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Sustainability Governance in China: An Analysis of Regional Ecological Efficiency

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Abstract: The Chinese government is committed to sustainability governance to alleviate the shortage of energy and the imbalance between ecological environment and economic development. This paper evaluates and analyzes the sustainability governance performance of China. A bootstrap data envelopment analysis (DEA) is proposed to evaluate sustainability governance performance of 30 provinces based on ecological efficiency in China from 1998 to 2015. The results indicate that the ecological efficiency of China significantly improved as a whole, which is related to the decline in sulfur dioxide emissions. Among these provinces, Jiangsu, Liaoning, and Inner Mongolia exhibited the highest values, while Gansu, Chongqing, and Sichuan had the lowest values. The 30 provinces were divided into four sub-areas. The average ecological efficiency of the eastern area was the highest, followed by the northeast area. Compared to the east area, northeast area, and central area, we find that west area obviously falls behind. As such, the results provide helpful guidance to improve ecological governance performance.

Keywords: sustainability governance; ecological efficiency; bootstrap DEA

1. Introduction

Since the reform, China's economic growth made remarkable achievements. However, the extensive growth pattern caused serious problems in sustainability, especially in environmental pollution. At present, China is one of the most polluted countries in the world [1,2]. China faces a series of great challenges in energy production and consumption [3]. For instance, China's energy consumption accounts for 36.65% of the total industrial output, and solid waste emissions account for 50.12% of the whole industry [4]. Undoubtedly, the economic development is labeled by high energy consumption and high emissions. In addition, China is experiencing a period of rapid industrialization and urbanization, which exacerbates the pressure of environmental pollution and energy consumption [5]. Therefore, the Chinese government took governance measures to reduce environmental pollutants and greenhouse gas emissions and improve energy efficiency and ecological performance [6].

Global environmental assessment is necessary for decision-making related to environmental development [7]. As a scientific performance evaluation index, ecological efficiency reflects both economic development and the ecological environment, and it was adopted by international organizations and research institutions as a core indicator to measure regional sustainable development and sustainability governance. The Organization for Economic Co-operation and Development (OECD) defines ecological efficiency as the ratio of input to output in order to achieve more valuable output with fewer resources. Subsequently, the World Business Council for Sustainable Development (WBCSD,

2000) promoted the concept to realize the balance between guaranteeing the quality of human life and sustainable development.

Compared with a single environmental emission indicator, ecological efficiency accurately represents the performance of ecological governance and technical progress. Although the estimation of ecological efficiency is a complex task [8], it is widely measured as the ratio between the ecological impact of products or services and the added value of products or services [9]. The bootstrap data envelopment analysis (DEA) is used to measure the ecological efficiency, which takes into account multiple indicators of undesirable output and corrects the deviation of efficiency estimation. However, the model fails to decompose the contribution of technological progress, which is also the content of future research. Our analysis focuses on the ecological efficiency of China over the period of 1998–2015, which reflects the performance of sustainability governance. Our study pays more attention to the distribution characteristics and the evolving trend of ecological efficiency in China. Meanwhile, the 30 provinces are divided into four sub-areas. We further analyze the regional differences of China's ecological efficiency. We attempt to provide a benchmark for evaluating the ecological governance performance of different countries.

The study's main contribution can be concluded as follows: firstly, there are few studies on the performance of ecological governance. The analysis of ecological governance performance can provide a valuable reference for government decision-making. Therefore, we use ecological efficiency to measure the performance of ecological governance to fill the relevant literature gap. Secondly, few studies and comparisons of ecological efficiency in China based on bootstrap data envelopment analysis (DEA) were made in the existing literature. The bootstrap method corrects the deviation of efficiency estimation and obtains more accurate and robust results.

The rest of the study is organized as follows: Section 2 reviews the available literature. Section 3 introduces the bootstrap DEA for empirical analysis. Section 4 analyzes and discusses the empirical results. Section 5 draws the conclusions and proposes the policy recommendations.

2. Literature Review

Improvement of ecological governance performance is extremely important for the ecological economy. Ecological efficiency was the focus of attention of academics and practitioners for decades [10,11]. The concept of ecological efficiency, first proposed by Schaltegger [12], is widely adopted as a core indicator to measure sustainable development and ecological civilization. Schmidheiny and Zorraquin [13] put forward the concept of "economic–ecological efficiency", which reflects the ability to reduce environmental impacts or natural resource consumption in production activities. The OECD defines ecological efficiency as the ratio of input to output in order to achieve more valuable output with fewer resources. Subsequently, the World Business Council for Sustainable Development (WBCSD, 2000) promoted the concept to realize the balance between guaranteeing the quality of human life and sustainable development. Oggioni et al. [14] argued that ecological efficiency is the ability to produce goods and services using energy conservation or reducing environmental pollution. Picazo-Tadeo et al. [15] argued that ecological efficiency refers to the reduction of environmental impacts and the consumption of fewer natural resources by enterprises, industries, or economies while producing goods and services. Ecological efficiency is also regarded as sustainability related to the environmental performance of a production system [16]. Generally speaking, ecological efficiency refers to obtaining more economic output with less ecological input [17,18]. Ecological efficiency indicates the relationship between the undesirable outputs and desirable outputs of the production process [19]. The improvement of ecological efficiency reduces the production of environmental pollution such as waste water, waste gas, and solid waste in the process of economic development.

At present, the research on ecological efficiency mainly focuses on the application and measurement of ecological efficiency [20,21]. There are many indicators to measure ecological efficiency, such as carbon dioxide emission and sulfur dioxide emission. These indicators are simple to calculate, and easy to understand and operate, but over-emphasize one factor's input and pollution emissions, which leads to the failure to reflect the substitution relationship between various resource inputs and pollution emissions in the production process, and the result of the efficiency measurement does not correlate with reality [22]. The use of indicators and models is the main method to evaluate ecological efficiency in more complex situations [21]. The quantitative estimation of ecological efficiency mainly follows the two directions of life-cycle assessment and DEA. DEA is widely used in most studies, and it has the ability to identify inefficient units [23]. As a non-parametric frontier analysis method, DEA does not need to pre-set the specific form of production function and obtain the information of input–output factors. The whole calculation process is not affected by human factors, and it reflects the interaction and substitution relationship between different input factors. It is considered to be a more scientific method to measure ecological efficiency.

The index system of ecological efficiency analyzes the interaction between economy and environment [24]. The DEA model, as a multi-index to evaluate the relative effectiveness of decision-making units, is widely used in ecological efficiency analysis [21]. Deilmann et al. [25] assessed the efficiency of land use using the DEA method. Korhonen and Luptacik [19] used the DEA method to measure the efficiency of 24 power plants in a European country. Michelsen et al. [26] constructed an index system for evaluating the ecological efficiency of furniture production by selecting nine environmental indicators. Oggioni et al. [14] selected 29 indicators to evaluate the ecological efficiency of cement industries by applying DEA and a direction distance function in different countries. Kuosmanen and Kortelainen [27] proposed a complete theoretical framework of ecological efficiency and assessed the eco-efficiency of road transportation using the DEA method. Zhang et al. [28] assessed the ecological efficiency of industrial systems in different regions of China by taking environmental pollution as an input factor and constructing various DEA models. Picazo-Tadeo et al. [29] used the bootstrap DEA method to measure the ecological efficiency of Spanish agricultural enterprises and to test the influencing factors by Tobit regression. Hu and Wang [30] constructed the total factor energy efficiency index based on DEA. Zhang et al. [28] treated an integrated environmental factor as an undesirable output to measure green total factor productivity using the DEA-based Malmquist–Luenberger index. Hu and Lee [31] evaluated the energy utility efficiency in China applying the DEA approach. Shi et al. [32] investigated the Chinese industrial energy efficiency and energy-saving potential based on DEA. Rao et al. [33] analyzed the energy efficiency and energy-saving potential in China during 2000–2009 based on a slacks-based measure model. Dyckhoff and Allen [34] emphatically analyzed the approach of dealing with undesirable output using the DEA model, and constructed a basic DEA model to evaluate ecological efficiency. Hadi et al. [35] constructed an input-oriented DEA model of ecological efficiency, which included environmental pollution as an unexpected output. Subsequently, the related studies on the measurement of ecological efficiency increased year by year.

From the perspective of research progress, many scholars explored the estimation of ecological efficiency using DEA and its derivative models. However, the traditional DEA method has statistical limitations [36]. Scholars rely on various improved DEA methods to measure ecological efficiency. The bootstrap procedure is used to account for some limitations. The bootstrap DEA model was first proposed by Simar and Wilson, and it was continuously improved and perfected by subsequent scholars [37], gradually applied to various fields of efficiency analysis. Specifically, the bootstrap DEA model provides confidence intervals for the efficiency estimations [23]. Staat [38] argued that bootstrap has advantages in identifying true differences in efficiency. Barros and Peypoch [39] measured the technical efficiency of thermoelectric power plants using the bootstrap DEA Model. Song et al. [40] analyzed the energy efficiency of Brazil, Russia, India, China and South Africa (BRICS) based on bootstrap DEA. Halkos and Tzeremes [41] evaluated industry performance applying the bootstrap DEA. Jebali et al. [42] analyzed the energy efficiency of Mediterranean countries based on a two-stage double bootstrap DEA. Wijesiri et al. [43] used a two-stage double bootstrap DEA approach to examine the technical efficiency of 36 microfinance institutions. Wang et al. [44] examined the energy efficiency of 35 sub-industrial sectors in Beijing using the improved bootstrap DEA model. Balcombe et al. [45] evaluated the source of technical efficiency of rice farming in Bangladesh based on the DEA double bootstrap.

To the best of our knowledge, few studies and comparisons of ecological efficiency in China based on bootstrap DEA were made in the existing literature. What is more, as reviewed above, the bootstrap method corrects the deviation of efficiency estimation and obtains more accurate and robust results. To sum up, based on the bootstrap DEA method proposed by Simar et al. [37], in this paper, we try to use the bootstrap DEA model to measure the regional ecological governance performance in China. The bootstrap method generates a large number of simulated sample values via the numerical simulation self-help method, corrects the error of DEA efficiency estimation, and obtains the confidence interval corresponding to the efficiency value, so as to analyze the changing trend and regional difference of ecological efficiency.

3. Methodology

For our research framework, we used the DEA method to measure ecological efficiency, as it involves setting multiple input and multiple outputs [46]. Considering several statistical limitations of conventional DEA, such as the accuracy of efficiency estimation [36], we used the bootstrap procedure to avoid these limitations. More precisely, we applied a bootstrap DEA model [47,48] to extract the branch efficiency. In this study, ecological efficiency was used to evaluate the performance of sustainability governance. Ecological efficiency means producing more economic outputs with minimal resource consumption [49]. The measurements of ecological efficiency were designed to help find effective ways to reduce environmental pressures.

Before building the bootstrap DEA model, we needed to define the basic assumptions of the conventional DEA model. The conventional DEA model assumes that there exists the production possibility set ψ as follows:

$$\psi = \left\{(x, y) \in R_{+}^{p+q} | xcanproducey\right\}. \tag{1}$$

We consider x as an input vector, and y as an output vector.

$$X(y) = \left\{x \in R_{+}^{p} | (x, y) \in \psi\right\}. \tag{2}$$

Equation (2) satisfies three assumptions: firstly, the convexity assumption is satisfied for all y, X (y); secondly, non-zero output y requires input variable x to be non-zero; thirdly, both input and output satisfy strong disposability.

The efficiency value of the i-th decision-making unit (DMU) is evaluated as follows:

$$\min\theta$$
$$\begin{cases} \sum\limits_{i=0}^{n} X_i\lambda_i + S^- = \theta X_0 \\ \sum\limits_{i=0}^{n} Y_i\lambda_i - S^+ = Y_0 \\ \sum\limits_{i=0}^{n} \lambda_i = 1 \\ S^-, S^+, \lambda_i \geq 0 \end{cases},$$

where S^- represents the slack variable of inputs, S^+ represents the slack variable of outputs, λ_i refers to the i-th DMU, and θ indicates the efficiency score for the i-th DMU. If $\theta = 1,\ S^- = 0,\ S^+ = 0$, the i-th DMU is efficient, indicating that the best combination of input and output was achieved in the production system. If $\theta = 1,\ S^- \neq 0$, or $S^+ = 0$, the i-th DMU is not very efficient, indicating that input S^- can be reduced while the original output remains unchanged, or output S^+ can be increased with the same input. If $0 \leq \theta < 1$, the i-th DMU is efficient, showing that the input can be reduced and the output remains at the original level.

Bootstrapping is a non-parameter Monte Carlo simulation method. The bootstrap method is a repeated sampling technique applied to statistical analysis to improve the estimation of confidence intervals and critical value precision statistics. It does not require additional assumptions and samples, and it uses stochastic simulation to maximize the use of existing information [44]. Based on the data of inputs and outputs, the bootstrap step is used to measure the regional ecological efficiency. The efficiency estimates of the bootstrap DEA model after the correction bias were obtained using Equations (3)–(8).

Firstly, we calculated the efficiency score ($\hat{\theta}_k$) for all decision-making units (DMUs) using the traditional data envelopment analysis (DEA) model. Secondly, for the efficiency score $\hat{\theta}_k$, N random efficiency values (θ^*_{kb}) were produced using the Bootstrap method. We calculate $X^*_{kb} = (\hat{\theta}_k/\theta^*_{kb}) \times X'_k$, and the simulation samples $\left(X^*_{kb}, Y_k\right)$. Thirdly, our model calculated each simulation sample using the DEA model and repeated the above steps to obtain a series of efficiency values $\hat{\theta}^*_{kb}(b = 1, \cdots, B)$. B indicates the total number of iterations.

$$Bias(\hat{\theta}_k) = E(\hat{\theta}_k) - \hat{\theta}_k; \tag{3}$$

$$Bias(\hat{\theta}_k) = B^{-1}\sum_{b=1}^{B}(\hat{\theta}^*_{kb}) - \hat{\theta}_k. \tag{4}$$

The corrected efficiency values were as follows:

$$\widetilde{\theta}_k = \hat{\theta}_k - Bias(\hat{\theta}_k) = 2\hat{\theta}_k - B^{-1}\sum_{b=1}^{B}(\hat{\theta}^*_{kb}). \tag{5}$$

The confidence interval was calculated as follows:

$$P_r\left(-\hat{b}_\alpha \le \hat{\theta}^*_{kb} - \hat{\theta}_k \le -\hat{\alpha}_\alpha\right) = 1 - \alpha; \tag{6}$$

$$P_r\left(-\hat{b}_\alpha \le \hat{\theta}_k - \widetilde{\theta}_k \le -\hat{\alpha}_\alpha\right) \approx 1 - \alpha; \tag{7}$$

$$\hat{\theta}_k + \hat{\alpha}_\alpha \le \theta_k \le \hat{\theta}_k + \hat{b}_\alpha. \tag{8}$$

4. Indicator Selection and Data Sources

Economic and environmental performance indicators are required to assess ecological efficiency [50]. Based on the literature analysis and taking the availability of data into consideration, the indicator selection and data sources for estimating input and output of ecological efficiency in this study are described below.

Ecological efficiency output indicators measure the total value of products or services produced by regions. The core of ecological efficiency is to maximize economic output by reducing resource consumption and environmental pollution [21]. Therefore, regional gross domestic product (GDP) of each province was chosen to represent the added value of products and services. Sulfur dioxide emissions, solid waste emissions, waste water emissions, and smoke and dust emissions were selected as undesirable outputs.

In terms of input indicators, labor input was expressed by the total number of urban employees, capital stock was measured by the fixed asset investment, and the total energy consumption, cultivated area, and total water consumption of the province were considered as resource inputs.

Chinese provincial administrative regions include 22 provinces, five autonomous regions, and four municipalities directly under the Central Government in China. Beijing, Shanghai, Tianjin, and Chongqing are the four municipalities directly under the Central Government, among which Shanghai has the highest economic development and Chongqing the lowest. Beijing is a political and cultural center, and Tianjin is an earlier city open to the outside world. Inner Mongolia, Guangxi, Tibet, Ningxia, and Xinjiang are the five autonomous regions. The economic development of Inner Mongolia improved rapidly, while the economic development of Xinjiang remains stable, and that of Ningxia, Guangxi, and Tibet is relatively backward. Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan are the most developed provinces in China. Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan are the main areas of industrialization and urbanization. Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, and Qinghai are the most undeveloped areas [51].

Taking into account the differences in the economic systems of the provinces, we analyzed the changing trend of ecological efficiency in each province. According to economic development and geographical location, we divided the 30 regions into four major groups [51]: east, northeast, central, and west. The east area includes 10 provinces: Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan, which are the most developed areas in China. The northeast area consists of three provinces including Liaoning, Jilin, and Heilongjiang. The central area includes six provinces, namely Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The west area includes 11 provinces: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Ningxia, Gansu, Qinghai, and Xinjiang, which are the most undeveloped areas. Both the northeast and central groups are more developed than the western area, but less developed than the east area.

The objective of this study was to measure ecological efficiency in China. The scope of research in this study includes 30 provinces (excluding Tibet) ranging from 1998–2015. All data were from the China Compendium of Statistics (1949–2008), China Statistical Yearbook, China Environmental Yearbook, China Environmental Statistics Yearbook, China Labor Statistics Yearbook, China Population and Employment Statistics Yearbook, and China Energy Statistics Yearbook.

5. Results and Discussion

In this section, we analyze the distribution characteristics, the changing trends, and regional differences of China's ecological efficiency. Figure 1 shows the distribution characteristics of each province's ecological efficiency score from 1998 to 2015. According to Figure 1, we can find that the average ecological efficiency of China during the period 1998 to 2015 was 0.8072; the maximum ecological efficiency was 0.9682 for Inner Mongolia in 2015, the minimum value was 0.5204 for Gansu in 2000. This implies that there is still much room to improve ecological efficiency. The empirical results also indicated that China's economic development produced severe environmental pollution at the cost of high energy consumption. Therefore, China has great potential for energy conservation. Figure 2 shows the average ecological efficiency of the 30 provinces during the period 1998–2015. Among them, the provinces with the highest ecological efficiency were Jiangsu, Liaoning, Inner Mongolia, and Heilongjiang; the provinces with the lowest ecological efficiency were Gansu, Chongqing, Sichuan, and Shanxi.

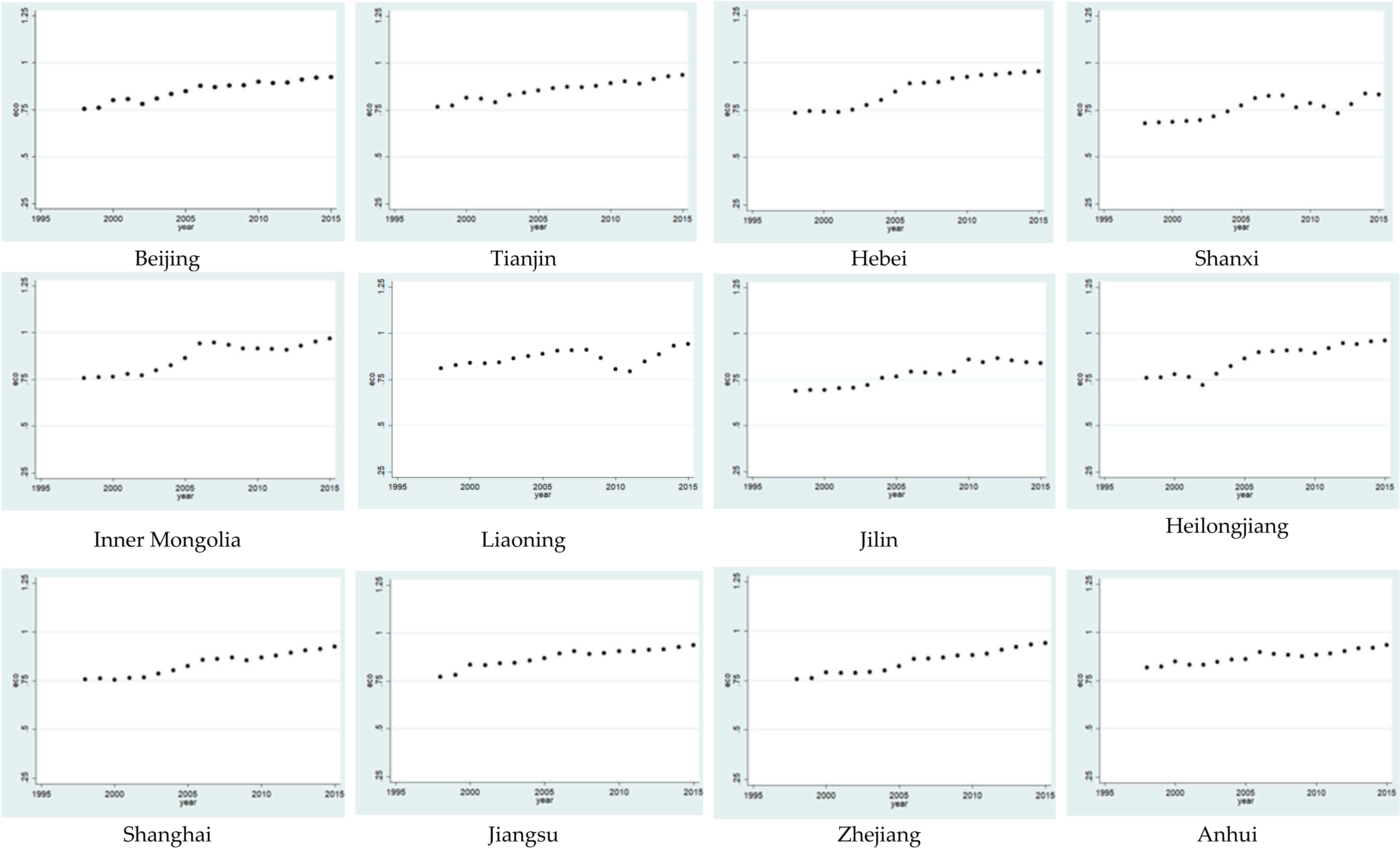
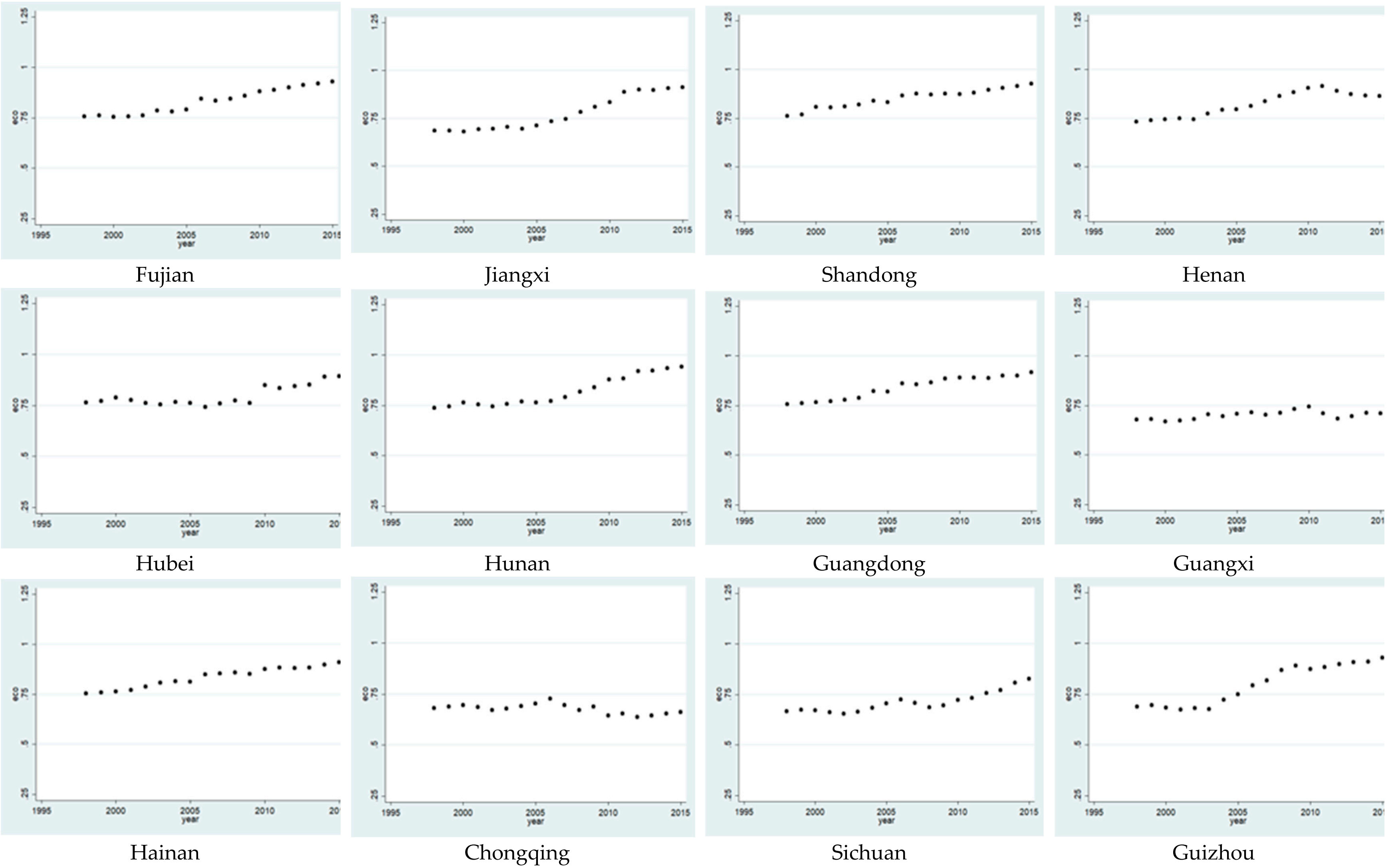


Figure 1. *Cont.*



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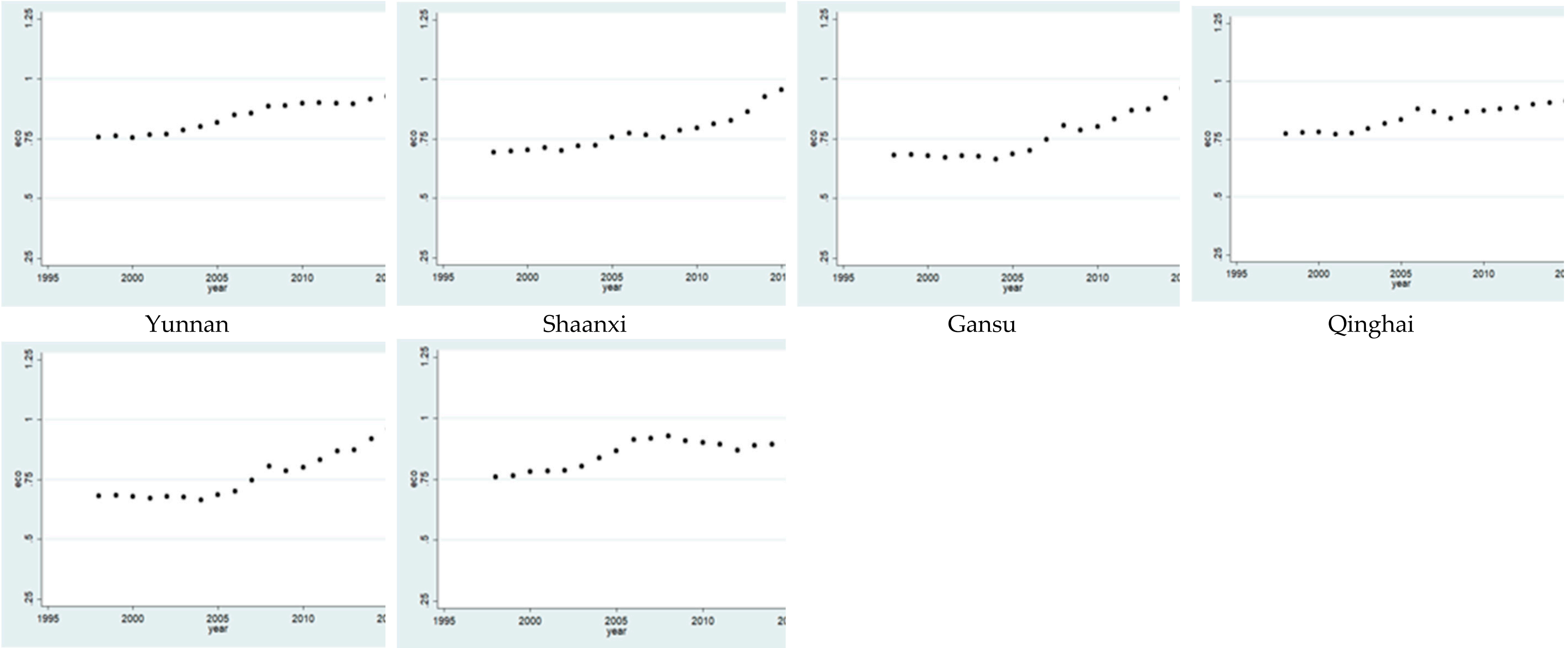

Yunnan Shaanxi Gansu Qinghai

Ningxia Xinjiang

Figure 1. Distribution characteristics of each province's ecological efficiency score from 1998 to 2015.

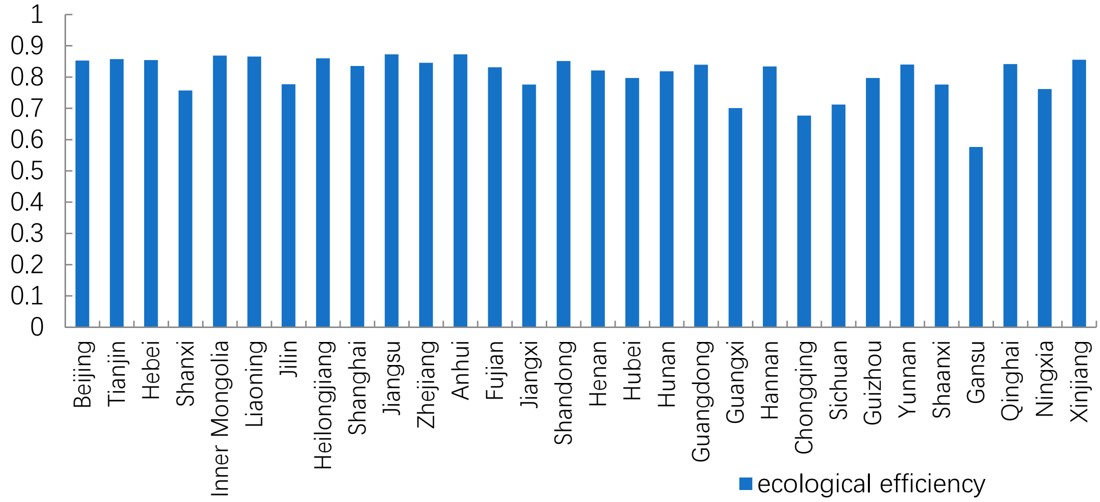

Figure 2. Average ecological efficiency of the 30 provinces during the period 1998–2015.

Figure 3 displays the trend of China's average ecological efficiency during the period 1998–2015. From 1998 to 2003, China's ecological efficiency was between 0.72 and 0.76, which indicates that the value of ecological efficiency was quite low. Subsequently, China's ecological efficiency increased significantly from 2004 to 2008, and the average ecological efficiency was 0.8350 in 2008. Finally, the ecological efficiency increased steadily from 2008 to 2015, and the average ecological efficiency was 0.8916 in 2015.

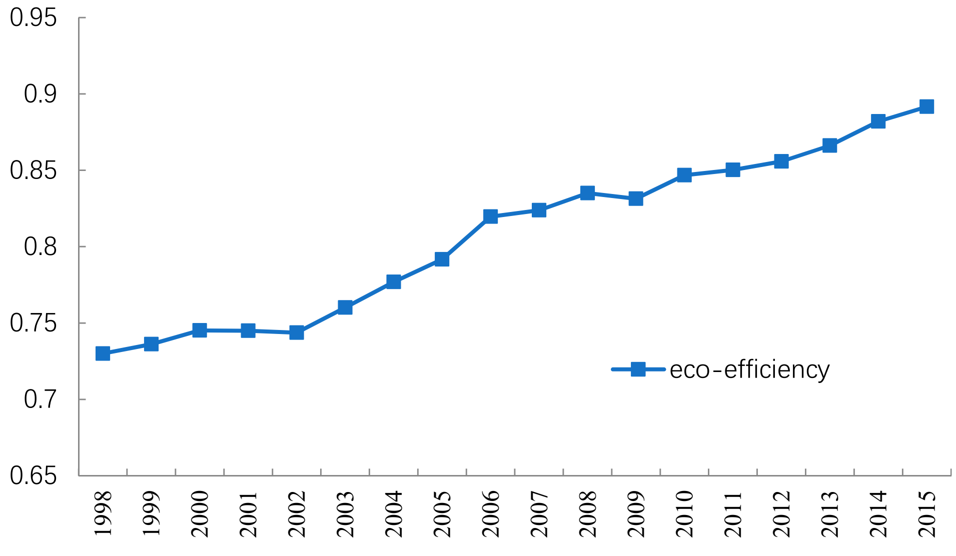

Figure 3. Trend of China's average ecological efficiency during the period 1998–2015.

In addition, to better understand the results of the ecological efficiency, an analysis of energy consumption and sulfur dioxide emissions was performed. Figure 4 shows the energy consumption of China during 1998–2015. According to Figure 4, we find that energy consumption increased year by year. The increasing investment in infrastructure and the rapid development of real estate and automotive industries led to a significant increase in the proportion of highly energy-consuming industries. Figure 5 presents the sulfur dioxide emissions of China during 1998–2015. Sulfur dioxide emissions decreased slightly from 1998 to 2002. Subsequently, sulfur dioxide emissions increased dramatically during the period 2002–2006. From 2007 to 2015, sulfur dioxide emissions showed a downward trend year by year. Sulfur dioxide emissions not only cause serious public health problems, but also bring about secondary pollution such as acid rain, haze, and Particulate Matter with diameter of 2.5 μm or less (PM2.5) The Chinese government regards sulfur dioxide emissions as one of its emission reduction targets. From the trend analysis of Figure 3, we can find that the goals of energy saving and emission reduction made some achievements.

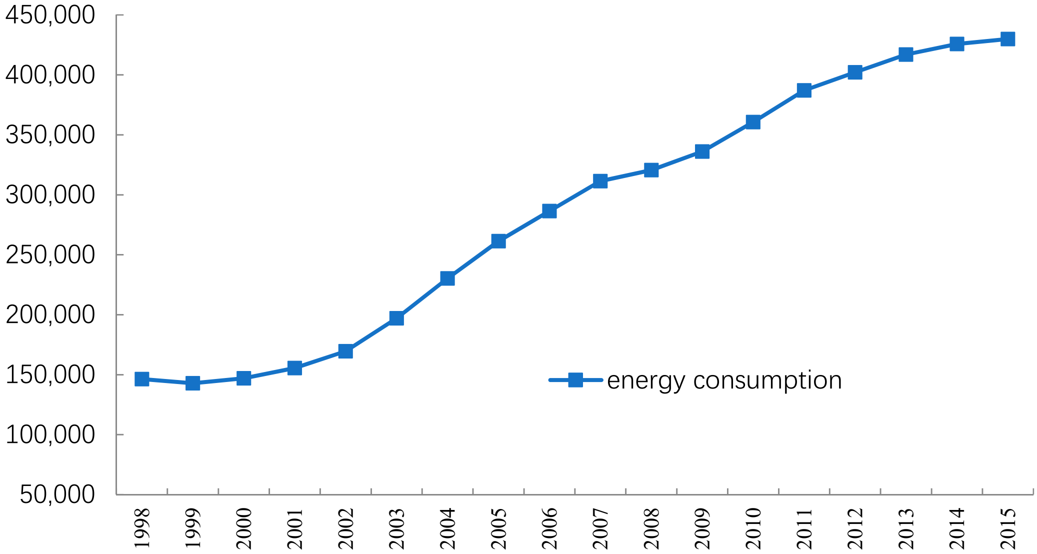

Figure 4. Energy consumption of China from 1998 to 2015.

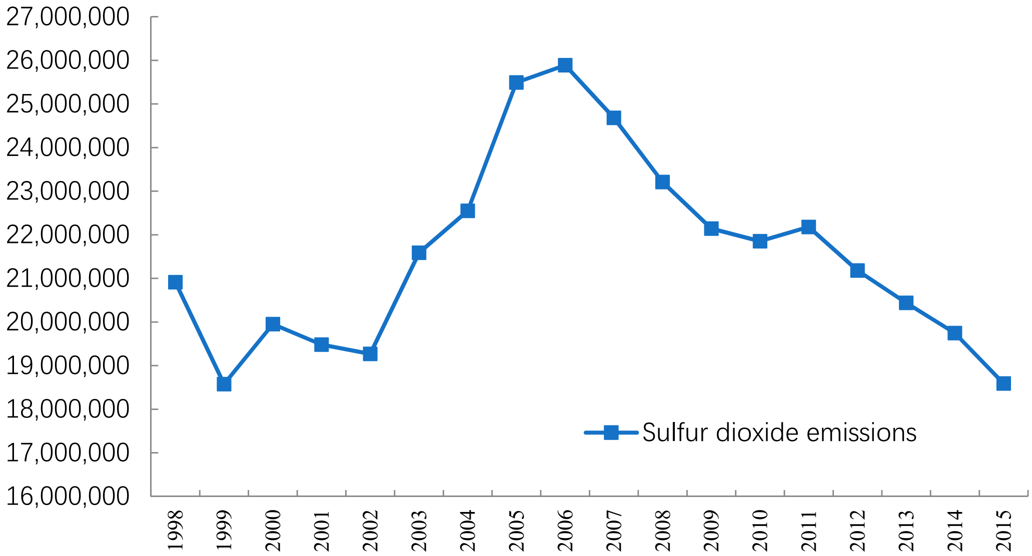

Figure 5. Sulfur dioxide emissions of China from 1998 to 2015.

Figure 6 presents the average ecological efficiency of the different Chinese regions during the period 1998–2015. According to Figure 6, we can see that the ecological efficiency in the four regions had an upward trend over the sample time as a whole. This shows that the harmony between economic development and environmental protection in China gradually improved. Therefore, in order to speed up the construction of ecological civilization and achieve sustainable development, China should further improve environmental protection to enhance ecological efficiency. The empirical results also indicate that there are significant regional differences for the ecological efficiency in the four groups of China. Specifically, compared to the east area, northeast area, and central area, we find that west areas obviously fall behind. Notably, the average ecological efficiency of sub-regions reached the maximum value of 0.92945 in the east area in 2015; the minimum of average ecological efficiency of the sub-regions was 0.6964 in the west area in 1998.

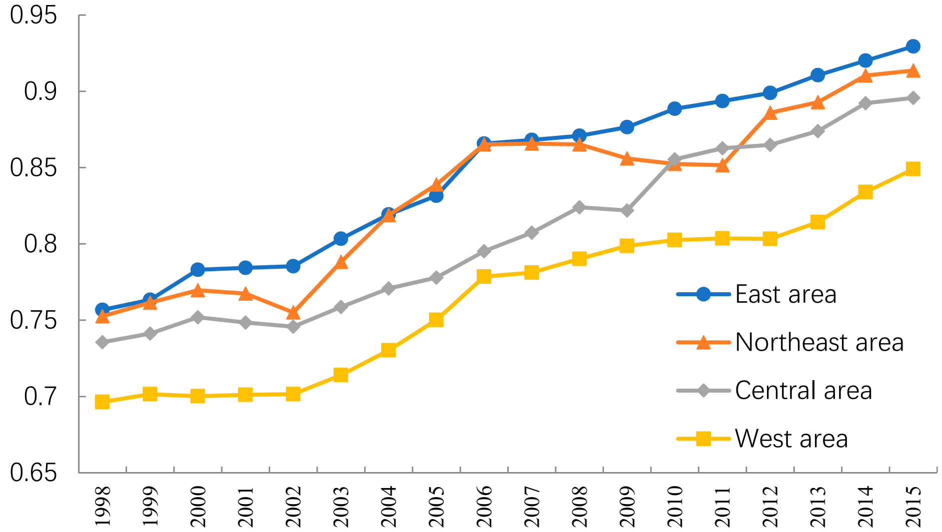

Figure 6. Average ecological efficiency of sub-regions during the period 1998–2015.

The trend of ecological efficiency value shows that the ecological efficiency of China significantly improved as a whole. Economic output consumes fewer resources and brings less unexpected output, which shows that China's economic output is less dependent on resources. The Chinese government's efforts to improve ecological efficiency contributed to these changes. However, it is noteworthy that there is still room for the improvement of ecological efficiency.

Specifically, the average ecological efficiency of the east area from 1998 to 2015 was 0.8472, which is higher than the national average of 0.8072, ranking first in the country. On the whole, the ecological efficiency of eastern provinces was on the rise for more than ten years. Among these years, the average value of ecological efficiency in 1998 was only 0.7567, and it reached 0.9294 by 2015. The provinces with the highest ecological efficiency in the eastern area were Jiangsu, Zhejiang, Tianjin, and Shandong. The improvement in ecological efficiency came from the remarkable achievements of technological progress in these provinces, the great efforts of environmental protection, and the high efficiency of transforming various elements into economic output. Fujian and Guangdong were provinces with lower ecological efficiency in the east, which was due to the aggregation of polluted enterprises.

We also find that the average ecological efficiency of the northeast area from 1998 to 2015 was 0.8339, which is higher than the national average of 0.8072. Ecological efficiency of the northeast area ranks second in China. Ecological efficiency in northeast area increased greatly, from 0.7525 in 1998 to 0.9136 in 2015. The ecological efficiency of Liaoning and Heilongjiang ranked among the top 10 provinces. Liaoning is a province with a key location and talented people in the northeast area. In recent years, Liaoning province continuously upgraded its industrial structure and rectified a number of enterprises with high pollution and energy consumption. These measures ensured the high level of ecological efficiency in Liaoning province. Heilongjiang province focuses on developing the tertiary industry, making full use of the natural environment to develop tourism, strengthening the construction of ecological function zones, and actively promoting energy saving and emission reduction, so as to greatly improve the ecological efficiency.

The average ecological efficiency of the central area from 1998 to 2015 was 0.8068, which is lower than the national average of 0.8072. The ecological efficiency of the central area showed an upward trend, with the average value of 0.7356 in 1998 and 0.8956 in 2015. The central area is an important agglomeration of heavy industry in China, and it has abundant coal resources. However, in the process of rapid economic development, there is still an extensive pattern of investment-driven growth, with high energy consumption. The low ecological efficiency in the central area is mainly due to the neglect of technological upgrading and environmental protection in the process of economic development, resulting in the low efficiency of resource utilization and the deterioration of the ecological environment. The highest ecological efficiency in the central area was in Anhui, whose average ecological efficiency was 0.8723.

According to Figure 6, the average ecological efficiency of the west area from 1998 to 2015 was 0.7639, which is lower than the national average of 0.8072. The ecological efficiency of the west area ranks lowest in China. In this area, the ecological efficiency of Shaanxi, Ningxia, and Inner Mongolia greatly improved. In the west area, the industrial development is relatively backward, and the output of pollution is relatively small. However, due to the low GDP output, the ecological efficiency value is generally low. The average ecological efficiency of Guangxi, Chongqing, and Gansu is low. Limited market capacity, imperfect infrastructure, and a lack of talent restrict the economic development and ultimately affect the improvement of ecological efficiency in the west area.

6. Conclusions and Policy Implications

Environmental pollution is a worldwide problem. The analysis of sustainability governance performance can provide a valuable reference for government decision-making. Ecological efficiency is an effective index for evaluating the performance of sustainability governance. Improving ecological efficiency is an important way to promote an economy's transformation from unsustainable to sustainable. Therefore, it is critical to analyze the ecological efficiency of China for evaluating the performance of ecological governance. This study used the bootstrap DEA model to estimate the performance of ecological governance based on ecological efficiency during the period 1998–2015. Our research objectives were to determine the distribution characteristics and the evolving trends of ecological efficiency in China.

From the results of ecological efficiency calculated directly using the bootstrap DEA model, the overall ecological efficiency ranged from 0.5204 to 0.9682. The average ecological efficiency of China during the period of 2003–2012 was 0.8072. The trend of ecological efficiency value showed that the ecological efficiency of China significantly improved as a whole. Among the 30 provinces, the provinces with the highest ecological efficiency were Jiangsu, Liaoning, Inner Mongolia, and Heilongjiang; the provinces with the lowest ecological efficiency were Gansu, Chongqing, Sichuan, and Shanxi. In addition, to better analyze the results of the ecological efficiency, an analysis of energy consumption and sulfur dioxide emissions was performed.

We further analyzed the regional differences of China's ecological efficiency. The empirical results also indicated that there were significant regional differences for the ecological efficiency in the four groups of China. Specifically, compared to the east area, northeast area, and central area, we find that the west areas obviously fall behind, which is similar to the results of Han [52]. Specifically speaking, the average ecological efficiency of the eastern area is the highest, followed by the northeast area. In 2015, the provinces with higher ecological efficiency were concentrated in the eastern and northeastern regions.

From the conclusion of this study, several policy implications were obtained. Firstly, the deterioration of ecological environment is the result of extensive economic growth, a large consumption of natural resources, and the emission of pollution. However, the improvement of ecological environment should be driven and supported by good governance of sustainability. In order to deal with the relationship between economic development and ecological environment, the government should adhere to the principle of sustainable development, accelerate market-oriented reform, save resources, and protect the environment to improve ecological efficiency [53]. Secondly, the government should control some high-pollution industries, improve energy-saving technologies, encourage and increase investment in new technology, explore clean energy, and ensure balance between the economy and society [54]. Thirdly, the government should strengthen cooperation in regional ecological governance, narrow the regional spatial gap, and promote regional coordinated development of ecological governance [52].

Each region relies on its own development conditions and comparative advantages to achieve rational division of work. It is also possible to complement resources by establishing cross-regional trading markets to optimize the allocation of production factors.

This study sheds light on the distribution characteristics and the evolving trend of ecological efficiency in China. Our results provide useful information for environmental policy. In addition, this study also puts forward some unresolved problems, and further measures can be taken in the future. For example, it is worth considering the impact of technological progress on the improvement of ecological efficiency. A non-parametric distance function approach can be used to decompose the ecological efficiency, which analyzes the contribution of technological progress.

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