A Study on the Measurement of Provincial Carbon Emission Efficiency and Influencing Factors in China

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Abstract: Carbon emission efficiency (CEE) was measured by using Epsilon-based Measure (EBM) based on 30 provinces of China by panel data from 2005 to 2019. After that, the spatial stratified heterogeneity (SSH) of CEE was explored by Geodetector and ArcGIS. The results show that :(1) China's eastern provinces perform better in terms of carbon emission efficiency compared with inland provinces, and their carbon emission efficiency values are generally higher. Overall, the average CEE level in China from 2005 to 2019 shows a decreasing trend year by year, with a decrease of 8.33%; (2) the investigation of the influencing factors finds that the influence of energy structure, economic development, foreign trade, and science and technology on the spatial heterogeneity of CEE is most prominent; (3) the influence of single factor on CEE is significantly lower than that of two-factor interaction. And the two-factor interaction shows linear enhancement or non-linear enhancement.

1. Introduce

With the rising industrial demand brought about by social development, the global greenhouse gases are increasing, putting the sustainability of the environment and society under serious threat. China is the second largest economy in the world and a major carbon emitter, has seen a dramatic increase in total carbon emissions while the total GDP has increased more than 80 times in the past four decades. The continuous rise of carbon emissions has made China face multiple challenges such as economic transformation and environmental protection.

In order to achieve the "1.5°C" temperature control target proposed in the Paris Agreement[1], China has independently committed to strive to reduce CO2 emissions per unit of GDP by 60%-65% by 2030 compared to 2005, and strive to "Emission Peak" by 2030. " in 2060 and " Carbon Neutrality" in 2060.Therefore, improve the carbon emissions efficiency(CEE) is significant[2]. It will accurately assess the CEE of each provinces in China at the present stage, clarify the key factors, and further promote the improvement of CEE in China as a guiding role. The main contributions of this paper are: (1)Previous research methods scaled or expanded the input and output in the same proportion, which to some extent affected the accuracy and objectivity of the results. In this paper, the hybrid distance function is used for measurement, which can reflect the CEE of each evaluation unit more realistically.(2)While previous methods based on regression analysis have ignored the spatial effects of space on CEE, this paper takes full account of the characteristics of spatial differentiation in order to draw other interesting conclusions.(3)The factors influencing carbon emission efficiency are often the result of multiple factors, and it is more beneficial to improve CEE by clarifying the interaction relationship between factors, and the two-factor interaction detection method chosen in this study can meet this need.

2. Literature review

In the early days, scholars mostly used single factors such as carbon intensity[3]and carbon productivity [4] to weigh carbon emission efficiency, but the single factor could not fully reflect the relationship between many factors of economic activities such as economy, energy and population. Later, it became popular to measure CEE comprehensively by introducing multi-input multi-output total factor CEE[45]. In the previous period, the academic community mainly used Data Envelopment Analysis (DEA) to measure CEE[67]. However, all these studies lacked consideration of non-desired outputs and did not take into account the effects of non-radial relaxation, resulting in overestimation for efficiency values. Therefore, some scholars have used non-radial SBM models to measure carbon emission efficiency[89]. Due to the need to minimize inputs and discard different proportions of the original input resources in the SBM calculation process, there is a problem of underestimation of efficiency values. In response, some scholars have used the directional distance function to measure carbon emission efficiency[10]. With the combination of radial and non-radial methods proposed, scholars began to use the hybrid distance function to measure carbon emission efficiency[1112]. On this basis, some scholars measured carbon emission efficiency from both static and dynamic aspects by combining the Malmquist index[13] For the influencing factors of CEE, existing studies mainly use

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regression analysis methods, such as double threshold models[14], SFA[15] and fixed effects[16]. The influence of factors such as economic development, industrial structure, government intervention and energy consumption structure on carbon emission efficiency has been verified。

In addition, in recent years, there have also been attempts to study the influence of certain key factors on carbon emission efficiency, such as urbanization[17] and foreign direct investment[18]. Geodetector has been widely used as a new tool for measuring, mining and exploiting spatial heterogeneity in agricultural eco-efficiency[19], exploring spatial heterogeneity and its influencing factors[20] and other influencing factors[21].

In summary, in terms of methodological choices, most scholars have used radial or non-radial models; or DEA models related to the Malmquist index to examine CEE from both dynamic and static perspectives, but there are still shortcomings. EBM can effectively reflect the radial ratio between the target value of inputs and the actual value of inputs, as well as the differences in the non-radial components of each input-output variable, The above problems are effectively addressed. In addition, most of the studies on the influencing factors of the CEE focus on regression analysis, which only studies its single factor and does not consider the changes of the influencing factors when the two factors are combined. Therefore, this paper first clarifies the existence of spatial heterogeneity in CEE by measuring the carbon emission efficiency of each province in China. It then analyses the interaction between the single and dual factors influencing carbon emission efficiency, draws conclusions and gives recommendations.

3.Methodology and data

3.1 Method of efficiency measurement

In this paper, we used a hybrid model incorporating radial and non-radial characteristics proposed by Tone & Tsutsui [22]. Assume that there are n decision making units (DMUs), denoted DUM_k (k=1,2,...,n). Each DMU contains j input indicators, denoted as P_j(j=1,2,...,m) and r output indicators, denoted as Y_r(r=1,2,...,v), and is modelled as follows:

$$\gamma^* = \min \frac{\theta - \varepsilon^- \sum_{i=1}^{m} \frac{\omega_i^- S_i^-}{P_{ij}}}{\eta + \varepsilon^+ (\sum_{r=1}^{S1} \frac{\omega_r^{+S1} S_r^+}{Y_{rj}} + \sum_{r=1}^{S2} \frac{\omega_r^{+S2} S_r^{+b}}{Y_{rj}}} \quad (1)$$

$$s.t. \begin{cases} \lambda P - \theta P_{ij} + S^- = 0 \\ \lambda Y - \eta Y_{rj}^+ - S^+ = 0 \\ \lambda Y - \eta Y_{rj}^{+b} + S^{+b} = 0 \\ \lambda_1 + \lambda_2 + ... + \lambda_3 = 1 \\ \lambda \geq 0, S^-,, S^+ S^{-b} \geq 0, \theta \leq 1, \eta \geq 1 \end{cases}$$

where γ denotes the optimal carbon efficiency of the decision making unit (DMU) when considering non-desired outputs, satisfying $0 \leq \gamma \leq 1$. S^- denotes the slack variable for input P_j; S^+ and S^{+b} are the slack variables for desired output Y_r^+ and non-desired output Y_r^{+b}, respectively; ω^- is the weight of input P_j; ω^{+S1}, $\omega^{+S2}$are the weights of desired and non-desired outputs, respectively, satisfying $\sum\omega^{+S1} + \sum\omega^{+S2} = 1$ (any $\sum\omega \geq 0$). ε is a key parameter indicating the importance of the non-radial component in the calculation of efficiency values, ε^+, ε^- indicate the key parameters of outputs and inputs, which are equivalent to the radial model when ε=0 and the SBM model when ε=1. λ indicates the reference decision unit's relative importance, and θ, η are variables.

The input indicators include labour(total number of employees at the end of the year)[23], capital(calculated using the perpetual inventory method) and energy(total energy consumption), and the output indicators contain desired output (GDP) and undesired output (total CO2 emissions).

3.2 Method of influencing factors analysis

In this paper we use the factor detector and the Interaction Detector in the Geodetector. This paper measures the q-value of each factor X by means of a factor detector and reveals the explanatory power of a factor on the spatial divergence of CEE, the expression of which is

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^{L} N_h \sigma_h^2 \qquad (2)$$

L is the number of stratification or classification of each influencing factor, N and N_h are the number of cells in the whole region and stratum h respectively. σ^2 and σ_h^2 are the variances of h and Y. q indicates the degree of influence of each influencing factor on the CEE.

The interaction detector determines the interaction effect of the two variables by superimposing the q-values of the single factor and the two factors, thereby fully exploiting any relationship that may exist. This not only increases the comprehensiveness of the results, but also explains whether the interaction of the two variables is attenuated, enhanced or independent of each other, which is a major advantage of the Geodetector. The results of multi-factor interactions can be classified into five categories: non-linear weakening, univariate weakening, linear enhancement, variable independent and non-linearly enhanced.

3.3 indicators Select and data source

From the literature, most scholars believe that carbon emission efficiency is influenced by various factors such as economy, technology and energy consumption. In order to clarify the key factors affecting the spatial heterogeneity of CEE, this paper selects eight indicators: the level of economic development(X1): Per capita GDP、industrial structure(X2): Share of Tertiary sector in GDP、Energy consumption structure(X3): Share of Coal consumption in energy consumption、Technology level(X4): Number of three types of patents granted by province、Government intervention(X5):Share of General public budget in GDP、Urbanization(X6): Share of urban population in population、Foreign trade(X7): Share of Total imports and exports in GDP、Environmental regulation(X8):Share of industrial pollution governance costs in gross industrial product to carry out the analysis.

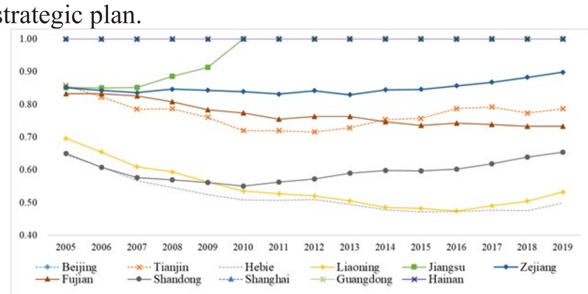
In this paper, relevant data from 30 are provinces in China from 2005-2019 were selected for the study. Due to some missing data, Tibet, Taiwan, Hong Kong and Macao were not included in the data sample of this paper. The data used in this paper are from the China Statistical Yearbook, the China Energy Statistical Yearbook and the statistical yearbooks of provinces, municipalities and autonomous regions.

4.Empirical analysis

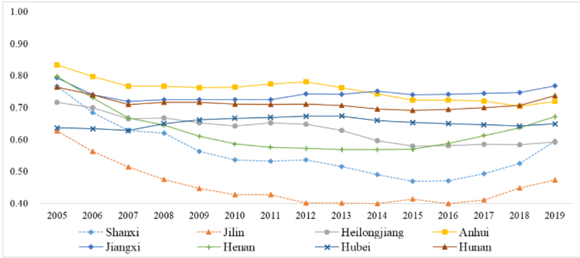
4.1 carbon efficiency measurement results

During the period 2005-2019，the CEE of each province can be obtained from formula(1). Considering the obvious differences in economic development and resources between the eastern, central and western regions of China。In order to make the measurement results more intuitive, the CEE of each province and region is plotted according to the eastern, central and western regions, as shown in Figure 1. The CEE levels of the provinces have changed significantly over the study period, and there are clear regional differences. The regions with better CEE (emission efficiency of 1) include: Beijing, Shanghai, Guangdong, Hainan and Qinghai; Jiangsu and Zhejiang have always been in an improved state and have contributed greatly to the improvement of China's carbon emission efficiency.

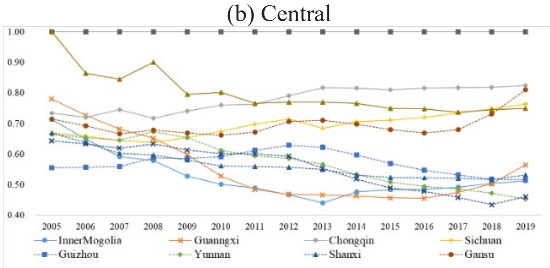
In addition, provinces such as Yunnan, Xinjiang and Ningxia have seen their CEE decrease year on year and by a large margin, especially Yunnan and Ningxia, which have seen their CEE fall by 0.21 and 0.25 respectively (a decline of 31.8% and 25%), the largest decline of any province. It is worth noting that, in the overall national context, China's average carbon emission efficiency level shows a decreasing trend year on year, with an overall decrease of 8.33%. This finding also indicates that there is no real "decoupling" between economic development and carbon efficiency in China, and that the practice of developing the economy at the expense of environmental efficiency has not yet been fundamentally changed, and that there is still a long way to go to achieve the "3060" strategic plan.



(a) Eastern



(b) Central



(c) Western

Fig 1. provinces' carbon emission efficiency

4.2 Analysis of the Spatial Divergence of Carbon Emission Efficiency in China

Based on the measured carbon emission efficiency of 30 provinces in China, four more typical time points, 2005, 2010, 2015 and 2019, were selected to derive the spatial trends of carbon emission efficiency in China in the short term. With the help of ArcGIS Trend Analysis tool, a three-dimensional trend map was drawn with X-axis (due east, indicating orientation), Y-axis (due north, indicating orientation) and Z-axis (vertical, indicating carbon emission efficiency values), and the green line indicates the east-west difference and the blue line indicates the north-south difference, as shown in Figure 2. As can be seen from Figure 2, throughout the period, the east-west and north-south trend lines are either skewed or curved, indicating a significant spatial heterogeneity in China's carbon emission efficiency.

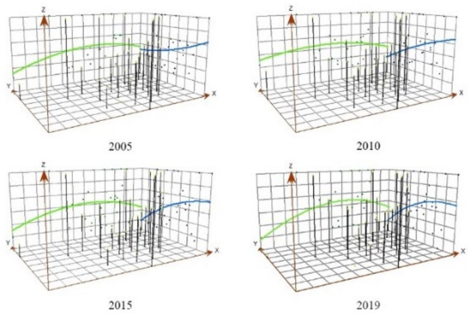


Fig.2. Trend lines of changing spatial patterns of carbon emissions efficiency

4.3 Factor detection analysis of factors influencing carbon emission efficiency

4.3.1 Single factor detection

This paper obtains the q-values of X1-X8 indicators from 2005-2019 based on equation (3), and the calculation results are shown in Figure 3. As can be seen from Figure 3, the influence of each influencing factor on carbon emission efficiency varies in different years, and the level of influence keeps changing. Although the explanatory power of energy structure is gradually decreasing, its influence on carbon emission efficiency is the strongest, followed by the level of economic development, foreign trade level, and science and technology level. At the same time, the level of economic development is generally on the trend of strengthening, indicating that economic development is an important link in the improvement of carbon emission efficiency. As the proportion of clean energy in China gradually increases, the influence of energy structure on China's carbon emission efficiency begins to show a decreasing trend. In addition, China's early tendency to adopt a command-and-control approach to promote the achievement of emission reduction targets, but the continued use of market-based regulatory instruments in recent years has led to an upward and then downward trend in government intervention and environmental regulation. The impact of urbanization on the spatial heterogeneity of carbon emission efficiency has remained almost stable.

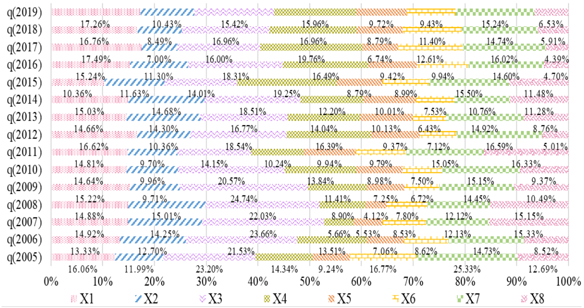


Figure 3. Single factor detection results

4.3.2 Two-factor interaction detection

To further test whether the explanatory power of the two-factor interaction on carbon emission efficiency is enhanced, diminished or independent of each other compared to the single-factor factor test, and to dissect whether the enhancement/diminution effect is linear or non-linear. In this paper, 2005, 2010, 2015 and 2019 were selected as the characteristic years to explore the interaction of the two factors.By probing the two-by-two interactions of the eight influencing factors in the paper, it is found that the effects of the two-factor interaction on carbon emission efficiency are all enhanced in this paper, and there are no independent factors among the influencing factors, and there is more linear enhancement (61.6%) than non-linear enhancement (36.4%). It is worth noting that the explanatory power of the two-by-two interaction of the factors for carbon efficiency is significantly higher than that of the single factor, especially X8.

5.Conclusions

Based on panel data of 30 provinces, municipalities and autonomous regions in China from 2005-2019, the EBM model was used to measure the carbon emission efficiency of 30 provincial in China; with the help of ArcGIS trend analysis tools, the spatial heterogeneity of China's carbon emission efficiency was explored, and the impact of factors affecting carbon emission efficiency and their interaction was explored using geographic probes. The study found that: (1) China's eastern coastal provinces performed better in terms of carbon emission efficiency compared with inland provinces, and their carbon emission efficiency values were generally higher; (2) from the overall national situation, China's average carbon emission efficiency level showed a decreasing trend year by year from 2005 to 2019, with a decrease of 8.33%; (3) among all factors, energy structure, economic development, foreign trade and the technology level have the most influence on carbon emission efficiency; in addition, the influence of the interaction of two factors on carbon emission efficiency is significantly higher than that of a single factor.

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