

Research Article

Dynamic Change and Spatial Correlation of Eco-Efficiency in China

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Abstract

High-quality economic development has become a goal in China. The measurement of eco-efficiency provides a comprehensive assessment for such development. However, the measurement of eco-efficiency is still based on the traditional data envelopment analysis model, and the analysis of eco-efficiency does not consider spatial correlation. In this study, the Super-SBM model considering undesirable output is used to measure eco-efficiency at the provincial level in China. Then, Moran's I index is adopted to investigate the spatial correlation of eco-efficiency. Results show that the eco-efficiency in China generally presents a downward trend. In terms of area, the central and western regions have generally declined, except for the eastern region. The reason for the decline in eco-efficiency is the continuous decline in technical efficiency. A significant positive spatial correlation of eco-efficiency exists at the national level. High-high and low-low agglomerations of eco-efficiency exist in China. High eco-efficiency is mainly distributed in Inner Mongolia, Heilongjiang, Hebei, Beijing, Tianjin, Henan, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan.

Keywords: Spatial correlation; Eco-efficiency; SBM; Technical efficiency; Technological progress

Aims and Background

China's economy has grown rapidly with the continuous market-oriented reforms. From 1980 to 2016, China's economy continuously grew at an average annual rate of 9.7%. However, various problems in the growth process, such as environmental pollution and energy consumption, have become increasingly prominent. Since 2010, China has become the world's largest energy consumer. China accounted for one-third of the incremental world energy consumption in 2017. In terms of environment, the ambient air quality of 239 cities, accounting for 70.7% of the total, is not up to standard. Furthermore, 66.6% of 5100 groundwater quality monitoring points are in poor or very poor state. Various concepts, such as "sustainable development" and "green development," have gradually been considered in policy design to reduce the high levels of consumption and high pollution brought by the pattern of extensive economic growth and achieve sustainable economic development. However, clear guiding principles and evaluation criteria on how to achieve sustainable or green development are lacking. The guiding principles and evaluation criteria should be based on the quantitative assessment of sustainable development. To this end, an indicator that comprehensively reflects the

environmental conditions and economic effects is necessary to provide a basis for building an incentive mechanism to promote sustainable economic development.

Eco-efficiency is a good measure of the sustainable development of natural-economic-social complex systems because it integrates economic and ecological assessments [1]. Eco-efficiency measures the capability to produce more products and services with less resource consumption and environmental pollution [2-4]. The underlying assumption is that the negative influence caused by the economic production will be reduced if we maintain the economic output, thereby improving the eco-efficiency [5]. Eco-efficiency is widely used to evaluate sustainable development at the regional [6-9], industry [10-13], and enterprise levels [14-16]. Various methods, including parametric and nonparametric types, have been proposed to measure eco-efficiency. Nonparametric methods are widely used because they do not need to set the model form. One of the most widely used nonparametric methods is Data Envelopment Analysis (DEA), which was first proposed by Charnes, et al. [17]. Since then, DEA has been applied to measure eco-efficiency gradually. DEA has received great popularity in measuring eco-efficiency because it appropriately incorporates undesirable outputs into the model. Rybczewska and Gierulski used life cycle theory and DEA to measure the eco-efficiency of the agricultural sectors from 28

member states of the European Union [18]. Masuda adopted the same method to measure the eco-efficiency of Japanese wheat production [19]. DEA techniques were applied to measure the eco-efficiency of a farm in Andalusia; the results showed that eco-inefficient management is common among olive growers [20]. Most of the previous studies were based on radial and input-oriented assumptions when measuring eco-efficiency. These assumptions suggest that all inputs are increased and decreased proportionally to be efficient, which is not in line with the reality [10]. Thus, the SBM model considering undesirable output has been proposed to evaluate the eco-efficiency. Considering nonzero relaxation, which allows the input and output to be adjusted in different proportions in efficiency calculation, can effectively solve the radial problem in the traditional DEA measurement. Many scholars have begun to apply the SBM model considering undesirable output in efficiency measurement [21-23]. However, the SBM model cannot compare the best performers whose efficiency value equals 1. To solve this problem, the Super-SBM model considering undesirable output has been applied to measure the efficiency. However, research has shown that the Super-SBM model with undesirable output is rarely used in eco-efficiency measurement to date.

Spatial units are not isolated but will interact with each other. Numerous studies have shown an interactive relationship between spatial units in terms of pollution or economy [24-26]. Zhao and Sing confirmed the mutually reinforcing economic relationship among prefecture-level cities by using data from China [25]. Hao and Liu investigated the spatial correlation of air pollution by using the PM_{2.5} and air pollution index data from China; they found that the deterioration of air pollution in a certain area leads to air quality degradation in adjacent areas [27]. A positive spatial correlation in terms of sulfur dioxide emissions exists between areas, that is, an

increase in sulfur dioxide emissions in one region increases the sulfur dioxide emissions in other regions [28]. Liu, et al. obtained different results by using industrial carbon emission data [29]. The results showed that industrial carbon emissions have a negative spatial correlation. However, most studies on regional eco-efficiency do not consider spatial correlation and are still based on the assumption that observations in cross section are independent of each other. Thus, the main contributions of the present study are to amend and improve eco-efficiency in this aspect.

This paper is structured as follows: Section 2 presents the methodology and data. Section 3 provides the results, followed by the discussion. Section 5 draws the conclusions.

Materials and Methods

The SBM Model Incorporating Undesirable Outputs

By considering non-radial and non-oriented measurements, the SBM model allows input and output to be adjusted in different proportions when calculating eco-efficiency, thereby solving the radial and oriented deviation [12]. However, the SBM model has the same problem as the traditional DEA model, namely, the best performers whose eco-efficiency is equal to 1 are difficult to distinguish. To provide a further comprehensive efficiency assessment, this study will adopt the Super-SBM model considering undesirable outputs to measure eco-efficiency in China following Tone (2002) and Tone (2004) [30,31].

Suppose n decision-making units (DMUs) exist. The numbers of inputs, desirable outputs, and undesirable outputs are m , r_1 , and r_2 , respectively. The Super-SBM model incorporating undesired outputs is as follows:

$$\min \rho = \frac{\frac{1}{m} \sum_{i=1}^m \bar{x}_{ik}}{\frac{1}{r_1 + r_2} (\sum_{s=1}^{r_1} \frac{\bar{y}^d}{y_{sk}^d} + \sum_{q=1}^{r_2} \frac{\bar{y}^u}{y_{qk}^u})} \quad (1)$$

$$\text{s.t. } \bar{x} \geq \sum_{j=1, \neq k}^{r_1} x_{ij} \lambda_j \quad (i = 1, 2, \dots, m)$$

$$\bar{y}^d \leq \sum_{j=1, \neq k}^n y_{sj}^d \lambda_j \quad (s = 1, 2, \dots, r_1)$$

$$\bar{y}^u \geq \sum_{j=1, \neq k}^n y_{qj}^u \lambda_j \quad (q = 1, 2, \dots, r_2)$$

$$\lambda_j > 0 \quad (j = 1, 2, \dots, n; j \neq 0)$$

$$\bar{x} \geq x_k \quad (i = 1, 2, \dots, m)$$

$$\bar{y}^d \geq y_k^d \quad (s = 1, 2, \dots, r_1)$$

$$\bar{y}^u \geq y_k^u \quad (q = 1, 2, \dots, r_2)$$

where \bar{x}_j , \bar{y}^d , and \bar{y}^u represent the redundancy values of the input, desirable output, and undesirable output, respectively. λ_j is the weight of the j th DMU. Table 1 shows the indicators used for eco-efficiency measurement.

Attribute	Variable	Data Sources
Input	Gross fixed capital formation	China Statistical Yearbook
	Year-end employment	Statistical yearbooks of provinces, cities, and autonomous regions
	Land consumption	China Land & Resources Almanac
	Energy consumption	China Energy Statistical Yearbook
	Water resource utilization	China Statistical Yearbook
Unexpected Output	Wastewater discharge	China Statistical Yearbook on Environment
	Chemical oxygen demand	
	SO ₂ emission Soot emission	
Expected Output	GDP	China Statistical Yearbook

Table 1: Indicators used to measure eco-efficiency.

Malmquist-Luenberger (ML) Index

The eco-efficiency calculated using the Super-SBM model incorporating undesirable outputs is only a level indicator; it cannot be used to analyze the dynamic variation in eco-efficiency directly. However, the analysis of dynamic variation can provide us with many inspirations, such as whether a convergence trend of eco-efficiency occurs among the eastern, central, and western regions, and explore the driving force of eco-efficiency changes. Therefore, this study draws on the approach adopted by Chung, et al. [32]. The SBM direction distance function is used to measure the ML index during t to $(t+1)$ to reflect the dynamic variation of regional eco-efficiency. The formula for calculating the ML index is as follows:

$$ML_t^{t+1} = \left\{ \frac{[1 + \bar{D}_t(x_t, y_t, b_t; g_t)]}{[1 + \bar{D}_t(x_{t+1}, y_{t+1}, b_{t+1}; g_{t+1})]} \times \frac{[1 + \bar{D}_0^{t+1}(x_t, y_t, b_t; g_t)]}{[1 + \bar{D}_{t+1}(x_{t+1}, y_{t+1}, b_{t+1}; g_{t+1})]} \right\}^{\frac{1}{2}}, \quad (2)$$

where $\bar{D}_t(x_{t+1}, y_{t+1}, b_{t+1}; g_{t+1})$ is the $(t+1)$ phase mixed distance function based on the t phase technique, $\bar{D}_{t+1}(x_t, y_t, b_t; g_t)$ is the t phase mixed distance function based on the $(t+1)$ stage technique, and $\bar{D}_t(x_t, y_t, b_t; g_t)$ and $\bar{D}_{t+1}(x_{t+1}, y_{t+1}, b_{t+1}; g_{t+1})$ represent the distance functions of the t and $(t+1)$ phases, respectively. When $ML_t^{t+1} > 1$, the eco-efficiency of the $(t+1)$ phase is higher than that of the t phase. When $ML_t^{t+1} < 1$, the eco-efficiency of the $(t+1)$ phase is lower than that of the t phase. The ML index can be decomposed into two parts: technological efficiency index (MLEFF) and technological progress index (MLTP). They represent the dynamic changes of technological efficiency and progress, respectively. The formulas are as follows:

$$MLT_t^{t+1} = MLEFF_t^{t+1} \times MLTP_t^{t+1}, \quad (3)$$

$$MLEFF_t^{t+1} = \frac{1 + \bar{D}_t(x_t, y_t, b_t; g_t)}{1 + \bar{D}_{t+1}(x_{t+1}, y_{t+1}, b_{t+1}; g_{t+1})}, \quad (4)$$

$$MLTP_t^{t+1} = \left[\frac{1 + \bar{D}_{t+1}(x_{t+1}, y_{t+1}, b_{t+1}; g_{t+1})}{1 + \bar{D}_t(x_t, y_t, b_t; g_t)} \times \frac{1 + \bar{D}_{t+1}(x_{t+1}, y_{t+1}, b_{t+1}; g_{t+1})}{[1 + \bar{D}_t(x_{t+1}, y_{t+1}, b_{t+1}; g_{t+1})]} \right]^{\frac{1}{2}}, \quad (5)$$

where $MLEFF_t^{t+1}$ represents the change in technological efficiency from the t phase to the $(t+1)$ phase. When $MLEFF_t^{t+1} > 1$, the technological efficiency is improved; otherwise, it is worsened. $MLTP_t^{t+1}$ represents the technological progress from the t phase to the $(t+1)$ phase. When $MLTP_t^{t+1} > 1$, the technological progress has been achieved; otherwise, the technology has regressed.

Moran's I Index

This study investigates the spatial correlation of eco-efficiency at the provincial level. To achieve this goal, global Moran's I index is used to measure the spatial correlation. Global Moran's I index can be defined as follows:

$$\text{Moran's } I = \frac{N \sum_{i=1}^N \sum_{j=1}^N W_{ij} (y_i - \bar{y})(y_j - \bar{y})}{(\sum_{i=1}^N \sum_{j=1}^N W_{ij}) \sum_{i=1}^N (y_i - \bar{y})^2}, (i \neq j), \quad (6)$$

where N represents the number of spatial units. i and j are observations of spatial units i and j , respectively. y_i is the eco-efficiency value of spatial unit i . \bar{y} is the average eco-efficiency. W_{ij} is a measure of the distance between spatial units i and j , such as economic and geographic distances. China's interprovincial relations are closely related to the marketization process, which is closely linked to the level of economic development. Hence, we will use the economic distance spatial weight matrix to measure the interprovincial spatial relationship. The range of global Moran's I index is $[0, 1]$. If the value is greater than 0, then a positive spatial correlation of eco-efficiency exists at the provincial level. If the value is less than 0, then a negative spatial correlation of eco-efficiency exists at the provincial level. If the value is equal to 0, then the distribution of spatial units is random and has no correlation among them.

The spatial correlation or agglomeration pattern can be further analyzed using local Moran's I index and Moran's I scatter diagram, when a spatial correlation of eco-efficiency exists at the provincial level. Local Moran's I index is calculated as follows:

$$\text{Moran's } I_i = (y_i - \bar{y}) \sum_{j=1}^N w_{ij} (y_j - \bar{y}), \quad (7)$$

where $(y_i - \bar{y})$ reflects the deviation degree of eco-efficiency from its average. w_{ij} is the spatial weight matrix. A positive local Moran's I index represents the agglomeration of similar values around the spatial unit. A negative local Moran's I index indicates the agglomeration of dissimilar values around the spatial unit. The spatial correlation mode can be determined by four quadrants [33]. Moran's I scatter diagram contains four quadrants. The first quadrant is high-high (H-H) agglomeration mode, which represents high eco-efficiency spatial units surrounded by high eco-efficiency spatial units. The second quadrant is high-low (H-L) agglomeration mode, which represents high eco-efficiency spatial units surrounded by low eco-efficiency spatial units. The third quadrant is low-low (L-L) agglomeration mode, which represents low eco-efficiency spatial units surrounded by low eco-efficiency spatial units. The fourth quadrant is low-high (L-H) agglomeration mode, which represents low eco-efficiency spatial units surrounded by high eco-efficiency spatial units.

Data Sources

The data collected in this paper spans from 2004 to 2015 and covers 30 provinces, municipalities, and autonomous regions in China (Tibet is excluded due to the lack of key data). Regional eco-efficiency calculations should use input-output data, drawing on the division method of Ren, et al. [34]. Input indicators in this study include capital, labor, land, energy, and water resources. Bin found that the total amount of fixed capital is the best for capital investment by comparing the different investment flow indicators [35]. Therefore, the present study uses the total fixed capital formation. To measure the capital investment, the data come from the China Statistical Yearbook

(2005-2016), and the fixed asset investment price index is adjusted to the base period of 2004. Labor input uses data on employment at the end of the year, from the statistical yearbooks of provinces, municipalities, and autonomous regions. Land input is measured by the supply of state-owned construction land, and the data come from the China Land & Resources Almanac (2005-2016). Energy use is measured by energy consumption, and the data come from the China Energy Statistical Yearbook (2005-2016). The water resource input is measured by the total amount of water, and the data come from the China Statistical Yearbook on Environment (2005-2016). Output is divided into expected and undesired outputs. The expected output is the actual Gross Domestic Product (GDP), and the data come from the China Statistical Yearbook (2005-2016). The undesired outputs are wastewater, chemical oxygen demand, sulfur dioxide, and dust emissions, and the data come from the China Statistical Yearbook on Environment (2005-2016).

Results

Actuality of Regional Eco-Efficiency

To examine the regional differences of eco-efficiency, the MaxDea software is used to measure the regional eco-efficiency

from 2005 to 2015 in China. For comparison, the study area is divided into eastern, central, and western regions (Figure 1). On the whole, the eco-efficiency showed a downward trend at the national level. For the different regions, the eco-efficiency in the central and western regions presented a decreasing trend, and that in the eastern region remained relatively stable without evident trend. The eco-efficiency value of the eastern region was higher than those of the central and western regions. From this, we can know that the eastern region consumed less natural resources and energy and used less land, with a certain economic output, than the central and western regions. In addition, the eco-efficiency of the western region was higher than that of the central region, except in 2005. The eco-efficiency of the western region fluctuated greatly from 2006 to 2008. However, this result may be affected by outliers. In all provincial areas, the eco-efficiency of Qinghai (western region) was extremely high, with values as high as 4.99 and 2.25 in 2007 and 2008, respectively, which explained why the eco-efficiency fluctuated greatly from 2006 to 2008. If we remove Qinghai from the western region, then the eco-efficiency of the western region will be significantly decreased, and in most years, the eco-efficiency of the western region will be lower than that of the central region.

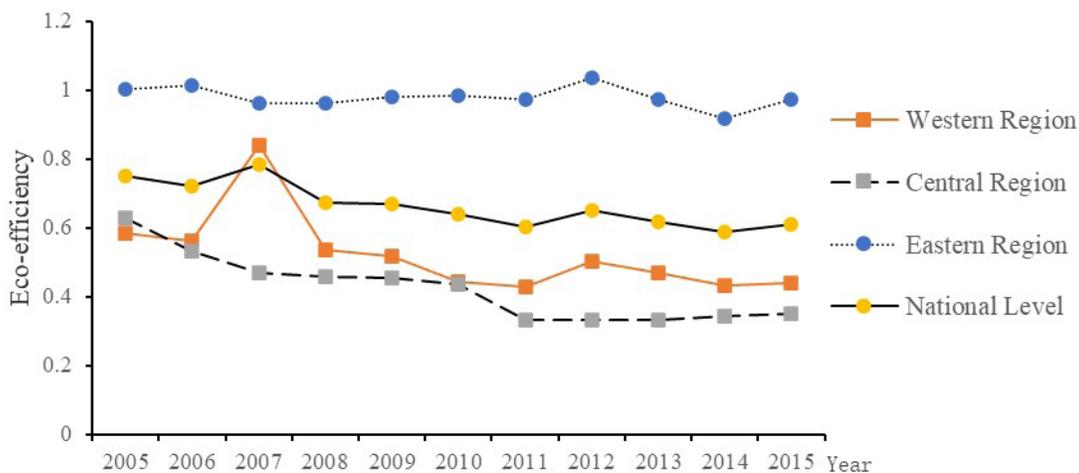


Figure 1: Variation of regional eco-efficiency from 2005 to 2015 in China.

Decomposition of Change in Eco-Efficiency

As shown in Figure 1, the eco-efficiency in the central and western regions generally declined. We try to explore the reasons from the decomposition perspective in ML index. On the basis of the decomposition perspective, the changes in eco-efficiency can be decomposed into a technological progress (MLTP) and changes in technical efficiency (MLEFF). If we find that MLEFF is less than 1 and MLTP is greater than 1, then the decline in eco-efficiency is caused by the decline in technical efficiency; otherwise, the decline is caused by the decline in technological recession (Figure 2).

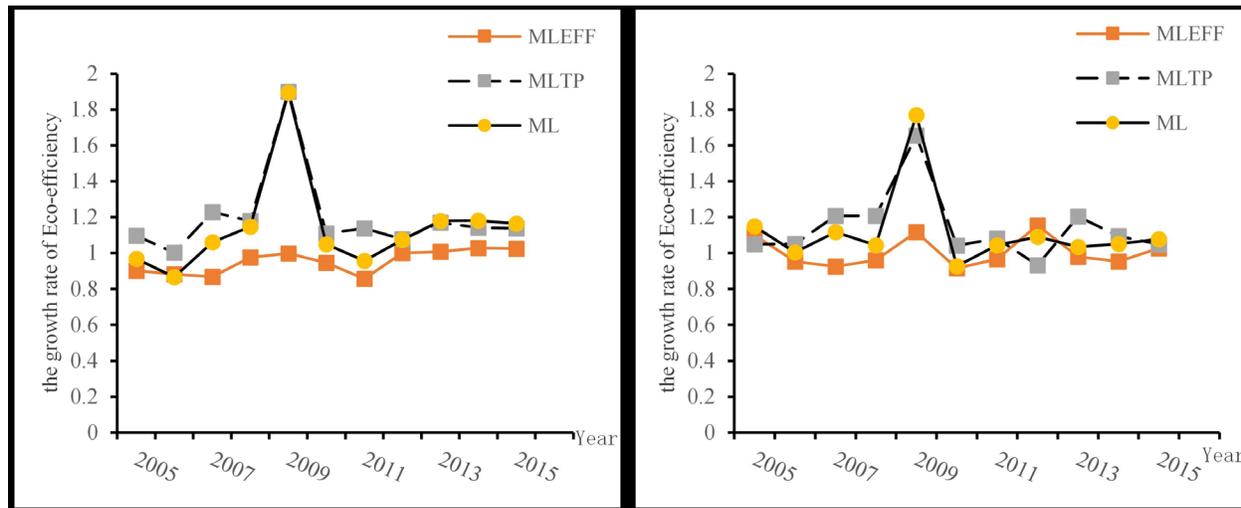


Figure 2: Variation of regional eco-efficiency from 2005 to 2015 in China.

Figure 2a shows that the MLEFF index in the central and western regions was less than 1 and the MLTP index was greater than 1 in most years. Hence, the technological progress and technical efficiency play positive and negative roles in the change of eco-efficiency, respectively. For more than 40 years of reform and opening up, China's rapid technological development has led to continuous improvement in per unit of output and continuous reduction in resource consumption per unit of output. The sustainable development of China's total factor productivity mainly comes from the green-biased technological progress [36]. In addition, the MLTP and ML indexes are highly coincident when we consider the change track of three types of index. Overall, the reason for the decline in eco-efficiency is the continuous decline in technical efficiency, and technological progress plays a positive role in the change of eco-efficiency.

Spatial Correlation and Distribution Analysis of Eco-Efficiency

As relations in different areas continue to strengthen, spatial correlations of eco-efficiency may exist in China. Global Moran's I indexes at the national level and in the eastern, central, and western regions are calculated to reflect the spatial correlation of eco-efficiency (Table 2). Global Moran's I index at the national level was almost positive and passed the significance test. Thus, a significant positive spatial correlation of eco-efficiency existed in China's provincial level, that is, regions with high (low) eco-efficiency were surrounded by regions with high (low) eco-efficiency. The spatial correlation of eco-efficiency was relatively different among eastern, central, and western regions. Global Moran's I index fail passed the statistical significance test in all years in the eastern region, and that fail passed the statistical significance test in all years in the central region, except for 2008. Different from the eastern and central regions, Global Moran's I index in the western region passed the statistical significance test in most years, indicating a spatial correlation. Moreover, the spatial correlation model of eco-efficiency in the western region was inconsistent for all years. Before 2010, Global Moran's I index fail passed the statistical significance test, except for 2008c. However, the index showed a positive spatial correlation after 2009 and was statistically significant, except for 2012.

	Global Moran's I test			
	National level	Eastern region	Central region	Western region
2005	0.167* (0.082)	0.050 (0.303)	-0.162 (0.926)	-0.079 (0.870)
2006	0.169* (0.079)	0.052 (0.233)	-0.245 (0.289)	-0.083 (0.893)
2007	-0.041 (0.914)	0.130 (0.271)	-0.265 (0.119)	-0.128 (0.588)
2008	0.087 (0.259)	0.161 (0.224)	-0.297** (0.043)	-0.026* (0.062)
2009	0.178* (0.068)	0.193 (0.177)	-0.253 (0.191)	-0.045 (0.685)
2010	0.181* (0.064)	0.219 (0.146)	-0.244 (0.238)	0.057*** (0.009)
2011	0.252** (0.014)	0.192 (0.179)	-0.242 (0.622)	0.095*** (0.004)

2012	0.226** (0.021)	0.193 (0.139)	-0.260 (0.595)	0.100 (0.163)
2013	0.378*** (0.000)	0.187 (0.184)	-0.291 (0.496)	0.626*** (0.000)
2014	0.241** (0.017)	0.175 (0.250)	-0.324 (0.392)	0.162*** (0.001)
2015	0.267** (0.010)	0.118 (0.309)	-0.363 (0.316)	0.209*** (0.000)
Note: ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively. Corresponding p-values in parentheses.				

Table 2: Spatial correlation of eco-efficiency.

Global Moran's I index can only examine the spatial correlation of the entire spatial sequence, but it cannot investigate the spatial correlation around a certain region. Hence, we use Moran's I scatter diagram based on local Moran's I index to measure the local spatial correlation of eco-efficiency. For comparison, Figure 3 presents Moran's I scatter plots for years 2005 and 2015. On the basis of Moran's I scatter diagram of the total sample (Figures 3a and 3b), most of the points in the diagrams of eco-efficiency are located in the first and third quadrants, which implies that H-H and L-L agglomerations existed. By 2015, the agglomeration characteristics of eco-efficiency in the first and third quadrants were further strengthened; the difference was the additional areas in the third quadrant. Thus, the positive spatial correlation pattern of L-L agglomeration became further significant. One reason may be related to the increasing tax competition among local governments. Bai found that interregional tax competition will not only worsen the local environment but also worsen the environment of the surrounding areas; thus, the eco-efficiency is at a low level [37]. As Global Moran's I index in the eastern and central regions has failed the significance test, only Moran's I scatter plot in the western region is drawn here (Figure 3c and 3d). Most of the points in Moran's I scatter diagrams of eco-efficiency are located in the third quadrants. The spatial agglomeration model of eco-efficiency is L-L agglomeration, which suggests that areas with low eco-efficiency are also surrounded by areas with low eco-efficiency. The characteristic of the western region, that is, the regional eco-efficiency cluster is in the third quadrant, is more evident than that of the national level. In general, the productivity

of the western region is lower than that of the central and eastern regions. Therefore, the per unit of output in the western region consumes more resources and energy than the central and eastern regions, thereby reducing the eco-efficiency.

Moran's I index presents the spatial correlation of eco-efficiency, but it can hardly show the spatial distribution of eco-efficiency. Therefore, ArcGIS 10.2 is used to draw the spatial distribution map of China's eco-efficiency in 2005 and 2015 (Figure 3). To reflect the distribution and changes of regional eco-efficiency further clearly, the eco-efficiency is divided into five levels. In 2005, Qinghai had the highest eco-efficiency. The second level included Inner Mongolia, Heilongjiang, Hebei, Beijing, Tianjin, Henan, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan. Hubei belongs to the third level. The fourth level included Liaoning, Jilin, Ningxia, Shanxi, Shaanxi, Sichuan, Guizhou, Yunnan, Hunan, Jiangxi, and Anhui. Chongqing, Xinjiang, Gansu, and Guangxi were at the lowest level of eco-efficiency in China. By 2015, the eco-efficiency declined in some areas, including Inner Mongolia, Heilongjiang, Hebei, Henan, Anhui, Hubei, Yunnan, Guizhou, and Hunan. Meanwhile, the eco-efficiency of Chongqing and Liaoning improved. In general, the characteristics of high eco-efficiency clustered in coastal provinces were enhanced from 2005 to 2015. Coastal regions are the most developed regions in China with the highest total factor productivity [38], economic sectors consume minimal input, and produce pollution emissions in respect of the current GDP level (Figure 4).

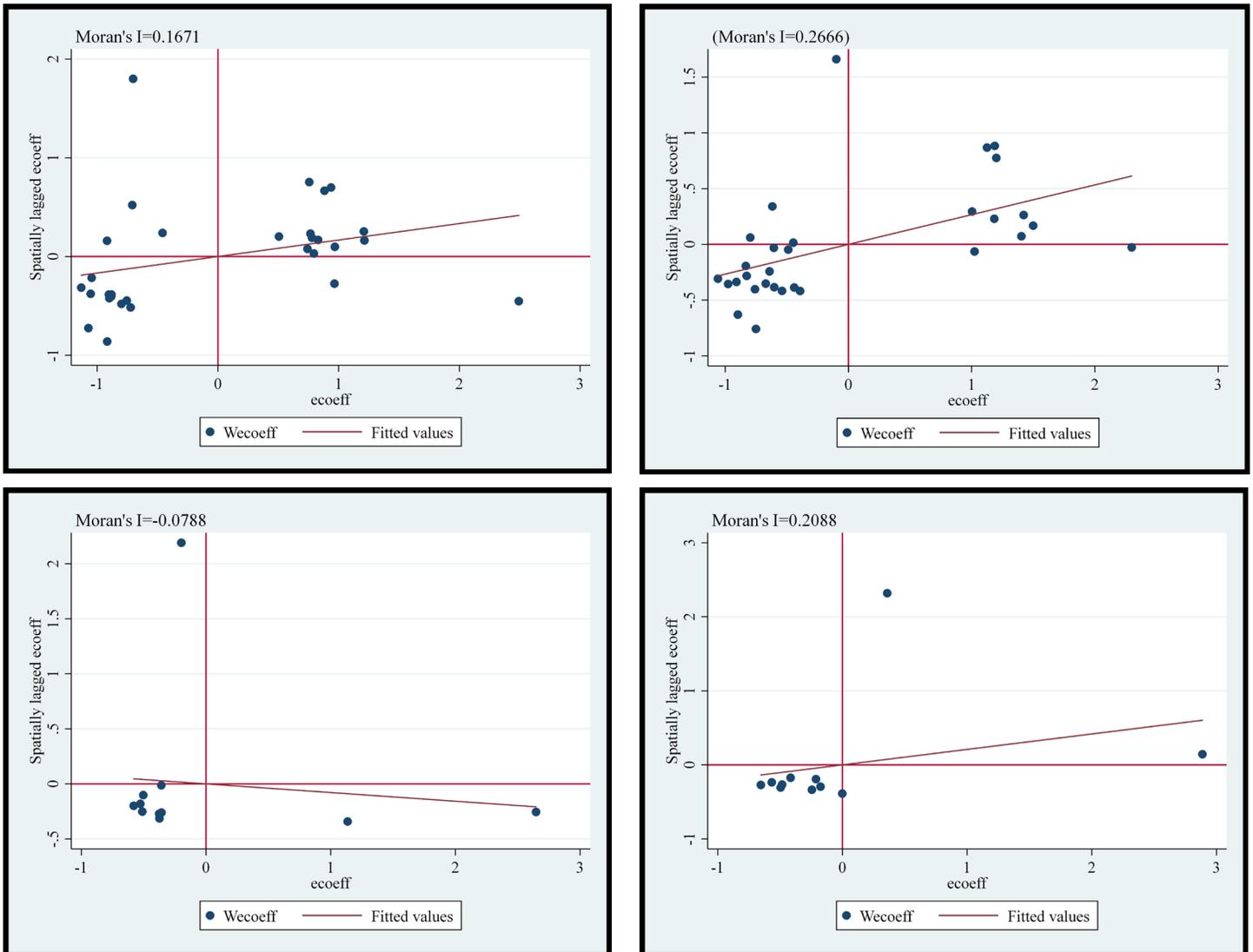


Figure 3: Spatial correlation of interregional eco-efficiency in China.

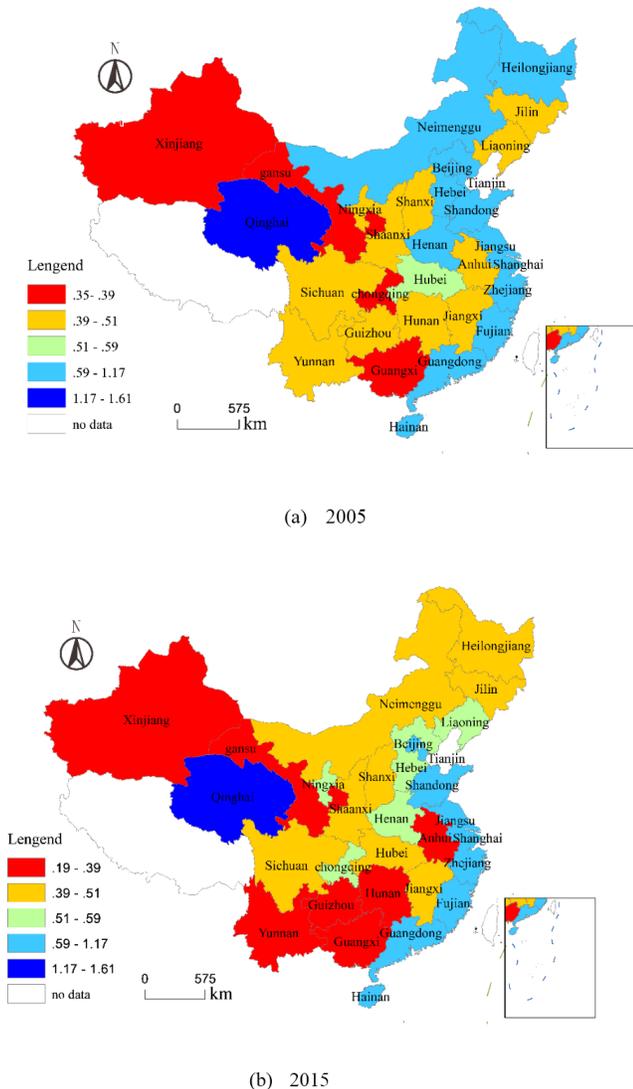


Figure 4: Evolution of the spatial distribution of regional ecological efficiency in China.

Conclusion and Discussion

China's regional eco-efficiency was investigated using the Super-SBM model incorporating undesirable outputs and ML index. From a regional perspective, the eco-efficiency of the central and western regions showed a downward trend, except for the eastern region. From 2005 to 2015, the eco-efficiency of the eastern region was higher than that of the western region, which in turn was higher than that of the central region. However, once Qinghai was removed from the west region, the eco-efficiency of the western region was significantly reduced. Considering technological advancement and technical efficiency, the decline in eco-efficiency in the central and western regions was driven by a decline in technical efficiency. We used Moran's I index

to examine the spatial correlation of eco-efficiency. The spatial correlation of eco-efficiency existed only at the national level and in the western region. H-H and L-L agglomerations existed at the national level. The eco-efficiency of the western region was mainly characterized by L-L agglomeration. From the perspective of distribution characteristics, the high eco-efficiency in 2005 was mainly distributed in coastal developed areas, and by 2015, this distribution became further evident.

As a developing country, China has maintained a rapid economic growth for 40 years. However, problems, such as environmental pollution and resource depletion, have also become increasingly prominent. Therefore, eco-efficiency evaluation and improvement are of great practical significance to promote the sustainable development of China's economy. However, most of the current research uses the SBM model incorporating undesirable outputs to evaluate China's eco-efficiency, and the eco-efficiencies of provinces cannot be compared in the effective state. This study uses the Super-SBM model incorporating undesirable outputs to solve the comparison problem in the provinces that perform best. In addition, current research on eco-efficiency is still based on the assumption that countries or regions are independent of each other. Eco-efficiency in geographically or economically adjacent regions is believed to not affect each other, but in terms of China's conditions, its developed infrastructure networks and population mobility enable frequent interaction in provinces. The credibility of research results will be greatly reduced if we ignore this spatial correlation. To this end, this study considers the interprovincial interactions of eco-efficiency in China by using global and local Moran's I indexes.

The eco-efficiency in the central and western regions generally declined, compared with the eastern region. The change of eco-efficiency in the eastern region was relatively stable without evident trend. In addition, the eastern region had the highest eco-efficiency, followed by the central and western regions. The reason for the decline in eco-efficiency in the central and western regions was the continuous decline in technical efficiency. The analysis of global Moran's I index showed a significant positive spatial correlation of eco-efficiency in China. The spatial correlation of eco-efficiency was relatively different among the eastern, central, and western regions. Global Moran's I index in the western region failed the statistical significance test in all years, and that in the central region failed the statistical significance test in all years, except for 2008. The analysis of Moran's I scatter diagram showed that most of the points are located in the first and third quadrants at the national level, which implies that H-H and L-L agglomerations existed. By 2015, the pattern of the L-L agglomeration became further significant. On the basis of the analysis of the spatial distribution of eco-efficiency, a high eco-efficiency was mainly distributed in Inner Mongolia, Heilongjiang, Hebei, Beijing, Tianjin, Henan, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan. From 2005 to 2015, the characteristics of high eco-efficiency clustered in coastal provinces were enhanced.

The findings in this study have numerous implications that are worthy of discussion. The achievements of China's economic development are undoubtedly significant when we evaluate only from the perspective of economic output. However, on the basis of this research, the capacity for sustainable development in China is gradually reduced when the factor input and pollution output are considered in economic growth assessment, which in a sharp contrast to the fact that China's economy continued to grow rapidly from 2005 to 2015. Therefore, from the perspective of sustainable development, the achievements of economic growth achieved by China may need to be greatly discounted. Spatial location data are also involved in most studies of eco-efficiency, and different spatial units may interact with one another. The findings in this study prove the positive spatial correlation between regional eco-efficiencies in China. Thus, spatial relationship variables between regions should be considered.

A few limitations in this study need to be presented. First, this study only provides the evidence of spatial correlation in eco-efficiency without further exploring whether a causal relationship exists between this spatial correlation and the reasons behind it. Second, the research samples in this study only focus on eco-efficiency at the provincial level due to data limitations. However, large heterogeneities also exist among prefecture levels in China, and research at the provincial level may ignore some important characteristics of eco-efficiency in China.

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