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Research on the spatial-temporal evolution pattern of China's industrial carbon emission efficiency-based on the super-efficiency SBM model

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Abstract

This paper uses the super efficiency SBM model based on unexpected output to calculate the industrial carbon emission efficiency of 30 provinces in China from 2005 to 2019, and uses spatial autocorrelation and other methods to conduct an empirical analysis on the dynamic evolution process and temporal and spatial differences of carbon emission efficiency. The results show that China's industrial carbon emission efficiency is still in the low efficiency stage, with an average value of 0.34. In the study period, although the overall trend is rising, the spatial and temporal differences between provinces are obvious. The overall Moran's I index is subject to the impact of social policy environment on the time path, showing an overall "M" type fluctuation trend, and its spatial difference characteristics change in stages. At the same time, there is a significant global spatial agglomeration effect across the country, and there is a spatial dependency between provinces. The agglomeration trend is significant, forming a cluster with the eastern coastal area as the high value center, and the northwest inland area as the low value center. The Getis OrdGI * index reveals that the local spatial agglomeration characteristics of China's industrial carbon emission efficiency always maintain the pattern of "hot in the east and cold in the west", which echoes the overall spatial evolution pattern of China. The hot spots and sub hot spots of China's industrial carbon emission efficiency are mainly concentrated in the southeast coastal areas with relatively superior economic development, and present a "semi enclosed" pattern. Cold spot area and sub cold spot area gradually evolved into a "suppression" pattern dominated by provinces in northwest China, comprehensively suppressing hot spots. This paper conducts an all-round evaluation of China's industrial carbon emission efficiency from the perspective of regional differentiation, and deeply studies the regional differences and spatial evolution pattern of carbon emission efficien cy in various provinces. It is crucial to achieve the goal of carbon emission reduction in China, and has important practical value and practical significance.

Keywords: Industrial Carbon Emission Efficiency; Super SBM Model; Spatial Autocorrelation Analysis

1. Introduction

After entering the new century, China's economy has developed rapidly and has become the second largest economy in the world. However, with the increasing ecological and environmental problems, China surpassed the United States in 2007 to become the world's largest carbon emitter [1]. Therefore, China not only shoulders the responsibility of sustainable economic development, but also faces the dual challenges of promoting carbon emission reduction and actively addressing global governance of climate change. To this end, China has actively participated in the international climate cooperation framework. At the 2009 Copenhagen Climate Conference, the Chinese government promised to reduce carbon emissions per unit of GDP by 40% to 45% by 2020 [2]. Subsequently, China also signed and implemented the Kyoto Protocol, the Paris Agreement, the National Strategy for Adaptation to Climate Change and other carbon emission reduction related contractual policies [3-5], and achieved remarkable results. In 2020, China also put forward the goal of "China strives to reach the peak of carbon dioxide emissions by 2030, and strive to achieve carbon neutrality

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by 2060". In order to achieve the goal of "double carbon", both the "Fourteenth Five Year Plan" and the "Twentieth National Congress" report put forward that we should actively and steadily promote carbon peaking and carbon neutralization, and implement carbon peaking in a planned way by stages to promote green and low-carbon development [6-8]. According to the statistics of relevant departments, the industrial sector contributes 40.1% to China's GDP, but its energy consumption and carbon emissions account for 67.9% and 84.2% of the national total respectively [9]. Although the industrial sector is the main source of China's economic growth, it is also a major factor in energy consumption and carbon emissions. Therefore, industrial carbon emission reduction is the key to achieve the committed carbon emission reduction target. However, due to the significant differences in technology level, economic strength, energy consumption and pollutant emissions between industries in different regions, industrial carbon emission efficiency has obvious spatial heterogeneity [4]. This means that in order to improve industrial carbon emission efficiency, we must accurately measure the industrial carbon emission rate of different regions. Therefore, it is very important to comprehensively evaluate China's industrial carbon emission efficiency from the perspective of regional differentiation, and deeply study the regional differences and spatial evolution pattern of carbon emission efficiency of each province, which is of great practical value and practical significance to achieve the goal of carbon emission reduction in China.

Under the "double carbon" goal, the research on carbon emission efficiency has gradually become the focus, and scholars at home and abroad also conduct research and analysis from different perspectives. As for the definition of carbon emission efficiency, early researchers Kaya and Yokobori put forward the concept of carbon production efficiency [10]. On this basis, some scholars have successively proposed carbon index, carbon intensity index and other indicators to express carbon emission efficiency based on the perspective of single factor [11-12]. However, carbon emission efficiency is the result of the interaction of multiple factors, and not a single indicator can be interpreted. Therefore, some scholars proposed total factor energy efficiency based on the perspective of total factor productivity [13-15], and then considered relaxation variables to integrate energy, economy and carbon emissions into the research framework of carbon emission efficiency, redefining the concept of carbon emission efficiency [16-17]. Compared with domestic and international carbon emission efficiency accounting standards, foreign research focuses more on the overall analysis and research on global or national organizations, such as ZofíO and Iftikhar conducted carbon emission efficiency accounting and evaluation for OECD member countries and major economies [18-19], and found that India, Russia and China have huge carbon dioxide emission reduction potential. Domestic scholars will choose different regional scales to calculate efficiency. On Friday and July, Li Jian, Zang Hongying and other scholars analyzed the spatial differences and correlations of each region with each economic region, province and city as the research object [20-23]. They found that the provincial carbon emission efficiency was rising at a slower rate, and the difference in carbon emission efficiency between provinces was gradually increasing. On the whole, the national carbon emission efficiency showed an upward trend. Some scholars, from the perspective of different industries, accounted for animal husbandry, thermal power industry, construction industry and other industries [24-30]; When calculating carbon emission efficiency, scholars will select the most appropriate accounting model based on the accounting data to obtain the expected results. Most foreign scholars use the DEA method of multiple emission reduction factors, including the metatron non radial Luenberger carbon emission efficiency index and the fuzzy Delphi method ANP and other methods[31-32]. Domestic scholars mainly use the relaxation variable based measurement model (SBM) and stochastic frontier function method (SFA) to measure and evaluate. Wu Qi[33] and other scholars uses the respective advantages of the SBM model and the super efficiency DEA model for neutral and unexpected output to conduct in-depth measurement of China's provincial carbon emission efficiency. Dukrui[34] and others used SFA to estimate, and the results not only showed that the carbon emission efficiency value of each province increased year by year, but also showed that the differences between them were increasingly obvious; With the increase of consideration factors, some scholars improved the accounting model on this basis. Zhang Shengli, Jiang Ziran and Xiang Tiandong used a three-stage DEA model to calculate the carbon emission efficiency of their research areas. It is found that the carbon emission efficiency of China and various regions shows an overall upward trend, with significant regional differences[35-37].

In general, previous studies broadened the research perspective of industrial carbon emission efficiency, and also laid a solid theoretical foundation for this study. However, most scholars only focus on the whole region and the whole industry, ignoring the correlation characteristics between provinces and the importance of subdividing industries for improving carbon emission efficiency. The choice of research model will also ignore the impact of time dimension. Therefore, based on the above analysis, this paper calculates the industrial carbon emission efficiency of 30 provinces in China from 2005 to 2019 based on the super efficiency SBM model including unexpected output, and uses spatial autocorrelation and other methods to conduct empirical analysis on the dynamic evolution process and temporal and spatial differences of carbon emission efficiency. It is expected to provide direct empirical evidence and reference for the government to implement the "dual carbon" goal and China's green and low-carbon economic transformation.

2. Research methods and data sources

2.1. Super efficient SBM model based on unexpected output

On the basis of SBM model, Tone learned the advantages of super efficient DEA model and redefined the super efficient SBM model by integrating the advantages of the two models. Compared with the general SBM model, the super efficient SBM model can give priority to comparing and distinguishing the efficient DMU in the frontier[38-42]. However, both the SBM model containing unexpected output and the traditional DEA model have a common defect, that is, when evaluating the same type of DUM, multiple decision -making units will be in the forefront of production, that is, multiple efficiency values are 1. It is impossible to compare the efficiency of these decision-making units. On the above issues, the most prominent advantage of the efficiency model is that it can compare the efficiency of multiple effective decision making units[43]. Its model is as follows:

（1）

$$min\rho^* = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{t_1+t_2}\left(\sum_{q=1}^{t_1}\frac{\overline{y^a}}{y_{qo}^a}+\sum_{q=1}^{t_2}\frac{\overline{y^b}}{y_{q0}^b}\right)}$$

（2）

$$s.t.\begin{cases} \bar{x} \geq \sum_{j=1,j\neq 0}^{n} x_{ij}\lambda_j, & i = 1,2,\cdots,m \\ \overline{y^a} \leq \sum_{j=1,j\neq 0}^{n} y_{qj}^a\,\lambda_j, & q = 1,2,\cdots,t_1 \\ \overline{y^b} \geq \sum_{j=1,j\neq 0}^{n} y_{qj}^b\,\lambda_j, & q = 1,2,\cdots,t_2 \\ \lambda_j \geq 0, \quad j = 1,2,\cdots,n; \quad j\neq 0 \\ \bar{x} \geq x_0, \quad \overline{y^a} \leq y_0^a, \quad \overline{y^b} \geq y_0^b \quad \lambda_j \geq 0 \end{cases}$$

2.2. Spatial autocorrelation analysis

Spatial autocorrelation analysis is an important indicator to judge the relationshi p between a variable and the attribute values of its adjacent spatial points. The co mbination of the two can comprehensively describe the relationship between variable s, and at the same time measure the degree of dispersion or aggregation between t he attributes ofspace elements of things. Analysis of global spatial autocorrelation T his paper selects the global Moran's I index to test [44-46], and its expression is:

$$Moran's\ I = \frac{m\sum_{a=1}^{m}\sum_{b=1}^{m}W_{ab}(x_a-\bar{x})(x_b-\bar{x})}{\sum_{a=1}^{m}\sum_{b=1}^{m}W_{ab}\sum_{a=1}^{m}(x_a-\bar{x})^2} \quad (3)$$

Where, m represents the number of samples, and xb are the attribute valuesof samples a and b respectively, wab is the spatial weight, $\bar{x}$ is the average value of the sample. Between I values [-1,1], the closer the absolute value of I is to 1, indicating that the research object has stronger spatial autocorrelation. When I>0, i

t indicates positive correlation, and the research object presents aggregation; I<0, in dicating negative correlation, and the study object is discrete; I=0, indicating no cor relation, and the study object is random.

The hot spot analysis method (Getis - OrdGi *) is an effective method of loca l spatial autocorrelation, which is used to measure the degree of correlation between local areas and adjacent spatial units in a region. In order to further explore, this study selects hot spots to analyze the spatial agglomeration characteristics of local areas of the sample [47-48], and its calculation formula is:

$$G_i = \frac{\sum_{a=1}^{n}W_{ab}(d)X_a}{\sum_{b=1}^{n}X_b} \quad (4)$$

Where w is the spatial weight matrix. $Gi>0$ is significantly positive, and thi s region is a "hot spot", indicating that the carbon emission efficiency of this provi nce is highly concentrated, otherwise it is a "cold spot".

2.2.1. Data source

The sample interval of this paper is selected from 2005 to 2019. In order to e nsure the consistency of the statistical caliber of industrial input and output data, th e industrial input and output data are calculated based on the industrial data above designated size. Among them, the industrial input indicators include the number of industrial employees above designated size, net value of fixed assets and energy co nsumption; Take the gross output value and carbon dioxide emissions of industrial i ndustries above designated size as expected output and unexpected output[2-4.49-50]. Th e above relevant data are from China Statistical Yearbook, China Energy Statistical Yearbook, China Industrial Statistical Yearbook, China Industrial Economic Statistical Yearbook and 2006 IPCC National Greenhouse Gas Inventory Guide.

2.3. Temporal and Spatial Evolution Analysis of National Industrial Carbon E mission Efficiency

2.3.1. Time Series Analysis of Industrial Carbon Emission Efficiency

This paper uses MAXDEAUltra8.0 software to calculate the industrial carbon e mission efficiency of 30 provinces in China from 2005 to 2019, and analyzes the ti me series characteristics of the national industrial carbon emission efficiency. It can be seen from Figure 1 that during the study period, the industrial carbon emission efficiency value showed a trend of continuous improvement, but the average nation al industrial carbon emission efficiency was 0.34, which was lower than the average level of 0.63 of the industry's carbon emission efficiency[50], indicating that China's industrial carbon emission efficiency is still at the low efficiency level. However, t he average change of industrial carbon emission efficiency in each province has cha nged from low value concentration to diffusion at both ends, showing a decentralize d trend, which indicates that the difference between provinces is gradually obvious. Guangdong, Shanghai, Jiangsu and other economically developed provinces have an annual average efficiency of more than 0.50, while the provinces with an average of less than 0.3 account for 43% of the country, with the maximum difference of 0.49. This shows that there are obvious regional differences in the national industrial carbon emission efficiency.

Based on the analysis of the production frontier formed by 30 provinces in 15 years, Guangdong, Beijing, Fujian and Shanghai have all reached the production fr ontier, among which Guangdong's industry has taken the lead in transforming to a s ustainable green and low-carbon development model, giving priority to reaching the optimal frontier in 2013. However, most provinces have not reached the production frontier, which means that their carbon emission efficiency has a large ineffective lo ss, which reflects their strong carbon emission reduction potential.

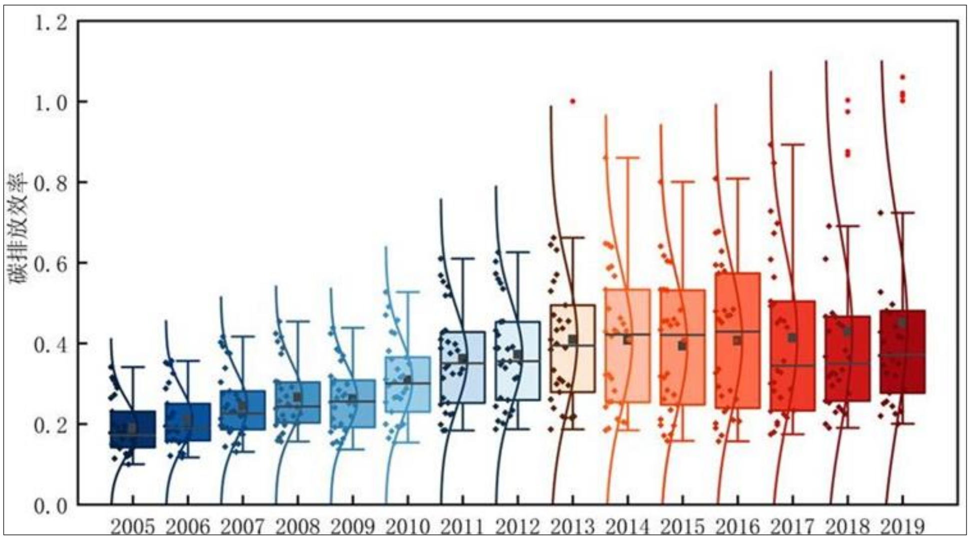

Figure 1 National Industrial Carbon Emission Efficiency Box Chart during 2005 to 2019 Referring to the practice of Friday and July[4], and taking into account the regional policies and regional differences implemented in China, the country is divided into four economic zones to more clearly analyze the convergence and divergence o f industrial carbon emission efficiency in the time sequence development of the cou ntry and the four economic zones. The results are shown in Figure 2.

From the national perspective, the average industrial carbon emission efficiency in the whole country showed a rising trend during the study period, with an avera ge annual growth rate of 6.35%, and only in 2008 showed a downward trend. The reason is that the outbreak of the international financial crisis in 2008 had a huge impact on the industrial industry, but after the financial crisis, China continued to p romote economic restructuring and the transformation of the economic development mode, and the industrial carbon emission efficiency continued to increase, reaching t he maximum average of 0.45 in 2019. It should be noted that during the period fr om 2009 to 2011, the national industrial carbon emission efficiency increased by 0. 10, with a maximum growth rate of 38.5%. This is due to China's implementation of the binding goal of energy conservation and emission reduction in the 11th Five Year Plan and the slowing down of heavy industry development, which led to the rapid increase of the national average industrial carbon emission efficiency, which is consistent with the analysis results of Li Tao and others[51]. Since 2012, the coef ficient of variation has increased significantly, showing an obvious divergent trend, which indicates that the industrial carbon emission efficiency of each province is si gnificantly polarized, with significant differences between provinces. At the same ti me, it was observed that the range value changed significantly in 2013, reaching 0.81 for the first time, which is closely related to the priority of Guangdong Province to reach the optimal frontier in 2013, opening up the relative differences among provinces. The above analysis proves that China has balanced and coordinated econ omic development and carbon emission development, but the national carbon emissi on efficiency has obvious inter group heterogeneity, which represents that each prov ince has huge space for energy conservation and emission reduction.

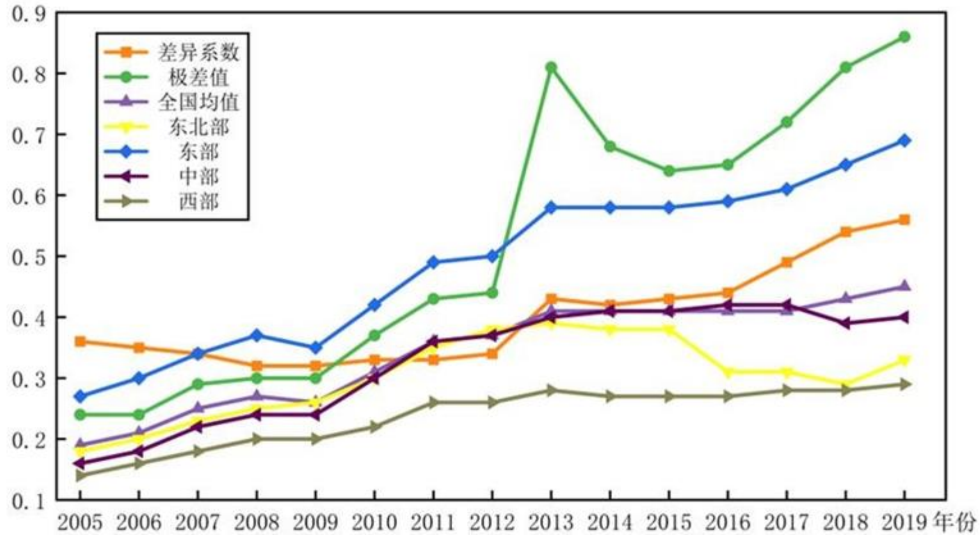

Figure 2 Differences in industrial carbon emission efficiency in China and economic zones from 2005 to 2019

For the four economic zones, the spatial differences of industrial carbon emissi on efficiency values are obvious. The average efficiency value of the eastern region reached 0.49, higher than the national average efficiency value as a whole, and it is the highest industrial carbon emission efficiency region in China. Due to its supe rior geographical location, strong economic foundation and the shift of economic str ucture to the tertiary industry, it has always maintained the development of high ca rbon emission efficiency. However, the industrial carbon emission efficiency of the central, western and northeastern regions has little difference, and their average effic iency values are 0.33, 0.24 and 0.30 respectively, which is closer to the national av erage industrial carbon emission efficiency values. The growth rate of these three re gions is slower than that of the east, and the relative gap with the east will gradu ally increase in the future. It is worth noting that although the industrial carbon em ission efficiency in the western region is low, it has always kept a slow rising stat e, which is closely related to China's active implementation of the western develop ment strategy, while the northeast region has developed heavy industry for a long ti me, and the contradiction between the system and structure has become increasingly prominent, the production technology is backward, the economic development is sl ow, and there are high pollution and high emissions, This makes the industrial carb on emission efficiency in Northeast China begin to decline year by year after 2013. It is not difficult to find that most of the provinces with strong technological innovation capacity and high energy utilization rate in the eastern coastal areas of Chin a are high efficiency regions. However, most of China's inland areas are distributed in provinces with low carbon emission efficiency, and industrial energy consumptio n and pollution are huge. Therefore, there is a significant correlation between eco no mic development and carbon emission efficiency.

2.4. Analysis of spatial pattern of industrial carbon emission efficiency

In this paper, the natural breakpoint method of ArcGIS software is used to sel ect the industrial carbon emission efficiency values [52] of all provinces in China i n 2005, 2010, 2015 and 2019. From high to low, they are divided into four types: high efficiency area, high efficiency area, low efficiency area and low efficiency a rea to show the spatial evolution characteristics of industrial carbon emission efficie ncy of each province (Figure 3).

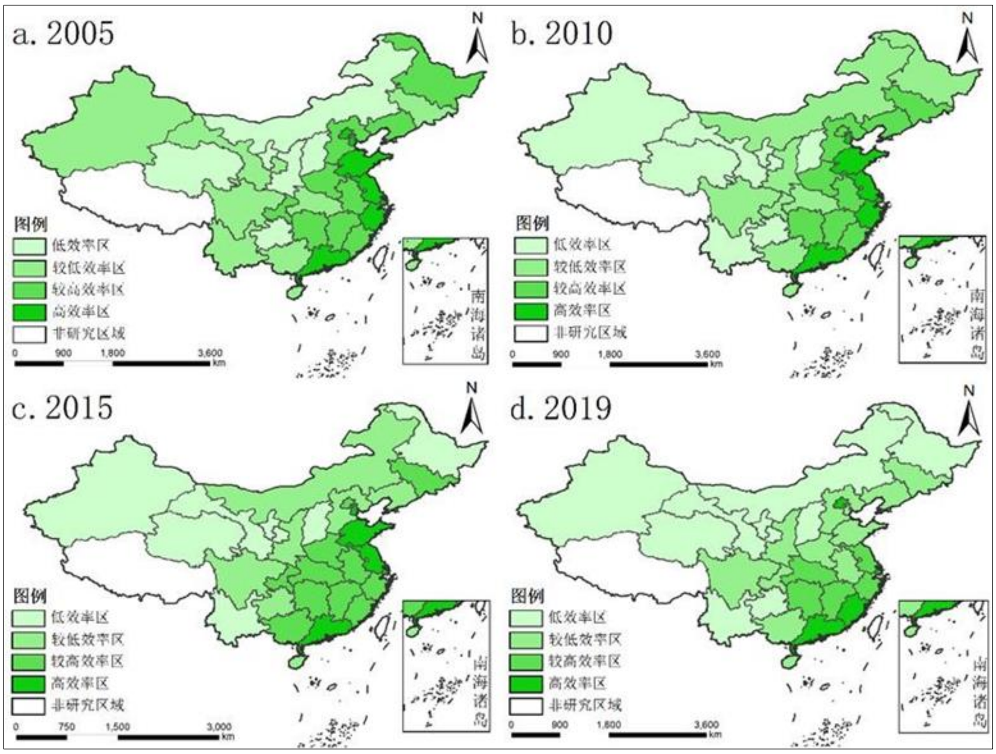

Figure 3 Spatial pattern of industrial carbon emission efficiency of provinces in China in typical years

On the whole, from 2005 to 2019, the spatial pattern of China's industrial carbon emission efficiency value gradually evolved from "high in the east and low in the west" to "high in the southeast and low in the northwest", showing a trend of east>middle>northeast>west. The reason is that in recent years, China's economic and scientific and technological focus has gradually moved to the east, causing efficient provinces to move to the east. High value areas are mainly distributed in the eastern coastal areas, while the western region has become the main gathering area of low value areas. The gap between regions is still very obvious, so reducing the difference in carbon emission efficiency between provinces has become the core goal of current energy conservation and emission reduction.

2.5. Global spatial autocorrelation analysis

Make a global autocorrelation analysis on industrial carbon emission effici ency of 30 provinces (Table 1). The overall Moran's I index of China's indust rial carbon emission efficiency was positive (0.12 -0.33) during the study period, and most of the years passed the significance test of $P<0.01$, which indicates that there is a significant global spatial agglomeration effect on China's indus trial carbon emission efficiency. Moran's I index shows an overall "M" type fl uctuation trend in the time path, and the spatial difference characteristics chan ge in stages. The development trend shows four stages: 2005 -2009 is the "stab le development" stage, in which Moran's I index tends to be stable as a whol e, with significant spatial agglomeration effect; The period from 2009 to 2013 is a period of "drastic changes". The impact of the 2008 international financi al crisis and the Industrial Transformation and Upgrading Plan proposed during the "12th Five Year Plan" have determined the main objectives of industrial t ransformation and upgrading in the next five years. As a result, Moran's I ind ex reached its peak and trough in 2010 and 2013, respectively, with a variation of 43.7%, which indicates that the provinces are converging spatially in an alternating manner.

From 2013 to 2016, the Moran's I index rose by 32.1%. The reason is th at the 18th National Congress of the Communist Party of China vigorously pr omoted the construction of ecological civilization, and provinces made efforts to promote industrial energy conservation and green development, so as to achi eve continuous improvement of industrial carbon emission efficiency, and rapidl y narrow the overall spatial differences; The period from 2016 to 2019 is a p eriod of "rapid decline", which is closely related to the Industrial Green Devel opment Plan (2016-2020) issued by the Ministry of Industry and Information T echnology in 2016. As a result, the concept of green development has become a common requirement in the whole process of the whole industry, promoting the gradual spatial convergence of the national industrial carbon emission efficiency, which led to the rapid decline of Moran's I index at this stage.

Table 1 Overall Moran'I Index of Industrial Carbon Emission Efficiency of All Provinces from 2005 to 2019

Particular year	**Morans I**	**Z value**	**particular year**	**Moran's I**	**Z value**
2005	0.278	4.938	2013	0.184	3.595
2006	0.285	5.045	2014	0.225	4.110
2007	0.275	4.888	2015	0.237	4.275
2008	0.285	5.049	2016	0.243	4.353
2009	0.269	4.785	2017	0.187	3.516
2010	0.327	5.694	2018	0.170	3.288
2011	0.308	5.391	2019	0.118	2.464
2012	0.309	5.402	—	—	—

2.6. Local spatial autocorrelation analysis

In order to deeply explore the local spatial correlation characteristics of i ndustrial carbon emission efficiency among provinces in China, this paper us es the Getis OrdGI * index to divide it into five categories (Figure 4) to reveal the spatial correlation characteristics of industrial carbon emission efficiency among provinces. In general, the local spatial agglomeration of China's industri al carbon emission efficiency has always maintained the pattern of "hot in the east and cold in the west", which echoes the overall spatial evolution pattern of China. From 2005 to 2019, the hot spots of industrial carbon emission eff iciency in China gradually shrunk to the southeast coastal areas, and the number of provinces in the hot spots decreased significantly. The cold spot region has expanded from the western region to the northeast region, forming a spati al correlation structure of low value clusters with provi nces in the western reg ion as the center and spreading to provinces in the northeast region, and this structural feature has gradually deepened and highlighted over time.When the overall spatial pattern is stable, observe the distribution of hot spots. The number and scope of hot spots have been greatly reduced. In 2005,the hot spots of China's industrial carbon emission efficiency were mainly co ncentrated in Shandong, Jiangsu, Shanghai, Zhejiang and other eastern province s with superior economic development conditions, while the secondary hot spot s were in a "semi enclosed" pattern, mainly including Liaoning, Hebei, Fujianand other provinces, fully surrounding the northern hot spots; In 2010, there was no significant change in the migration of hot spots, in which Jiangxi Pro vince replaced Hebei Province to join the hot spots, leading to the weakening of the concentration of Beijing Tianjin Hebei provinces and the strengthening of the concentration in the central region; In 2015, the agglomeration situatio n in Northeast China was reduced, and the range of hot spots moved significantly southward and narrowed sharply. The sub hot spots only include Beijing, Zhejiang and Fujian provinces, which makes the hot spots and sub hot spots p resent a core fringe pattern centered on the Yangtze River Economic Belt.In 2019, the spatial concentration scope of hot spots and sub hot spots continued to shrink, and the core hot spots were mainly concentrated in Guangdong Fujian and Shanghai and other southeast coastal provinc es, while the sub hotspot region only retains Zhejiang Province, mainly because of the close re lationship between provinces in the southeast coastal region, which has a signi ficant radiation and driving role. It is worth noting that Shandong Province an d Jiangsu Province have withdrawn from the hot spots, which reflects that the agglomeration characteristics of these two provinces tend to weaken, and thespatial correlation with surrounding provinces is weakened.

At the same time, observe the cold spot area and sub cold spot area, and their development trends are different from the hot spot area. On the whole, it will gather in the west and then continue to expand to the northeast, formi ng a "suppression" spatial pattern that gradually encircles hot spots. In 2005, t he cold spots and sub cold spots were mainly concentrated in the western and central provinces with weak economic foundation and slow in dustrial develop ment, and the distribution of cold spots was more inclined to Inner Mongolia, Shaanxi, Shanxi and other provinces. In 2010, on the basis of maintaining th e stability of the original scope, Heilongjiang Province replaced Hainan Provin ce as a sub cold spot area, which gradually converged to the northeast, while the core cold spot area moved to the northwest. In 2015, the concentration d egree of cold spots in central China was weakened, and the core cold spots c ontinued to move north, evolving into a spatial pattern of "four zones" and the trend continued to increase. In 2019, the cold spot area and sub cold spot area will completely form a "suppression" pattern dominated by provinces in n orthwest China, comprehensively suppressing hot spots. The spatial linkage of industrial carbon emission efficiency in Inner Mongolia, Heilongjiang, Xinjiang,Gansu and other provinces has been significantly improved.

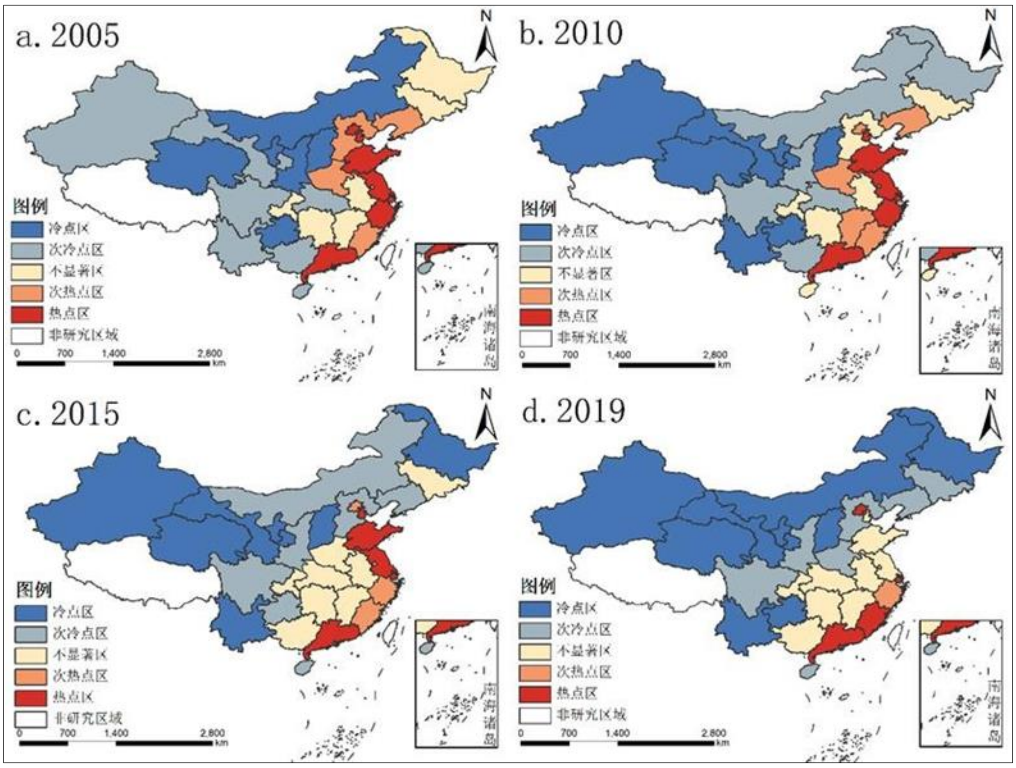

Figure 4 Evolution Trend of Industrial Carbon Emission Efficiency in Different Provinces in Typical Years

3. Conclusion

From 2005 to 2019, China's industrial carbon emission efficiency was in a low efficiency stage as a whole, with an average value of 0.34 and an a verage annual growth rate of 6.35%, showing a rising trend as a whole, but t he spatial differences between provinces and regions became more significant. From 2005 to 2019, the spatial pattern of China's industrial carbon emission e fficiency value gradually evolved from "high in the east and low in the west"to "high in the east and south and low in the northwest", showing a trend o f gradual decline from the eastern coastal areas to the western inland areas. The gap between regions is still very obvious, so reducing the difference in car bon emission efficiency between provinces has become the core goal of curren t energy conservation and emission reduction.

Through spatial autocorrelation analysis, the overall Moran's I index is subject to the impact of social policy environment in the time path, showing a "M" type fluctuation trend, and the spatial difference characteristics change in stages. The national industrial carbon emission efficiency has a significant global spatial agglomeration effect, and each province has a spatial dependence. The agglomeration trend is significant, forming a cluster with the eastern c oastal area as the high value center, and the northwest inland area as the lowvalue center.

The Getis OrdGI * index reveals that the local spatial agglomeration characteristics of China's industrial carbon emission efficiency always maintain the pattern of "hot in the east and cold in the west", which echoes the overal l spatial evolution pattern of China. The hot spots and sub hot spots of China 's industrial carbon emission efficiency are mainly concentrated in the southeas t coastal areas with relatively superior economic development, and present a "s emi enclosed" pattern. Cold spot area and sub cold spot area form a "suppress ion" pattern with northwest provinces as the core, comprehensively suppressinghot spots.

Suggestions

Eliminate technical barriers to emission reduction and reduce reg ional differences. Northeast China should limit the excessive use of coal resources, encourage the development of emerging industries and high -tech industries, andaccelerate the promotion and application of green energy conservation and em ission reduction technologies. The central and western regions continue to givefull play to the role of the "Western Development" and the "the Belt and Ro ad" strategies, fully commercialize low-carbon technologies, vigorously promote cleaner production, minimize the carbon emissions of industrial production inenergy conversion, upgrade and transform industrial enterprises in high energy consuming regions, fundamentally reduce industrial carbon emissions, and impro ve industrial carbon emission efficiency. The eastern regi on should give play t o its "top" advantages, export advanced technologies to inefficient regions, andpurposefully assist the rapid development of inefficient provinces with industri al carbon emissions. At the same time, we will improve our energy structur e, promote low-carbon urbanization, and fully realize green, energy-saving and ind ustrialized cities.Change the mode of economic development and create new advantages for economic development. Promoting economic development is an effective m eans to improve industrial carbon emission efficiency. We should strengthen ex changes and cooperation between regions on production technology and environ mental systems, and promote the transfer of advanced technology and managem ent experience from the east to the central and western regions. For provinces with low industrial carbon emission efficiency, it is necessary to formulate lo w-carbon development strategic objectives in line with the province, form a sy nergistic emission reduction effect with surrounding provinces, transform to high-quality low-carbon green economy development, and achieve China's goal of developing low-carbon economy.

To develop green industry, enterprises should implement green develop ment strategies. Industrial enterprises above designated size in all provinces sh ould actively realize transformation and upgrading, expand the group of green industrial enterprises, and accelerate the construction of a green industrial syst em. In policy formulation, it can create a superior development envi ronment fo r green and low-carbon industries, strengthen the emphasis on environmental pr otection, strengthen the promotion of industrial development towards green and low-carbon sustainable development, and effectively improve the overall carbo n emission efficiency of China's industry.

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