Measurement and Spatio-temporal evolution of China’s Regional Eco-efficiency

Jian Li* and Yanran Zhang*
School of Management, Tianjin University of Technology, Tianjin 300384, China

*Corresponding author e-mail: 16622900637@163.com, *lijian631219@163.com

Abstract. Based on panel data from 2008 to 2017, the Super-SBM model that considers undesired output has been to measure the eco-efficiency of 30 provinces in China. Meanwhile, the spatial autocorrelation analysis is incorporated into the spatiotemporal evolution law in order to calculate the global and local Moran’s I index, and combining the Moran scatter plot to explore the spatiotemporal evolution and agglomeration characteristics of regional eco-efficiency. The results show that the overall level of China's eco-efficiency has improved, but the regional differences are obvious, shows a gradient descending pattern of “East, Northeast, Middle and West ”. The regions with familiar eco-efficiency level showed the volatility clustering phenomenon, and that the regions and their neighbors have potentially similar trends. Eco-efficiency in China was improved followed by the improvement of local polarization situation and regional differences have narrowed.

1. Introduction
At present, China has entered the middle stage of industrialization. The extensive and high-energy-consuming economic development mode has caused serious damage to the ecological environment in China. The increasing pollution of the ecological environment has seriously affected local industrial production, residents’ lives and health. Under the dual pressure of improving the ecological environment and changing the mode of economic development, the Fifth Plenary Session of the 18th CPC Central Committee proposed to adhere to the concept of green development, which includes economy, society and ecological environment and emphasizes the coordinated development of them, and the fundamental way to promote green development is to improve eco-efficiency. Therefore, in the context of promoting the construction of ecological civilization, how to protect the environment and improve eco-efficiency while maintaining rapid economic growth, combining the economic and geographical connections between different regions in China to understand the spatial and temporal differences and dynamic evolution laws of eco-efficiency between regions is one of the issues that need to be resolved.

2. Literature Review
Academia's research on eco-efficiency mainly focuses on two aspects. First, using different measurement methods to analyse and evaluate eco-efficiency. Shi Dan [1] calculated the eco-efficiency of China from 1991 to 2013 based on the ecological footprint. Qu [2] used the Super-DEA model to measure the eco-efficiency of 30 provinces in China from 2004 to 2014. Li Ming sheng [3]
combined the emergy analysis and MFA to build an expression of eco-efficiency in Jilin Province. Yang Yong [4] used SFA to evaluate the eco-efficiency of Chinese cities in 2006-2013. The second is to analyse regional differences in eco-efficiency from static and dynamic perspectives. From static perspectives, Hu Biao [5] based on the results of the SBM model of undesired output, analysed the spatial differences of regional eco-efficiency in China from the perspective of time and space by using spatial autocorrelation analysis. At the dynamic research level, Hou Mengyang [6] based on the results of Super-DEA and the time comparison analysis and spatial correlation analysis, analysed the temporal-spatial evolution pattern of urban eco-efficiency by constructing traditional and spatial Markov chain transition probability matrix, and then discusses its dynamic evolution characteristics.

To sum up, based on the existing research, this paper uses the Super-SBM model that considers undesired output to measure the eco-efficiency of 30 provinces in China from 2008 to 2017. Secondly, the spatial autocorrelation method was used to calculate the global and the local Moran's I index, and combining the Moran scatter plot to explore the spatiotemporal evolution and agglomeration characteristics of regional eco-efficiency. The results have important practical significance for the local government to formulate policies and measures tailored to local conditions for improving eco-efficiency to ensure coordinated economic, social and environmental development.

3. Research Methods and Data Description

3.1. Research methods

3.1.1. Super-SBM. Taking environmental undesired output into account is the key to measuring eco-efficiency. Because the traditional DEA model ignores the effects of undesired output and slack variables in the process of measuring efficiency, and causing problems such as the deviation of efficiency evaluation from reality. Therefore, this study uses the Super-SBM model proposed by Tone [7] to measure eco-efficiency. This model allows the efficiency value of the DMU to exceed 1, and then evaluates the DMU whose eco-efficiency value is at the forefront. The Super-SBM model for measuring eco-efficiency is constructed as follows:

$$
\min \rho = \frac{\frac{1}{m} \sum_{i=1}^{m} \frac{\bar{x}}{x_{ik}}}{r_{1} + r_{2} \left(\sum_{s=1}^{r_{1}} y_{s}^{d} + \sum_{q=1}^{r_{2}} y_{q}^{u}\right)}
$$

s.t. \quad \bar{x} \geq \sum_{j=1,j \neq k}^{n} x_{ij} \lambda_{j}, \quad i = 1, 2, ..., m

$$
\bar{y}_{d}^{d} \leq \sum_{j=1}^{n} y_{j}^{d} \lambda_{j}, \quad s = 1, 2, ..., r_{1}
$$

$$
\bar{y}_{u}^{u} \geq \sum_{j=1,j \neq k}^{n} y_{q}^{u} \lambda_{j}, \quad q = 1, 2, ..., r_{2}
$$

$$
\lambda_{j} \geq 0, \quad j = 1, 2, ..., n
$$

$$
\bar{x} \geq x_{k}, \quad k = 1, 2, ..., m
$$

$$
\bar{y}_{d}^{d} \geq y_{k}^{d}, \quad d = 1, 2, ..., r_{1}
$$

$$
\bar{y}_{u}^{u} \geq y_{k}^{u}, \quad u = 1, 2, ..., r_{2}
$$

Among them, DMU represents decision unit. Where n is the total number of DMU, and each DMU contains an input m, an expected output, an undesired output. \( x, y_{d}^{d} \text{ and } y_{u}^{u} \) are the corresponding input, expected output and undesired output matrix respectively.

3.1.2. Spatial correlation analysis. Spatial autocorrelation is an important indicator to test whether the attribute value of a certain feature is significantly associated with the attribute value on its neighbouring spatial points. It contains global spatial autocorrelation and local spatial autocorrelation.
The global spatial correlation is used to analyse the distribution characteristics of the research objects in the global space. Generally, the global Moran’s I index is used to measure the overall spatial correlation and spatial difference of the region. The formula for calculating the global Moran’s I index is:

$$\text{Moran's I} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}}$$  \hspace{1cm} (2)$$

Where $S^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2$; $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$. $x_i$ is the eco-efficiency of province $i$, $\bar{x}$ represents the average of the eco-efficiency of all provinces, $n$ is the total area. $w_{ij}$ is the spatial weight matrix, in this paper, we choose a binary adjacency weight matrix, if the two regions are adjacent in the spatial distribution, $w_{ij}$ takes the value of 1 and 0 otherwise. The value of Moran's I statistic is generally between $[-1, 1]$, when it less than 0 indicates a negative spatial correlation of regional eco-efficiency and greater than 0 indicates a positive spatial correlation, if it equal to 0 indicates no spatial correlation.

Local Indicators of Spatial Association is a local form of Moran's I index. It is used to test the agglomeration and dispersion effects of local areas, in order to reveal the degree of spatial autocorrelation between the local or each spatial unit and its neighboring units, its expression is:

$$I_i = \frac{(x_i - \bar{x})}{\sqrt{\sum_j w_{ij}(x_j - \bar{x})}}$$  \hspace{1cm} (3)$$

When $I_i$ is positive, it indicates that the attributes of the region are similar to those of the adjacent region; when $I_i$ is negative, it indicates that the attributes of the region are not similar to those of the adjacent region.

### 3.2. Selection of indicators and data sources

Based on the existing literature and considering the availability of data, this paper constructed a measurement index system for eco-efficiency in China, in which the capital stock was borrowed from the method of Shan Haojie [8] which used the perpetual inventory method and the depreciation rate was selected at 10.96% for estimation.

| Table 1. The measurement index system for eco-efficiency |
|--------------------------------|
| index | variables | Units of variables |
|-------|-----------|-------------------|
| input | Employees at the end of the year | person |
|       | Capital stock | yuan |
|       | Total urban water use | m³ |
|       | Construction land area | Km² |
|       | Total electricity consumption of the whole society | Kw/h |
| Desirable outputs | GDP | yuan |
|       | Green area | hm² |
| Undesirable outputs | Wastewater emissions | t |
|       | SO₂ emissions | t |
|       | Smoke (powder) dust emissions | t |

Due to the lack of some data in Hong Kong, Macao, Taiwan, and Tibet, this study selected 30 provinces of China from 2008 to 2017 as samples to measure eco-efficiency. The data of all indicators are derived from the China Statistical Yearbook, the China Environmental Statistical Yearbook and the regional statistical yearbooks.
4. Result Analysis

4.1. Analysis of the temporal and spatial characteristics of eco-efficiency in China

Considering the existence of regional differences, this paper divides 30 provinces into four regions: east, middle, west, and northeast. The eastern region includes 10 provinces (cities), the middle region includes 6 provinces, the western region includes 11 provinces, and the northeast Provinces include Liaoning, Jilin and Heilongjiang. Using MaxDEA software to calculate the eco-efficiency of China from 2008 to 2017, and drawing a graph of the variation trend of Chinese regional eco-efficiency (see Table 2 and Figure 1).

(1) From the interprovincial level, Table 1 shows that the eastern region represented by Beijing, Tianjin, Shanghai, Guangdong, Zhejiang, Jiangsu, Hainan and Shandong has been among the top 10 in the country during the study period. Among them, Beijing has the highest eco-efficiency, with an average value of 1.2422. In 2009, the eco-efficiency was 1.2718, which is the highest value in years. This is related to Beijing’s efforts to strengthen the ecological environment and implement the concept of green environmental protection during the 2008 Olympic Games. The 10 provinces with the lowest eco-efficiency are Chongqing, Sichuan, Guizhou, Shanxi, Henan, Jiangxi, Gansu, Hubei, Yunnan and Qinghai, all of which are mainly in the western region. Among them, Shanxi Province, which is rich in coal resources in the central region, has the lowest eco-efficiency in the country. Due to its abundant resources, technological innovation was ignored in the process of production development, which resulted in lower eco-efficiency. The average eco-efficiency of the remaining 10 provinces ranged from 0.66 to 0.81, and all of them were mainly in the central region, there is a large room for improvement of eco-efficiency.

![Figure 1. The variation trend of Chinese regional eco-efficiency in 2008-2017](image-url)

(2) From regional perspective, Figure 1 shows the changes in eco-efficiency of China's eastern, central, western, and northeastern regions from 2008 to 2017. The average eco-efficiency in the eastern region is between 0.95 and 1.01, showing a slight downward trend overall, but the overall level is still high; the average eco-efficiency in the northeast is between 0.64 and 0.93, the average eco-efficiency in the central region ranged from 0.62 to 0.79, the average eco-efficiency in the western region is between 0.59 and 0.78, and the changing trend of eco-efficiency in the northeast, central, and western regions is basically the same as that in the whole country, all showing an upward trend. Through comparative analysis, the eco-efficiency in the east is higher than the national average (0.7821), and the central and western regions are not only lower than the national average, but also significantly lower than the northeast. It appeared the situation which the eastern region> northeast region> central region> western region overall.
In order to scientifically reflect the spatial differentiation characteristics of eco-efficiency, according to the calculation results of regional eco-efficiency in China, with the help of ArcGIS 10.2 software, based on the data of 2008, 2013 and 2017, this paper draws the spatial distribution map of regional eco-efficiency in China, as shown in Figure 2.
Figure 2. The spatial distribution of regional eco-efficiency in China

Figure 2 reflects the spatial evolution pattern of China's regional eco-efficiency from 2008 to 2017. This generally reveals the imbalance in the spatial distribution of China's regional eco-efficiency, which is "high in the east and low in the west", and that the distribution of eco-efficiency has a certain degree of synchronization with the gradient of economic development, that is the provinces with higher levels of eco-efficiency are mainly concentrated in the eastern coastal areas, followed by the northeast and central regions, and the western regions have the lowest eco-efficiency. In view of the obvious marginalization and agglomeration characteristics of the distribution of eco-efficiency, it is necessary to use spatial correlation methods to analyze the regional spatial differences of China's eco-efficiency.

4.2. Spatial autocorrelation analysis of China's eco-efficiency

4.2.1. Global space autocorrelation analysis. This paper uses GeoDa to calculate the global Moran’s I index of the eco-efficiency of 30 provinces in China from 2008 to 2017, and tests its significance, the results are shown in Table 3. This paper uses GeoDa to calculate the global Moran’s I index of the eco-efficiency of 30 provinces in China from 2008 to 2017, and tests its significance. The results are shown in Table 3, Moran’s I values in all years are significantly positive, except for individual years, which have passed the test at a significance level of 1%, which indicates that China's eco-efficiency has a significant global spatial agglomeration effect. Further observation also reveals that the degree of
agglomeration has fluctuated over time, indicating that regions with similar levels of eco-efficiency in China are showing a constantly changing agglomeration phenomenon.

| Years | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|-------|------|------|------|------|------|------|------|------|------|------|
| Moran’s I | 0.2905 | 0.3458 | 0.3456 | 0.3173 | 0.2996 | 0.2174 | 0.2384 | 0.1374 | 0.1717 | 0.2465 |
| P-value | 0.0076 | 0.0030 | 0.0035 | 0.0053 | 0.0067 | 0.0263 | 0.0206 | 0.0872 | 0.0543 | 0.0190 |
| z-value | 2.7165 | 3.1672 | 3.1604 | 2.9317 | 2.7602 | 2.1082 | 2.2607 | 1.4241 | 1.7073 | 2.3236 |

4.2.2. Local spatial autocorrelation analysis. In order to further measure the spatial relationship and the distribution pattern of the differences between the eco-efficiency of each province and the surrounding eco-efficiency, the Moran scatter plot is used to analyse the level of China's eco-efficiency. In view of space, this article only analyses the spatial autocorrelation of regional eco-efficiency in China in 2008, 2012, and 2017, and draws a regional Moran scatter plot. Quadrant I indicates the area with high eco-efficiency, and its adjacent areas are also high, namely the high-high (H-H) concentration area, with obvious diffusion characteristics; Quadrant II indicates that the region with low eco-efficiency, but its adjacent region is high, that is the low-high (L-H) cluster area, with obvious transition characteristics; Quadrant III indicates that the region with low eco-efficiency and the adjacent region is also low, that is the L-L cluster area with obviously slow growth characteristic; Quadrant IV indicates that the eco-efficiency of this area is high, but that of adjacent areas is low, that is the H-L concentration area has obvious polarization characteristics. The quadrants I and III belong to the positive spatial autocorrelation cluster pattern, that is, they have the characteristics of agglomerated distribution; the quadrants II and IV are negative spatial autocorrelation cluster patterns, which have the characteristic of discrete distribution.

As shown in Figure 3, the provinces that belong to high or low agglomeration areas accounted for 67%, 70%, and 67% in 2008, 2012, and 2017 respectively, which shows that the agglomeration of regional eco-efficiency shows a trend of first enhancement and then weakening. Through comparative analysis, it is found that: (1) Beijing, Tianjin, Shandong, Jiangsu, Zhejiang, and Shanghai, which belong to H-H concentration area, have always maintained the situation of high-high agglomeration. These provinces are mainly located in the eastern coastal areas. Under the comprehensive role of obvious location advantages, reasonable industrial structure and appropriate environmental protection measures, the eco-efficiency of the six provinces has maintained a high level and has positive effect on adjacent areas, with significant diffusion effects. (2) The L-H concentration area is mainly located in the northeast and a few provinces of central regions. The provinces in the agglomeration area are adjacent to Beijing, Tianjin, Shanghai, Shandong and other provinces and cities with high eco-efficiency, and have advantageous "diffused" location advantages. Therefore, the eco-efficiency of the agglomeration area is increasing rapidly, and the improvement space is large. (3) L-L cluster areas mainly distributed in the less developed provinces in the west and some provinces in the middle. These regions have relatively low levels of development and lack of policy support. Although some regions are rich in energy, low levels of technology have led to low energy efficiency and severe damage to the ecological environment. (4) Provinces belonging to H-L cluster areas include Inner Mongolia and Guangdong in 2008, and Liaoning, Inner Mongolia, Guangdong, Ningxia, and Hunan were included in 2017. Among them, Guangdong has been in the H-L agglomeration area for a long time. Although the province's economic development level is high, due to the lack of regional cooperation mechanisms and a reasonable industrial chain layout of labour division, it has not formed a strong radiation drive to neighboring low-value provinces.
5. Conclusion

Based on the panel data of 30 provinces in China from 2008 to 2017, the paper use Super-SBM model to measure the eco-efficiency of China's provinces and analyse the results. Moreover, spatial autocorrelation method was used to systematically explain the evolution of the spatial pattern of regional eco-efficiency in China, and discussed the agglomeration and radiation effects of eco-efficiency in various provinces and regions the main conclusions are as follows:

(1) On the whole, China’s average eco-efficiency showed a slow growth trend from 2008 to 2017, and the level of eco-efficiency was between 0.70 and 0.85. From regional perspective, the regional differences in China’s eco-efficiency levels were obvious, shows a gradient descending pattern of “East, Northeast, Middle and West ”. At the inter-provincial level, the eastern regions represented by Beijing, Tianjin, Shanghai, Guangdong, Zhejiang, Jiangsu, Hainan, and Shandong from 2008 to 2017 have been among the top ten nationwide eco-efficiency during the study period. Western regions such as Chongqing, Sichuan, Guizhou, Gansu, and Qinghai need to further change resource inputs and strengthen environmental protection to improve eco-efficiency.

(2) China's eco-efficiency has obvious spatial correlation and agglomeration characteristics, and areas with similar eco-efficiency states affect each other. Combined with the Moran scatter plot, the H-H cluster areas of China’s eco-efficiency is mainly distributed in Beijing-Tianjin Bohai Rim and Yangtze River Delta, the L-L quadrants is mainly distributed in the western region, and the L-H
quadrants decreased, while the H-L quadrants increased, which indicates that the original polarization situation in China is improved while the eco-efficiency is constantly improving.

Acknowledgments
This work was financially supported by “Tianjin Science and Technology Plan Projects” fund.

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