase from 2005 to 2010, a sharp decline from 2010 to 2015, and a gradual increase from 2015 to 2019. However, compared with 2005, it had an overall downward trend, indicating

Table 4. Detection results of spatial differentiation factors of China's Carbon emission performance.

Factor	2005		2010		2015		2019	
	q	Ranking	q	Ranking	q	Ranking	q	Ranking
X_1	0.6231	5	0.6443	3	0.3160	8	0.3889	8
X_2	0.6710	2	0.6253	5	0.5126	7	0.6559	3
X_3	0.4590	8	0.5536	8	0.7522	1	0.5111	7
X_4	0.6706	3	0.5780	7	0.7515	2	0.7400	1
X_5	0.5184	7	0.6586	2	0.5183	6	0.6075	5
X_6	0.5767	6	0.5804	6	0.7393	3	0.6668	2
X_7	0.6233	4	0.6602	1	0.6860	5	0.6445	4
X_8	0.6857	1	0.6397	4	0.7169	4	0.5699	6

Table 5. The top five influencing factors of interaction factor detection.

Ranking	2005	2010	2015	2019
1	$X_8 \cap X_4$	$X_5 \cap X_7$	$X_4 \cap X_5$	$X_3 \cap X_7$
2	$X_2 \cap X_4$	$X_3 \cap X_8$	$X_7 \cap X_5$	$X_4 \cap X_8$
3	$X_5 \cap X_3$	$X_4 \cap X_2$	$X_3 \cap X_8$	$X_1 \cap X_6$
4	$X_6 \cap X_5$	$X_6 \cap X_7$	$X_3 \cap X_5$	$X_7 \cap X_5$
5	$X_7 \cap X_5$	$X_4 \cap X_8$	$X_2 \cap X_5$	$X_3 \cap X_5$

that with the gradual improvement of China's level of opening to the world, the degree of opening-up's influence on carbon emission performance decreases gradually in the selected factors. In terms of energy structure, the q value dropped from 0.67 in 2005 to 0.51 in 2015, showing a downward trend, and gradually increased its influence in 2015-2019, but the overall change was slight and showed steady development. Moreover, basically relying on coal in industrialization, China becomes one of the few countries using coal as the main energy source, thus forming an energy consumption structure that has a relatively large and stable impact on carbon emission performance. Thirdly, the influence of industrial structure on carbon emission performance showed an upward trend from 2005 to 2015, but began to decline from 2015 to 2019. Specifically, from 2005 to 2015, with the rapid development of energy-consuming tertiary industries such as transportation, storage and postal services, the impact on carbon emission performance gradually increased and from 2015 to 2019, with the development and application of new technologies, its impact on carbon emissions gradually decreased. Then, the degree of government intervention has the greatest influence on carbon emission performance, with q value above 0.55 in all four years and over 74% in 2015 and 2019, indicating that the Chinese government has played an important role in the development of low-carbon economy and the measures taken have achieved obvious results. Therefore, the degree of government intervention has a great influence on carbon emission. Fifthly, the influence of technology on carbon emission performance has not changed much, and it is basically maintained between 0.5 and 0.65, which shows that China has been quite mature in technology on the road to achieve carbon emission reduction. Furthermore, from the aspect of economic development level, q value changed slightly, showing an upward trend from 2005 to 2015, reaching 74% in 2015, and then slightly decreased. In addition, economic development is conducive to increasing people's income and enhancing people's awareness of environmental protection, which is the way to low-carbon economic development indicating its influence. Besides, the influence of ownership structure is stable, basically maintaining at about 65%, indicating its little influence on carbon emissions while that of foreign investment became slighter and slighter. Its strength went through decrease, increase and then significant decrease, showing that with the development of China's economy and the enhancement of independent innovation capacity, the degree of industrial development relying on foreign investment is becoming less and less.

Analysis of Interactive Detection Results

To further explore the impact of interaction between different driving factors on carbon emission performance, this paper selects and classifies the pair-based interaction results of 8 factors to summarize the top 5 interaction results in each year, as shown in Table 5.

Interaction detection can analyze whether there is an interaction on the carbon emission performance of each driving force. The interactions can be divided into the following five categories: if $q(X_i \cap X_j) < Min(q(X_i), q(X_j))$, then the interaction between the two is nonlinear weakening; if $Min(q(X_i), q(X_j)) < q(X_i \cap X_j) < Max(q(X_i), q(X_j))$, it is a single-factor nonlinear weakening; If $q(X_i \cap X_j) > Max(q(X_i), q(X_j))$, it is double-factor enhancing; If $q(X_i \cap X_j) = q(X_i)+q(X_j)$, it is independent; If $q(X_i \cap X_j) > q(X_i)+q(X_j)$, it is nonlinear enhancing. The study shows that the influence of interactor interaction on carbon emission performance is far more than the monofactor effect, namely, the combined effect of two factors will improve the spatial variation and explanatory power of carbon emission performance. In terms of action type, a non-linear enhancement effect was produced between the factors. This shows that carbon emission performance is the result of the combination of multiple factors, with a complex integration of influencing factors and spatial differentiation characteristics. As can be seen from the table, in 2005, the strongest interaction explanatory power was the degree of foreign investment and government intervention, and the energy structure and government intervention degree ranked second. In 2010, it was mainly affected by technological progress, industrial structure and the degree of government intervention; in 2015, by government intervention, ownership structure and industrial structure, and in 2019, by industrial structure, government intervention and opening up. It can be seen from the analysis that the degree of government intervention and industrial structure had the greatest impact on the spatial distribution of China's carbon emission performance, and the interaction effect of government intervention and other factors had always had a significant influence in four years, indicating that the Chinese government has made a great contribution to carbon emission reduction. Industrial structure also had a great impact on it, which shows that the development of the tertiary industry is conducive to adjusting the energy structure, thus promoting the sustainable development of low-carbon economy. In terms of technological progress and opening-up, the improvement of the opening up level is conducive to the introduction of advanced science and technology level and management methods, so as to improve energy utilization efficiency and reduce carbon emissions.

Discussion

Carbon emission is both a hot spot of global concern and a frontier field of academic research that involves complex scientific issues, such as the scientific selection of indicators and evaluation criteria, as well as the applicability and rationality of research methods, which have not yet formed a unified understanding in the academic community. Compared with previous studies, this paper is based on the data in 2005, 2010, 2015, 2019, referring to the IPCC method, estimating China's carbon emissions, and using DEA model and geographic detector method for empirical research, which better reveals the evolution of carbon emission performance and its factors and provides scientific basis for relevant government departments to develop differentiated carbon reduction strategy. For example, Local government departments in recognizing the region carbon emissions under the premise of performance level, from the energy structure, the degree of government intervention, technological progress, industrial structure and economic development index, combined with the situation in the region, under the premise that ensure the quality of residents to take targeted measures, in order to realize the regional sustainable development.

Meanwhile, further exploration and improvement is still requisite for the following aspects in this study. First of all, the performance level of carbon emission is affected by many aspects. When establishing the input-output index system, this paper considers the use of alternative data for the accessibility and convenience of data, but the research accuracy is still slightly inadequate. For example, the use of electricity consumption to replace energy input does not take into account the energy consumption of different provinces and the use of employment number at the end of the year to replace labor input ignores the impact caused by differences in labor types and quality in different industrial structures. Therefore, it is necessary to further refine data comprehensiveness and accuracy and select evaluation indicators more carefully since constructing an indicator system of carbon emission performance evaluation remains as a complex comprehensive task. Moreover, There are many variables affecting carbon emission performance, and this paper lacks an in-depth analysis of whether the index selection is comprehensive and which are the most fundamental influencing factors. Therefore, in the context of carbon peak and carbon neutrality, how to derive it from the theory or through the establishment of microscopic models needs to be further studied. Besides, due to time limit, This paper only studies the carbon emission performance from a macro perspective, but the selection of different perspectives will have different conclusions on the carbon emission performance level of different regions. In the future, the development level of carbon emission in different regions can be studied from multiple perspectives such as industry, agriculture and service industry to provide more targeted carbon emission reduction measures. Last but not least, the selection of research scale units has a great impact on the spatial differentiation characteristics of carbon emission performance, and different research scales will even produce large different differentiation rules. Limited by the availability of data, this paper explains and analyzes exploratorily base on national macro pattern, without comparing the development characteristics of multi-scale regional carbon emissions performance. If we can compare the performance characteristics or influencing factors of carbon emissions at city, county, town or multi-scale in China in the future, we can reveal the influencing factors of the performance pattern change and spatial differentiation of carbon emissions at different scales in depth, so as to explore the spatial characteristics and formation mechanism of low-carbon economic development in a more detailed way.

Ulteriorly, in the results of this paper, the pure technical efficiency is the main factor affecting the carbon emission performance, which is consistent with the conclusion of the scholar Xie Zhixiang [4]. In terms of spatial differences, the overall carbon emission performance is characterized by „high in southeast and low in northwest", which is basically consistent with the conclusions of Wang Shaojian [6] and Jiang Hong [40]. In terms of influencing factors, the degree of government intervention and ownership structure have a great impact on the carbon emission performance in China, which is roughly the same as the research conclusions of scholars Cao Ke [41] and Wang Qunwei [42].

Conclusions

This paper takes 30 provincial units in China as the research object by virtue of DEA model in measuring carbon emission performance of China in 2005, 2010, 2015 and 2019 and explores and analyzes the spatial-temporal evolution rule of carbon emission performance in China by geographic detector on the basis of spatial visualization and trend surface analysis The conclusions are shown as follows:

(1) The overall level of carbon emission performance in China is not high. Except for Beijing, Shanghai, Hainan and Qinghai provinces, the carbon emission performance of most provinces and municipalities has not yet reached the best, and there is great room for improvement. The fluctuation of carbon emission performance in various provinces and regions in China changes greatly, which is manifested as the larger change trend in the east-west direction than the north-south direction.

(2) There are significant spatial differences in China's carbon emission performance. Generally speaking, the performance of the central and eastern regions is higher than that of the western regions, while that of the southern regions is higher than that of the northern regions. There is no obvious agglomeration effect among the various types of areas, showing a trend of „overall mixed distribution, partial aggregation".

(3) In terms of influencing factors, the degree of single factor government intervention has a strong explanatory power to the spatial differentiation of the performance, followed by ownership structure, foreign investment, energy structure, technological progress, industrial structure, and the degree of opening-up. Meanwhile, the effect of factor interaction on carbon emission performance far exceeds nonfactor effects and shows nonlinear enhancement.

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Conflict of Interest

The authors declare no conflict of interest.

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