A study on the spatial and temporal evolution of carbon emission efficiency in China's provincial power industry

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Abstract. Promoting the low carbon development of the power industry is an essential path for China to achieve the "3060" dual carbon goal. This paper uses the SBM model and the Moran index to construct a carbon emission efficiency assessment system that meets the requirements of a high proportion of renewable energy access in China. The spatial and temporal evolution and correlation of the carbon emission efficiency of the power industry in 29 provinces in China were analyzed. The results show that the carbon efficiency of China's power industry has been increasing year by year since the 13th Five-Year Plan, and the overall pattern is that the periphery has led to the gradual development of the center, while the Yangtze River Delta and Northeast China show a clear spatial correlation, with prominent policy and technology spillovers. The results may provide scientific guidance for efficiency improvements in each region.

Keywords: component, power industry, carbon efficiency, SBM model, Moran index, spatial correlation analysis.

1. Introduction

Since the "dual carbon" goal was put forward, China's power industry has begun a comprehensive energy structure reform, but as of 2020, China's non-fossil energy accounted for 15.9%, and coal consumption accounted for 57%, far higher than the world average. Low-carbon transformation is the only way for China to achieve emission reduction goals [1]. How to maximize the social and economic benefits of the power industry with the lowest carbon emission cost is of great significance for accelerating the low-carbon development of the power industry and the country's energy transformation.

At present, domestic and foreign scholars mainly use SFA, DEA, and other methods in the analysis of carbon emission efficiency. Lei Meng et al. [2] used the Malmquist index considering undesired output to study the dynamic change of carbon emission efficiency in China's logistics industry. Wang Yanping [3] combined SBM and spatial autocorrelation analysis to calculate the accumulation of eco-efficiency in different regions of China and the radiation of high eco-efficiency areas to the surrounding area. In terms of carbon emission research in the power industry, Yan Dan [4] studied the development law of carbon emission efficiency in the provincial power industry. Wang Lijuan [5] studied the carbon emission trends and main driving factors of the power industry based on scenario analysis. However, there are still few studies on the carbon emission efficiency of the power industry. At the same time, as the government gradually guides the transformation and upgrading of the energy supply structure, the proportion of new energy power generation has increased significantly, and the construction of a "high proportion of renewable energy" and "high proportion of power electronic equipment" It is necessary to analyze the carbon emission efficiency of the power industry from the unified perspective of new energy and traditional thermal power generation. Based on this, this paper defines related hydropower, nuclear power, wind power, and solar power as new energy sources that do not produce carbon emissions in a narrow sense.

Based on the above literature, this paper takes 29 Chinese provinces and cities as examples, defines hydroelectric power, nuclear power, wind power, and solar power as "new energy without carbon emission" in a narrow sense, and constructs an input-output index system from the perspectives of new energy and traditional thermal power generation, based on which the DEA-SBM model based on non-expected output and Moran index are used to analyze the spatial and temporal evolution and spatial correlation of the carbon emission efficiency of the provincial power industry, with a view to suggesting the carbon emission reduction path for China's provincial power industry.

2. Methodology and selection of variables

This paper firstly constructs a carbon emission efficiency assessment system from three dimensions, based on the SBM model and spatial autocorrelation analysis, to study the spatial and temporal evolution characteristics and autocorrelation evolution characteristics of the carbon emission efficiency of the power industry in each province during 2015-2019, respectively, in order to make suggestions for the reform of China's power industry, fig.1 presents the process framework.

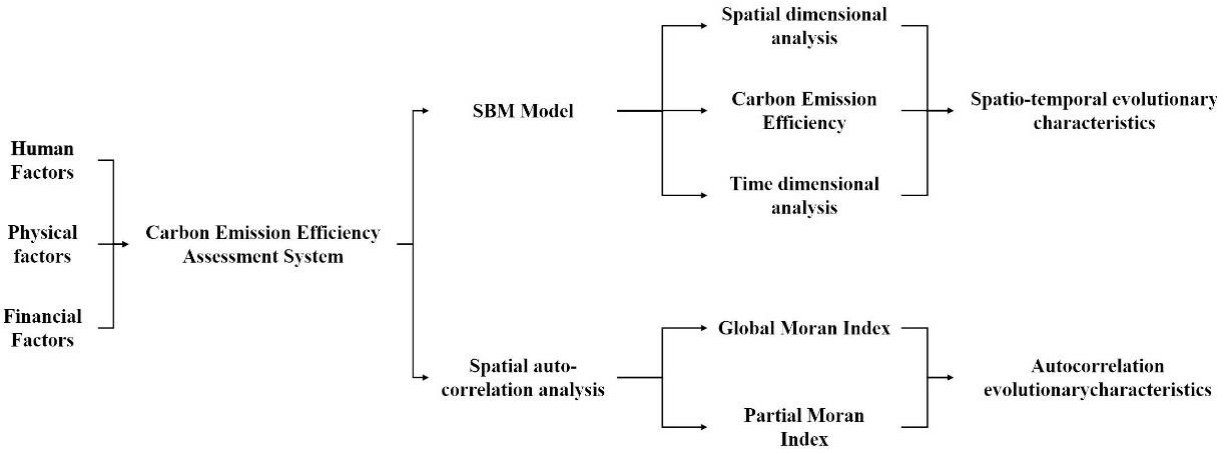


Figure 1. Process Framework

2.1. SBM model

The SBM model is a non-radial and non-oriented optimization model proposed by Tone in 2001 [6] to solve the errors in evaluation results caused by too much input or insufficient output of the traditional DEA model. At the same time, on this basis, Tone further proposed an improved SBM model considering undesired output in 2004 [7], and its formula is shown below:

$$\begin{aligned} \min p' = & \frac{1-(1/m)\Sigma_{i=1}^{m} s_i^- / x_{i0}}{1+\frac{1}{s_1+s_2}\left(\Sigma_{r=1}^{s_1} s_r^g / y_{r0}^g + \Sigma_{r=1}^{s_2} s_r^b / y_{r0}^b\right)} \\ & s.t.\ x_0 = X\lambda + s^-; \\ & y_0^g = Y^g\lambda - s^g; \\ & y_0^b = Y^b\lambda - s^b; \\ & \lambda \geqslant 0,\ s^- \geqslant 0,\ s^g \geqslant 0,\ s^b \geqslant 0 \end{aligned} \tag{1}$$

In equation (1), y_0^g is the desired output in the power generation process, such as power generation, etc.; y_0^b is the undesired output in the power generation process, such as carbon emissions, etc.; s is the slack vector of input and output; s^g and s^b represent insufficient expected output and excessive undesired output, respectively; λ is the weight vector; s_1 and s_2 denote the quantity of desired

output and undesired output, respectively; The numerator and denominator of p' represent the input inefficiency and output inefficiency respectively. If a given province is efficient, then the optimization objective is observed at $p'=1$, besides, $s^g=0$ and $s^b=0$, otherwise, the province is inefficient.

2.2. Moran Index

The Moran index is mainly used to illustrate the spatial characteristics of the carbon emission efficiency of the power industry in a particular region. The Moran index can be further divided into the global Moran index and the local Moran index. The local Moran index used here is shown in equation (2).

$$I_i=\frac{\left(x_i-\bar{x}\right)}{S^2}\sum_{j=1}^{n}w_{ij}\left(x_j-\bar{x}\right) \tag{2}$$

In equation (2), I_i denotes the local Moran index of the province which represents the spatial correlation between two regions; x_i and x_j are the carbon emission efficiency of province i and province j respectively; $\bar{x}$ is the average for all regions' efficiency; w_{ij} is the element value of the spatial weight matrix.

2.3. Description of data and selection of variables

Hong Kong, Macau, and Taiwan due to institutional differences, while Tibet and Inner Mongolia have more missing severe data, so this paper takes the power generation industry of 29 Chinese provinces and cities as the primary decision-making unit, and the study span is chosen as a 5-year interval from 2015-2019. The input-output indicator system is shown in Table 1.

Table 1. Input-output indicator system

Input indicators	Output indicators
Manpower input: Electricity workforce (10,000 people)	Desired output: new energy generation (billion kWh)
Capital investment: fixed investment in power generation ($ billion)	Desired output: thermal power generation (billion kWh)
Energy input: 6000 kW and above-installed capacity of new energy generation (million kW)	Non-desired output: power plant CO_2 emissions (million tons)
Energy input: installed thermal power generation capacity of 6,000 kW and above (million kW)	
Energy input: the amount of standard coal consumed by power plants of 6,000 kW and above to generate electricity (million tons)	

3. Empirical analyses

3.1. Analysis of the spatial and temporal evolution of the provincial electricity industry

3.1.1. Characteristics of the time evolution of carbon emission efficiency in the power industry

The CO_2 emission efficiency of the power industry in 29 provinces from 2015-to 2019 was measured based on the SBM model considering non-desired outputs, The specific calculation results are shown in Table 2.

Table 2. Carbon emission efficiency of the power sector by province, 2015-2019

Province	2015	2016	2017	2018	2019	Average value
Beijing	1.000	1.000	0.785	0.866	1.000	0.930
Tianjin	1.000	0.549	0.792	0.602	0.685	0.726
Hebei Province	0.439	0.490	1.000	1.000	1.000	0.786
Shanxi Province	0.505	0.542	0.575	0.650	0.749	0.605
Liaoning Province	0.721	0.703	0.703	0.761	0.782	0.734
Jilin Province	0.491	0.561	0.564	0.606	0.603	0.565
Heilongjiang	0.443	0.492	0.544	0.573	0.611	0.533
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu Province	1.000	1.000	1.000	1.000	1.000	1.000
Zhejiang Province	0.985	0.969	0.944	0.950	1.000	0.969
Anhui Province	0.793	0.723	0.764	1.000	1.000	0.856
Fujian Province	0.941	1.000	1.000	0.963	1.000	0.981
Jiangxi Province	0.940	0.788	0.844	0.912	1.000	0.897
Shandong Province	1.000	0.655	0.510	0.696	0.826	0.737
Henan Province	0.702	0.532	0.524	0.620	0.634	0.602
Hubei Province	0.874	0.928	1.000	1.000	1.000	0.960
Hunan Province	0.857	0.874	0.829	0.778	0.848	0.837
Guangdong Province	0.954	1.000	0.929	0.921	1.000	0.961
Guangxi Zhuang Autonomous Region	1.000	0.933	0.953	0.965	1.000	0.970
Hainan Province	0.502	0.852	0.875	0.785	0.841	0.771
Chongqing	0.814	0.843	0.811	0.777	0.769	0.803
Sichuan Province	0.932	1.000	1.000	0.990	1.000	0.984
Guizhou Province	0.908	0.877	0.893	0.899	0.902	0.896
Yunnan Province	0.892	0.966	1.000	1.000	1.000	0.972
Shaanxi Province	0.675	0.537	0.530	0.645	0.661	0.610
Gansu Province	0.659	0.637	0.693	0.752	0.765	0.701
Qinghai Province	1.000	0.862	1.000	1.000	1.000	0.972
Ningxia Hui Autonomous Region	1.000	0.732	0.913	1.000	1.000	0.929
Xinjiang Uyghur Autonomous Region	1.000	1.000	0.970	0.952	1.000	0.985

The carbon emission efficiency of non-desired output selected in this paper characterizes the ratio of actual CO_2 to the minimum possible CO_2 emissions under the condition of certain production factors, or the extent to which CO_2 can reduce emissions can be reduced under the condition of a given output. According to the results of the table, only Shanghai and Jiangsu provinces have an average carbon emission efficiency of 1 among the provinces, indicating that the carbon emission efficiency of these two provinces (municipalities directly under the central government) is on the production frontier and can reasonably control the level of CO_2 emissions to drive economic development, while the average carbon emission efficiency of other cities fails to reach the production frontier. Except for Shanghai and Jiangsu Province, the carbon emission efficiency of Xinjiang Uygur Autonomous Region, Sichuan Province, Fujian Province, Qinghai Province, Yunnan Province, Guangxi Zhuang Autonomous Region, Zhejiang Province, Guangdong Province, Hubei Province, Beijing Municipality, Ningxia Hui Autonomous Region, Jiangxi Province, Guizhou Province, Anhui Province, Hunan Province, and Chongqing Municipality are all above 0.8, with a high level of carbon emission efficiency but still room for improvement; Hebei Province, Hainan Province, Shandong Province, Liaoning Province, Tianjin, Gansu, Shaanxi, Shanxi, and Henan provinces have relatively average carbon emission efficiency, between 0.6 and 0.8; while Jilin and Heilongjiang provinces have low carbon emission efficiency, both around 0.5, and rank last.

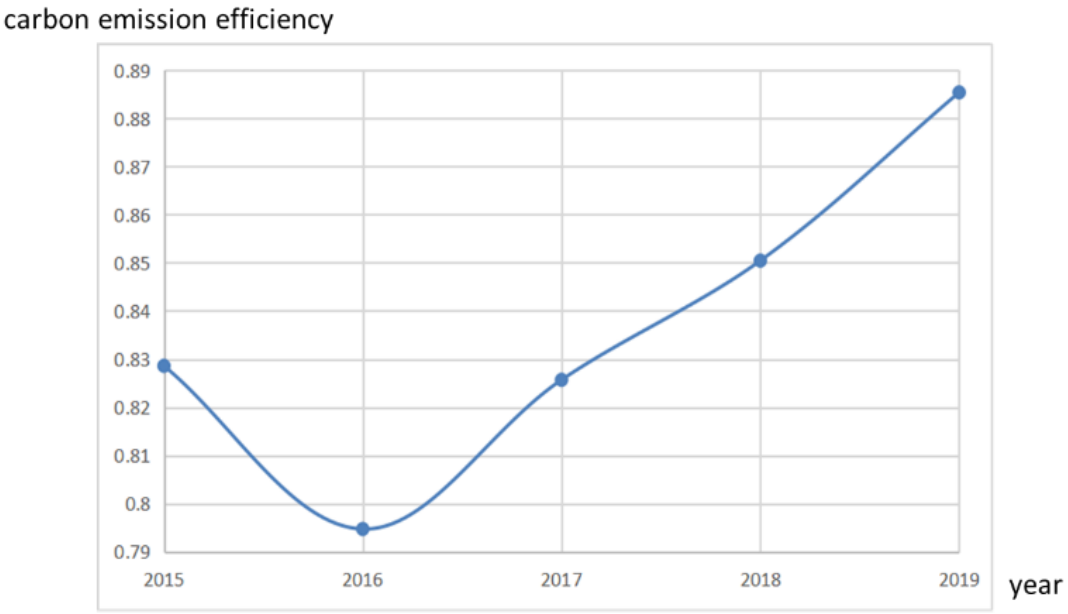


Figure 2. National average carbon emission efficiency trend

As shown in Figure 2, with the vigorous advocacy of energy conservation and emission reduction measures in China, the overall trend of emission reduction efficiency has fluctuated upward, with the average value of carbon emission efficiency in China's sample provinces reaching the lowest in 2016 and then rising continuously. 2015 was the closing year of China's 12th 5-year plan, and in order to achieve the relevant goals, different measures were taken around the country to expand production to complete the goals. The national average of the decline in carbon emissions in 2016 is likely to be a follow-up effect of the relevant measures in 2015. With the gradual establishment of the national pilot carbon emission pilot, and the release of the National Development and Reform Commission's "National Carbon Emission Trading Market Construction Program (Electricity Industry)" document in 2017, the positive carbon emission control and guidance have led to a steady increase in efficiency, and has exceeded 0.85 in 2019. It can be found that the national provinces have gradually established appropriate carbon emission reduction measures for the power industry, and tend to be optimal but still have some room for development.

3.1.2. Characteristics of the spatial evolution of carbon emission efficiency in the power industry

The spatial evolution of the carbon emission efficiency of the power industry in each province during the five-year period is visualized in Figure 3. Between 2015 and 2019, the spatial distribution of carbon emission efficiency in China's power industry in each province shows a pattern of "high around, low in the middle", with the periphery driving the development of the center. The high-value area is mainly concentrated in the new energy provinces in the northwest and the southern provinces with a high proportion of hydropower, while the low-value area is mainly concentrated in the central cities of Shaanxi Province, Henan Province, Shanxi Province, and the northeastern cities of Jilin Province and Heilongjiang Province, which have not reached the optimal frontier surface for many years and have more room for improvement. The standard deviation of carbon emission efficiency of the power sector in each province is 0.23 in 2015,0.18 in 2019, which indicates that the spatial difference in carbon emission efficiency of the power sector is significantly reduced.

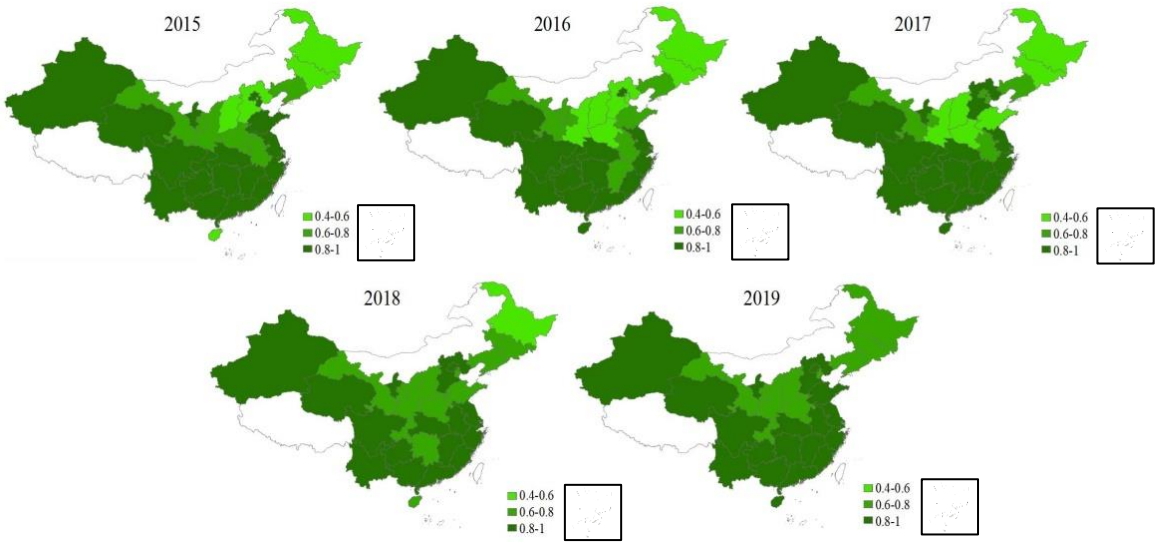


Figure 3. Evolution of the carbon efficiency of the national inclusion of new energy considerations

According to some studies, the efficiency of basic thermal power in China can be divided into three echelons, the first echelon is the North and East China represented by Beijing and Shanghai, whose thermal power-related technologies are more advanced and relatively more carbon-efficient, and the second echelon is the Northwest and the South, and the third echelon is the Central and Northeast China with the lowest carbon emission efficiency. It can be found that in the second echelon, Northwest China has a large amount of solar and wind power generation, Southwest provinces have a high proportion of hydropower, and Guangzhou and other Pearl River Delta regions have rapid development of nuclear power, which all make their comprehensive carbon emission efficiency tied with Beijing, Shanghai and other regions with advanced thermal power technology, but the carbon emission efficiency of Northeast and Central China is still relatively low.

3.2. Spatial correlation analysis of the electricity industry by province

3.2.1. Global spatial auto-correlation analysis

The global Moran's I index of carbon emission efficiency of China's power industry from 2015 to 2019 was measured and tested for significance. The results are shown in Table 3. It can be found that the Moran index each year is greater than 0 and passes the significance test, indicating that there is a positive spatial aggregation of the carbon emission efficiency of the power industry in each province and city. At the same time, the global Moran's I index showed a downward trend as a whole with the evolution of time, indicating that the spatial auto-correlation of the carbon emission efficiency of the provincial power industry gradually weakened.

Table 3. Global Moran's I index of carbon efficiency in the power industry, 2015-2019

year	I	E(I)	Sd(I)	Z	P-value
2015	0.3108	-0.0357	0.1368	2.5328	0.0113
2016	0.4622	-0.0357	0.1388	3.5875	0.0003
2017	0.2852	-0.0357	0.1378	2.3294	0.0198
2018	0.2083	-0.0357	0.1384	1.7624	0.0780
2019	0.2897	-0.0357	0.1377	2.3634	0.0181

3.2.2. Local spatial auto-correlation analysis

In order to To further examine the spatially aggregated changes in carbon emission efficiency in 29 provinces and cities, this paper measures the local Moran index [8] and makes a local Moran scatter plot from 2015-to 2019 which is visualized in Figure 4, and to visualize the significant spatial types existing in each province, this paper draws a five-year LISA agglomeration map and a significance map to show the overall spatial agglomeration evolution during the five years.

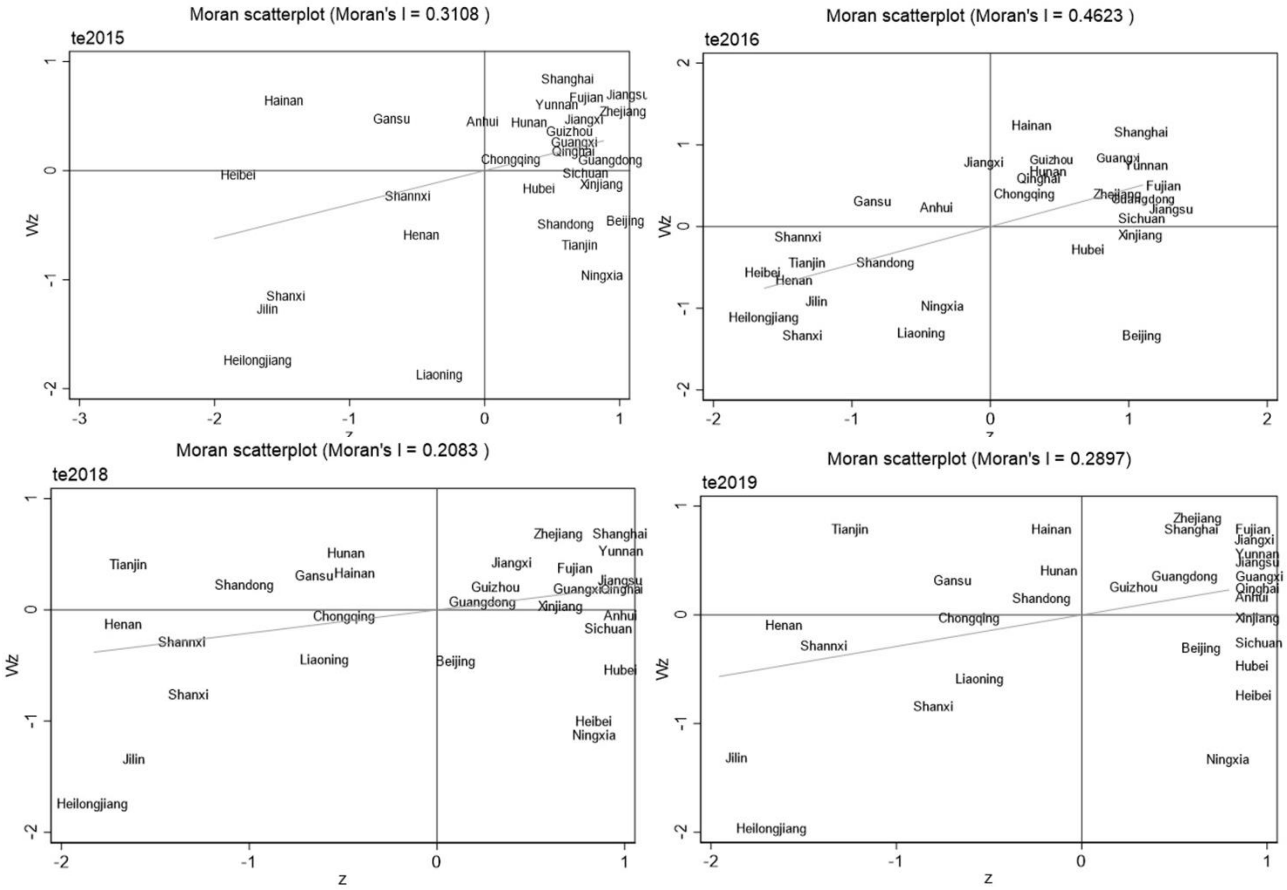


Figure 4. LISA Cluster Map by Province

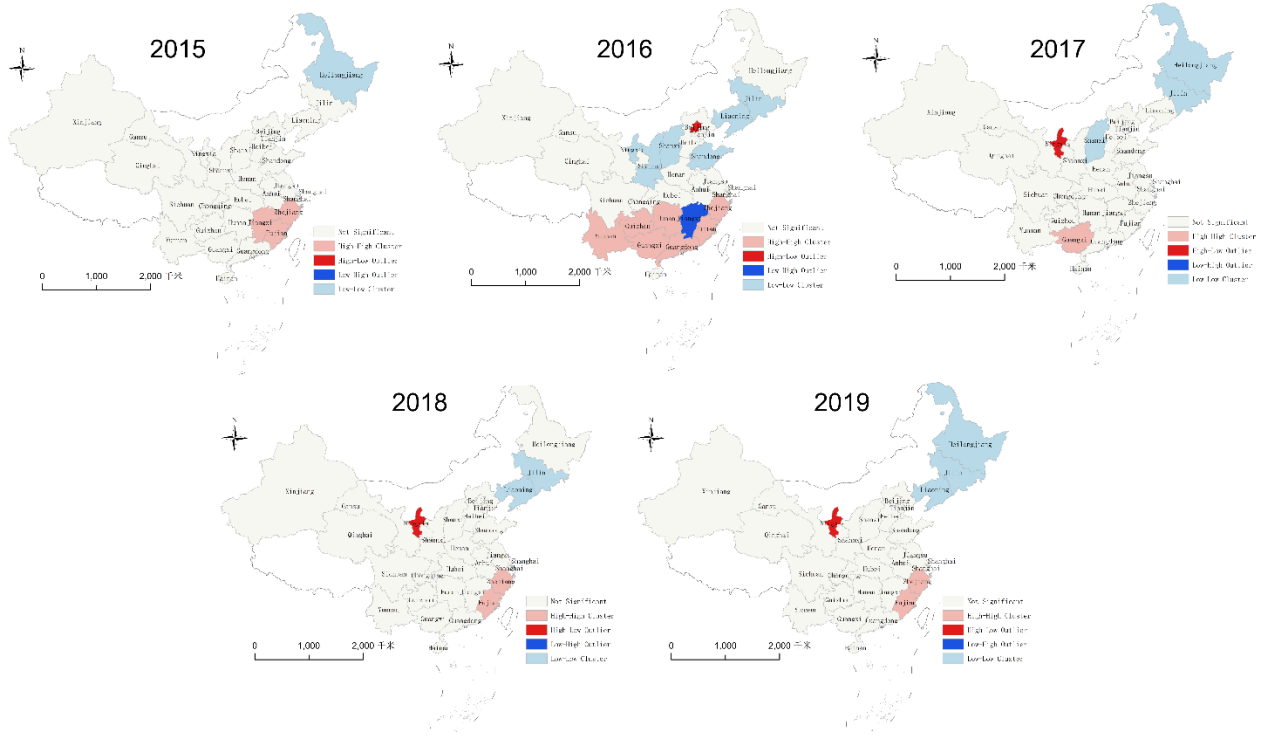


Figure 5. Spatial Correlation Map of Provincial Carbon Emission Efficiency

Using this index, we can obtain an aggregation graph of the carbon emission efficiency of the power industry in each province in China. [9] As shown in Figure 5, it can classify the aggregation into four types: high-high (H-H), high-low (H-L), low-low (L-L), and low-high (L-H) clusters. Dark blue indicates that low carbon emission efficiency areas are surrounded by high carbon emission efficiency

areas (L-H), light blue indicates that low carbon emission efficiency areas are also clustered near low carbon emission efficiency areas (L-L), and light red indicates that high carbon emission efficiency areas are also clustered near high carbon emission efficiency areas (H-H), and dark red indicates that high carbon emission efficiency areas are surrounded by low carbon emission efficiency areas (H-L). It can be found that similar to the H-L region of Ningxia, which has been in a high efficiency state for a long time after 2017, although the renewable energy generation ratio of Ningxia province is not high, the installed scale of its thermal power is generally larger and the thermal power technology is more advanced, so the comprehensive carbon emission efficiency is higher; the formation of the H-H high carbon emission efficiency region of Zhejiang-Fujian is due to the developed economic level, with advanced low carbon processing technology and The spillover effect is obvious, while the establishment of the Zhejiang-Fujian networked extra-high voltage AC transmission project also has a positive impact on the overall power industry and its carbon emission efficiency; while the Northeast is in the L-L low carbon emission efficiency gathering because the relative development of the three eastern provinces is more backward, the technology level and resource utilization rate are low, the environmental management standards are not perfect, and its carbon emission efficiency still has There is much room for improvement, and an efficient cooperation mechanism is a major breakthrough point for its development [10].

4. Conclusions and recommendations

In this paper, by constructing a carbon emission efficiency assessment system, we measured the carbon emission efficiency of 29 Chinese provinces during 2015-2019 based on SBM, and on this basis, we conducted a spatial and temporal evolution analysis and a spatial autocorrelation analysis of their carbon emission efficiency by combining the Moran index and found that the overall emission reduction efficiency in China showed an increasing trend, while the spatial autocorrelation tended to weaken. Therefore, this paper puts forward the following suggestions

(1) Optimizing carbon emission environmental rules and regulations. According to the distribution of solar and wind energy in each province and city, rationally formulate renewable energy consumption weight quotas and corporate carbon emission quotas.

(2) Optimize the proportion of power generation structure. According to the research results, it can be found that the significant increase in the proportion of new energy power generation will help to improve the carbon emission efficiency of the power industry. Therefore, the distributed renewable energy and energy storage industries should be vigorously developed, and the energy supply-side structure should be optimized in combination with smart microgrids.

(3) Actively play the role of the market mechanism. The government should gradually release the right to operate the distribution network side, guide the formation of healthy market competition, and develop diversified and optional power consumption schemes. At the same time, each province implements differentiated innovation according to its own energy structure characteristics, improves the carbon emission efficiency of the power industry, and achieves a win-win situation for economic benefits and environmental protection.

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