



Ecological efficiency in China and its influencing factors—a super-efficient SBM metafrontier-Malmquist-Tobit model study

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Abstract

Ecological problem is one of the core issues that restrain China's economic development at present, and it is urgently needed to be solved properly and effectively. Based on panel data from 30 regions, this paper uses a super efficiency slack-based measure (SBM) model that introduces the undesirable output to calculate the ecological efficiency, and then uses traditional and metafrontier-Malmquist index method to study regional change trends and technology gap ratios (TGRs). Finally, the Tobit regression and principal component analysis methods are used to analysis the main factors affecting eco-efficiency and impact degree. The results show that about 60% of China's provinces have effective eco-efficiency, and the overall ecological efficiency of China is at the superior middling level, but there is a serious imbalance among different provinces and regions. Ecological efficiency has an obvious spatial cluster effect. There are differences among regional TGR values. Most regions show a downward trend and the phenomenon of focusing on economic development at the expense of ecological protection still exists. Expansion of opening to the outside, increases in R&D spending, and improvement of population urbanization rate have positive effects on eco-efficiency. Blind economic expansion, increases of industrial structure, and proportion of energy consumption have negative effects on eco-efficiency.

Keywords Ecological efficiency · Super efficiency SBM model · Malmquist index · Metafrontier-Malmquist index · Technology gap ratio · Influence factors

Introduction

In 2015, a successful global climate conference in Paris, France, unanimously adopted, the epoch-defining “Paris

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Agreement.” The Chinese government solemnly promised at the conference that China will firmly implement the “Paris Agreement” and continue to provide China's solution, contribute China's wisdom, and expand China's operations to cope with global climate change as well as strengthen global climate governance. However, China is also facing unprecedented ecological challenges. Since its reform and opening, China's economy has maintained good growth and is becoming the engine of world economic growth in the twenty-first century. However, the predatory exploitation and use of natural resources has not only caused excessive consumption and serious waste, but also great environmental pollution and damage; water safety, soil pollution, and other issues occur frequently. In 2014, China's utilization efficiency is low, with considerable waste of resources. The average output value of energy intensity per 10,000 GDP is much higher than that of the world average. It is equivalent to 1.3 times of that of the USA, 1.9 times of that of Japan, and 2.0 times of that of the European Union. In 2015, China's total investment in environmental pollution control has reached as high as 880.63

billion yuan, accounting for 1.28% of the annual GDP. However, pressure for addition pollution control continues to increase. The PM_{2.5} index, nitrogen dioxide index, and other indicators were greatly exceeded in China. In the “2016 Environmental Performance Index (EPI) report” ranking published by Yale University, China ranked second among the 180 countries surveyed with PM_{2.5} index, nitrogen dioxide index, and other indicators that greatly exceeded the standard limit. Therefore, solving the ecological problems is the key to achieving sustainable economic, social, and ecological development and is an important cornerstone for realizing the promise of the Paris Agreement.¹

Schaltegger and Sturm (1990) first proposed the concept of “eco-efficiency” in 1990 to measure the impact of resources and the environment on economic activities. The World Business Council for Sustainable Development (WBCSD) (Schmidheiny, 1992, Stigson, 1999, Schmidheiny and Stigson, 2000, Stigson 2001) presented the currently widely accepted definition of “eco-efficiency,” which provides bidding products and services that meet human needs and improves quality of life, and, at the same time, reduces the ecological impact and resource intensity of the entire life cycle to a level that is at least consistent with the estimated carrying capacity of the Earth. With continued progress of the research, this concept has been gradually simplified to “achieve more value with less cost” (Litos et al. 2017).

At present, research on ecological efficiency is broadly divided into three dimensions: Decompose eco-efficiency into resource efficiency and environmental efficiency, and conduct research on one of the sub-sectors separately; or consider eco-efficiency as a whole, and study its changing trends and major influencing factors. Scholars have made some achievements in the study of resource efficiency (RE) and environmental efficiency (EE): (1) Research on resource efficiency focuses on calculating energy efficiency. Liu et al. (2015) and Ma et al. (2017) performed studies from the perspective of the total factor and used the SBM model and Malmquist index to calculate the total factor energy efficiency of western China and the three northeastern provinces. Wang et al. (2014) and Zhang et al. (2015) further revealed the spatial and temporal variability of energy efficiency and the influencing factors and proposed key policy direction of energy efficiency improvement in China based on the data envelopment analysis (DEA) method for measuring energy efficiency. (2) Studies of environmental efficiency are focused on calculating environmental efficiency values at different levels and analyzing of influencing factors: Wang et al. (2010a, b) used the SBM directional distance function and the Luenberger productivity index, whereas Wang et al. (2010a, b) and Zeng (2011) used the DEA method and Tobit model to measure the

environmental efficiency of 30 provinces in China and analyzed the effects of influencing factors.

However, ecological efficiency is not a simple summary of environmental efficiency and ecological efficiency, nor is it a one-sided research to replace ecological efficiency. Therefore, a more comprehensive study of ecological efficiency from a holistic and systematic perspective is needed. The systematic research on eco-efficiency in China is still in an elementary stage. Existing research results involve very few fields and are mainly concentrated on the calculation of efficiency values of ecological efficiency and analysis of space-time differences: Pan et al. (2013) used Gray correlative degree analysis, Yang et al. (2014) used a super-efficient DEA method, and Li (2016) used the random frontier model. They all used a spatial statistical model to conduct an empirical analysis of the spatial correlation, change mechanism, and influencing factors of the ecological efficiency of provincial regions in China. However, research of eco-efficiency by foreign scholars is relatively wide-ranging, covering manufacturing, commerce, agriculture, the economy, and the environment.

Regarding the calculation of eco-efficiency values, most scholars have adopted traditional or improved DEA models: Lee and Park (2017) proposed an extended DEA model that allows the decision maker to evaluate eco-efficiency, appropriately depending on the business environment. Other scholars combine DEA with life cycle assessment (LCA). Gumus et al. (2016) used an integrated input-output life cycle assessment (LCA) and a multi-criteria decision-making (MCDM) approach to perform an eco-efficiency evaluation of 276 US manufacturing sectors. Egilmez et al. (2016), Masuda (2016), Lijó et al. (2017), and Ullah et al. (2016) all measured eco-efficiency differently. Egilmez used a fuzzy data envelopment analysis model that was coupled with an input-output-based life cycle assessment approach to perform a sustainability performance assessment of 33 food-manufacturing sectors. Masuda and Lijó measured the eco-efficiency of wheat production in Japan at a regional scale using a combined methodology and proposed measures to improve eco-efficiency based on the goal of effectively operating factories. Ullah used data envelopment analysis to integrate the economic and environmental performance determined through life cycle assessment. In addition, some scholars have adopted the stochastic frontier analysis (SFA): Orea and Wall (2017) used a stochastic frontier analysis (SFA) method that not only controls random noise in the data but also analyzes the potential for substitution between environmental pressures. Carvalhaes et al. (2017) assessed the ecological efficiency of locomotives based on the indicators of the World Business Council for Sustainable Development (WBCSD).

Under the data envelopment model (DEA), the accuracy of eco-efficiency measurement is highly related to the quality of input-output indicators selected: Yang (2009) brought “three

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industrial wastes” into the input indicators, whereas Chen et al. (2009) added two input indicators: regional total energy consumption and regional total production power consumption based on the “three industrial wastes” index. Wang et al. (2011) added four indicators on the basis of the “three industrial wastes” index, namely, arable land, construction land area, total water consumption, and energy consumption; regional GDP was chosen as the output indicator to calculate ecological efficiency. Passetti and Tenucci (2016) analyzed environmental planning, business strategy, operational practices, environmental management system certification, and environmental management accounting as factors that affect ecological efficiency. Based on consideration of the negative impacts, Gumus et al. (2016) proposed five environmental impact categories including greenhouse gas emissions, energy use, water use, hazardous waste generation, and toxic emissions and defined economic output as a position output. It should also be pointed out that the traditional DEA method has certain defects in the processing of undesired outputs. Although some scholars tried to use the method of reciprocal indicators to process data, they were still using input indicators of pollutant discharge (such as “industrial wastes”) that reflect pollutions that are included in the input indicators. These indicators were confused with the real energy input indicators such as water and electricity, which results in a significant error in the accuracy of eco-efficiency measurement. Therefore, we need to consider some negative factors in the analysis by introducing a DEA method with undesirable output in the study of ecological efficiency.

In the research on the relationship between ecological efficiency changes and technological progress, the Malmquist index method under traditional thinking is still the top choice for most scholars. However, this evaluation method urgently requires new breakthroughs. Beltrán-Esteve (2017) used a metafrontier (MF) directional distance function (DDF) method to assess the technical and managerial differences in eco-efficiency between production systems. The method of metafrontier (MF) can help us to solve the ecological and technological problems of technology and management by comparing the ecological efficiency of two agricultural systems. For Moutinho’s (Moutinho et al. 2017) analysis, once DEA results (eco-efficiency scores) were analyzed, the Malmquist productivity index (MPI) was used to assess the time evolution of the technical efficiency, technological efficiency, and productivity. When analyzing the results of interprovincial energy efficiency calculations, Zhang (2015) applied the common frontier approach to verify the heterogeneity of different groups to obtain the differences among the group’s technical efficiency and the common frontier technical efficiency. In addition, Ma and Wang (2015) and Wang and Meng (2015) also used the metafrontier-Malmquist-Luenberger productivity index in their research to measure changes in total factor productivity and the

technology gap ratio. Thus, it is seen that the Malmquist index under the metafrontier approach analyzes dynamic changes of efficiency more deeply, and the technology gap ratio (TGR) between the same DMU and the cluster boundary under the same DMU can measure how close the current production technology level is to the potential level (Ma and Wang 2015).

Due to strong truncated characteristic, many scholars use ecological efficiency as an explanatory variable in the Tobit regression method to explore its main influencing factors of eco-efficiency and the degree of impact. Passetti and Tenucci (2016) used environmental planning, business strategy, operational practices, environmental management system certification, and environmental management accounting as factors that influence eco-efficiency. However, their selection criteria are biased toward business/management ecological values. Other scholars are more inclined to tap into the economic/ecological sustainable development potential: Wu and Ma (2016) selected factors such as economic scale, industrial structure, regional factors, and regional dummy variables. Chen (2017) selected the urbanization level, industrial structure, environmental protection, and technological innovation level of the population. Wang and Fang (2017) selected factors such as population size, economic scale, industrial structure, openness to the outside world, science and technology level, and environmental regulation and finally analyzed the promotion/suppression effects of various factors on ecological efficiency based on the regression results eventually.

In summary, this article makes innovations in the following aspects: First, the system extracts and integrates outstanding research results of resource efficiency (RE) and environmental efficiency (EE), and integrates frontier research concepts and methods into ecological efficiency. This paper, based on China’s national and regional levels, explores and analyzes the potential ecological issues behind China’s rapid economic development. Second, this research builds a more scientific eco-efficiency measurement system and selects more practical input and output indicators. At the same time, the undesired output is introduced into the super-efficient SBM model, and the traditional DEA model is reconstructed. On the one hand, the negative effects brought by unintended output to the ecological environment are more realistically displayed, and on the other hand, the feasibility and accuracy of the results of the SBM model calculation are maximized. Third, based on the traditional Malmquist index, a common frontier is introduced to improve it. Then, the trend of ecological efficiency and technological progress is compared in Malmquist index results under two different ideas to analyze the trend between eco-efficiency changes and technological advancement. More importantly, this paper uses innovative technical gap ratio (TGR) to measure the technological gaps of production units under different technological frontiers, making the Malmquist

index more economical and in-depth analysis space under the common frontier thinking. Fourth, based on the results of the Tobit regression analysis, the PCA method is used to rationally integrate the main influencing factors, resulting in a more holistic and representative comprehensive index. Therefore, it is more convenient and in-depth to explore and examine the links between different influencing factors and its specific degree of influence. On this basis, this paper selects cross-sectional data of 30 provinces, municipalities, and autonomous regions in China (excluding Tibet, Hong Kong, Macao, and Taiwan) and uses the optimized super-efficient SBM model, which introduces undesirable output, to measure the ecological efficiency of China; then, this paper uses the Malmquist index method under the traditional and common frontiers as well as the technical gap ratio (TGR) to investigate the changing trend of ecological efficiency, and finally, the Tobit regression analysis and the principal component analysis method are used to explore and test the main factors that affect ecological efficiency as well as the effect degree of each factor, summarize experience and find out problems, and strive to achieve coordinated, sustainable development of China’s economy, society, and ecology better.

Material and methods

Super efficiency SBM model introducing undesirable outputs

Tone proposed a non-radial DEA model in 2002—a method for evaluating DMU_s efficiency based on slack-based measure (SBM). In contrast to the traditional BCC and CCR models, the SBM model directly incorporates the slack variable into the objective function, making the economic objective of the SBM model to maximize the actual profits, not just maximize the proportion of benefits. In the same year, Tone also proposed a super-efficient SBM model, which can be used to evaluate the effective DMU_s of SBM. With this model, we can make up for the defects that cannot be calculated for all DMU_s efficiency values. Super-efficient SBM evaluation first requires evaluation of DMU_s using the SBM model, and then uses super-efficient SBM to evaluate the effective DMU_s for SBM.

To be consistent with actual production to the maximum, the undesirable output is introduced into the super-efficient SBM in this paper, so that we can obtain an improved super-efficient SBM model that considers undesirable output. There are $nDMU_s$, and each DMU is composed of three elements: input— m , desirable output— r_1 , and undesirable output— r_2 . The form of the vector is expressed as $x \in R^m, y^d \in R^{r_1}, y^u \in R^{r_2}; X, Y^d$, and Y^u are matrices, $X = [x_1, \dots, x_n] \in R^{m \times n}, Y^d = [y_1^d, \dots, y_n^d] \in R^{r_1 \times n}$, and

$Y^u = [y_1^u, \dots, y_n^u] \in R^{r_2 \times n}$, assuming that these data are positive numbers. The SBM model is shown below:

$$\begin{aligned} \min \rho &= \frac{1 - (1/m) \sum_{i=1}^m (w_i^- / x_{ik})}{1 / (r_1 + r_2) \left(\sum_{s=1}^{r_1} w_s^d / y_{sk}^d + \sum_{q=1}^{r_2} w_q^u / y_{qk}^u \right)} \\ \text{s.t.} \quad x_{ik} &= \sum_{j=1}^n x_{ij} \lambda_j + w_i^- & i = 1, \dots, m \\ y_{sk}^d &= \sum_{j=1}^n y_{sj}^d \lambda_j - w_s^d & s = 1, \dots, r_1 \\ y_{qk}^u &= \sum_{j=1}^n y_{qj}^u \lambda_j + w_q^u & q = 1, \dots, r_2 \\ \lambda_j &> 0 & j = 1, \dots, n \\ w_i^- &\geq 0 & i = 1, \dots, m \\ w_s^d &\geq 0 & s = 1, \dots, r_1 \\ w_q^u &\geq 0 & q = 1, \dots, r_2 \end{aligned} \tag{1}$$

If and only if $\rho=1$, that is $w^-=0, w^d=0, w^u=0$, then DMU_k is effective for SBM. When discussing super efficiency SBM, this thesis defines that DMU_k is valid for SBM. The super-efficient SBM model with undesirable output is shown below:

$$\begin{aligned} \min \rho &= \frac{1 / m \sum_{i=1}^m (\bar{x} / x_{ik})}{1 / (r_1 + r_2) \left(\sum_{s=1}^{r_1} \bar{y}_s^d / y_{sk}^d + \sum_{q=1}^{r_2} \bar{y}_q^u / y_{qk}^u \right)} \\ \text{s.t.} \quad \bar{x} &\geq \sum_{j=1, \neq k}^n x_{ij} \lambda_j & i = 1, \dots, m \\ \bar{y}_s^d &\leq \sum_{j=1, \neq k}^n y_{sj}^d \lambda_j & s = 1, \dots, r_1 \\ \bar{y}_q^u &\geq \sum_{j=1}^n y_{qj}^u \lambda_j & q = 1, \dots, r_2 \\ \lambda_j &> 0 & j = 1, \dots, n \\ \bar{x} &\geq x_k & i = 1, \dots, m \\ \bar{y}_s^d &\leq y_k^d & s = 1, \dots, r_1 \\ \bar{y}_q^u &\geq y_k^u & q = 1, \dots, r_2 \end{aligned} \tag{2}$$

Directional distance function and Malmquist productivity index

Malmquist productivity index

Malmquist index under traditional thinking

The Malmquist index method is based on the DEA method. The total factor productivity can be decomposed into technological progress rate changes, pure technical efficiency changes, scale efficiency changes, and so on. This can give us a better understanding of the composition of productivity. According to Fare et al. (1992, 1994),

from the t period to the $t + 1$ period, the Malmquist index can be expressed as:

$$M(x_{t+1}, y_{t+1}, x_t, y_t) = \sqrt{\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}} \tag{3}$$

where $D^t(x^t, y^t)$ and $D^{t+1}(x^t, y^t)$ respectively refer to the technology of period t as a reference (that is, the data in the t period as a reference set) and the decision-making unit of the distance function of periods t and $t + 1$ period; $D^t(x^{t+1}, y^{t+1})$ and $D^{t+1}(x^t, y^t)$ have similar meanings. The Malmquist productivity index represents the degree of change in productivity of a decision-making unit during the period t to $t + 1$. If $M > 1$, it represents a productivity rise; if $M < 1$, it represents a declining trend.

According to Fare et al.'s study under variable pay variable (VRS) assumptions, the Malmquist productivity index is divided into two parts: technical efficiency change (effch) and technological change (techch), and effch can be further decomposed into pure technical efficiency change (pech) and scale efficiency change (sech). Therefore, Eq. (3) can be decomposed into:

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D^{t+1}(x^{t+1}, y^{t+1}|VRS)}{D^t(x^t, y^t|VRS)} \cdot \frac{D^{t+1}(x^{t+1}, y^{t+1}|CRS)}{D^{t+1}(x^{t+1}, y^{t+1}|VRS)} \cdot \frac{D^t(x^t, y^t|VRS)}{D^t(x^t, y^t|CRS)} \cdot \sqrt{\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \cdot \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}} = \text{pech} \times \text{sech} \times \text{techch} \tag{4}$$

Malmquist index under the common front thinking

Based on the directional distance function of slack-based measure (SBM), the metafrontier idea was introduced to optimize and improve the traditional Malmquist productivity index and the metafrontier-Malmquist-Luenberger (MML) productivity index was constructed (Wang Ling and Meng Hui 2015). The optimal DMU that contains the directional distance function of all the samples constitutes the metafrontier. When all the samples are grouped, the optimal DMU of the SBM directional distance function of the group constitutes the group boundary. Under the metafrontier idea, the MML productivity index between t and $t + 1$ is

$$MML_t^{t+1} = \left[\frac{1 + D_M^{t+1}(x_k^t, y^{dt}, y^{dt}; -x_k^t, y^{dt}, -y^{dt})}{1 + D_M^{t+1}(x_k^{t+1}, y^{dt+1}, y^{dt+1}; -x_k^{t+1}, y^{dt+1}, -y^{dt+1})} \times \frac{1 + D_M^t(x_k^t, y^{dt}, y^{dt}; -x_k^t, y^{dt}, -y^{dt})}{1 + D_M^t(x_k^{t+1}, y^{dt+1}, y^{dt+1}; -x_k^{t+1}, y^{dt+1}, -y^{dt+1})} \right]^{\frac{1}{2}} \tag{5}$$

An MML value greater than 1 indicates that the productivity from t to $t + 1$ increases, and otherwise it decreases. Under the VRS assumptions, MML can be further decomposed into a

technology improvement index (M_TECH) and a technology efficiency change (M_EFFCH) as follows:

$$MML_t^{t+1} = M_TECH_t^{t+1} \times M_EFFCH_t^{t+1} \tag{6}$$

$$M_EFFCH_t^{t+1} = \frac{1 + D_M^t(x_k^t, y^{dt}, y^{dt}; -x_k^t, y^{dt}, -y^{dt})}{1 + D_M^{t+1}(x_k^{t+1}, y^{dt+1}, y^{dt+1}; -x_k^{t+1}, y^{dt+1}, -y^{dt+1})} \tag{7}$$

$$MML_t^{t+1} = \left[\frac{1 + D_M^{t+1}(x_k^t, y^{dt}, y^{dt}; -x_k^t, y^{dt}, -y^{dt})}{1 + D_M^t(x_k^{t+1}, y^{dt+1}, y^{dt+1}; -x_k^{t+1}, y^{dt+1}, -y^{dt+1})} \times \frac{1 + D_M^{t+1}(x_k^{t+1}, y^{dt+1}, y^{dt+1}; -x_k^{t+1}, y^{dt+1}, -y^{dt+1})}{1 + D_M^t(x_k^{t+1}, y^{dt+1}, y^{dt+1}; -x_k^{t+1}, y^{dt+1}, -y^{dt+1})} \right]^{\frac{1}{2}} \tag{8}$$

M_TECH and M_EFFCH values greater than 1 indicate that the DMU's technology has progressed and efficiency has increased toward the production possibility boundary; M_TECH and M_EFFCH values less than 1 indicate that the technology of DMU is regressive and inefficient, being far from the production possibility frontier.

Similarly, we can calculate the total factor productivity index under the group boundary:

$$GML_t^{t+1} = \left[\frac{1 + D_G^t(x_k^t, y^{dt}, y^{dt}; -x_k^t, y^{dt}, -y^{dt})}{1 + D_G^t(x_k^{t+1}, y^{dt+1}, y^{dt+1}; -x_k^{t+1}, y^{dt+1}, -y^{dt+1})} \times \frac{1 + D_G^{t+1}(x_k^t, y^{dt}, y^{dt}; -x_k^t, y^{dt}, -y^{dt})}{1 + D_G^{t+1}(x_k^{t+1}, y^{dt+1}, y^{dt+1}; -x_k^{t+1}, y^{dt+1}, -y^{dt+1})} \right]^{\frac{1}{2}} \tag{9}$$

Common border and group border

The technical gap ratio (TGR) refers to the same DMU under the common border and group boundaries under the technical efficiency of the difference. A greater value of TGR indicates that the closer the actual production technology used is to the potential overall production technology level, the better the implied level of technology.

$$TGC = \frac{TE^M(x^t, y^{dt}, y^{dt}; -x^t, y^{dt}, -y^{dt})}{TE^G(x^t, y^{dt}, y^{dt}; -x^t, y^{dt}, -y^{dt})} = \frac{1 + D_M^t(x^t, y^{dt}, y^{dt}; -x^t, y^{dt}, -y^{dt})}{1 + D_M^t(x^t, y^{dt}, y^{dt}; -x^t, y^{dt}, -y^{dt})} \tag{10}$$

In the above formula, $TE^M(x^t, y^{dt}, y^{dt}; -x^t, y^{dt}, -y^{dt})$ is the technical efficiency under the common frontier, and relatively, $TE^G(x^t, y^{dt}, y^{dt}; -x^t, y^{dt}, -y^{dt})$ is the technical efficiency under the front of the group.

Tobit regression analysis and principal component analysis

The eco-efficiency obtained using the SBM model is not only affected by the selected inputs, the output indicators

that are generated by the SBM model, but also by other factors beyond the input, output indicators. Hengen et al. (2016) used a hybridized model including CNES modeling, LCA, PCA, and economic analyses, through a nested PCA to determine the relative contributing weight of each impact and the environmental category of the overall system. Bonfiglio et al. (2017) and Masternak-Janus (2017) divided the research process into two stages. Therefore, this paper uses the “two-stage method” derived from SBM analysis to measure the main influencing factors of eco-efficiency and the degree of impact. The first step of this method is to evaluate the efficiency of the DMU using the DEA model discussed above; the second step is to take the efficiency value obtained in the first step as the dependent variable and the influence factors as an independent variable; then, establish a regression model and analyze the direction and degree of influencing factors on eco-efficiency from the coefficient of the independent variable; moreover, principal component analysis is used to analyze the possible influencing factors and a more accurate analysis is made by means of a comprehensive index.

Tobit regression analysis is a variable-limited model. It is always used when the dependent variable is the cut value or fragment value, the eco-efficiency value is taken as a positive variable, so the truncation point can be set to 0 without loss of generality (Guo and Lu 2012, Xia et al. 2012, Tong et al. 2015). The Tobit regression model can be written as:

$$Y = \begin{cases} Y^* = \alpha + \beta X + \varepsilon & Y^* > 0 \\ 0 & Y^* \leq 0 \end{cases} \quad (11)$$

where X is the independent variable vector; Y is the truncated dependent variable vector; α is the intercept vector; β is the regression parameter vector; and ε is the disturbance item,

$\varepsilon \sim N(0, \sigma^2)$. In the Tobit regression model, the efficiency value as the dependent variable belongs to the truncated discrete distribution data. When the dependent variable is a partial continuous distribution or partial discrete distribution, ordinary least squares (OLS) estimates of the parameters are biased, so the maximum likelihood (ML) method must be used.

Indicator selection and data sources

Taking the integrity and availability of data into consideration, the scope of research in this paper includes 30 provinces, municipalities, and autonomous regions (excluding Tibet, Hong Kong, Macao, and Taiwan). Then, this paper uses annual panel data ranging from 2011 to 2015. The research data come from provinces, municipalities, and autonomous regions for the period 2011–2016 in the China Statistical Yearbook and the China Environment Yearbook.

On the one hand, during the calculation of ecological efficiency value and Malmquist index analysis, the indicators used in this paper include input indicators and output indicators: the input indicators are divided into resource input indicators, labor input indicators, and capital investment indicators. Whereas, resource input indicators select the total amount of water and energy consumption in each province; labor input indicators select the sum of employed persons, private enterprises, and individual employees in urban units; and capital investment indicators select investment in fixed assets. Output indicators are divided into desirable outputs and undesirable outputs: desirable output indicators select the GDP of each province; undesirable output can have a negative effect, so we select the total emission of “three industrial wastes”. As shown in the following table:

Index selection of ecological efficiency value calculation

Project	Category	Specific indicators	Remarks
Input indicators	Resource input indicators	Total water consumption	
Total energy consumption	All types of energy consumption are converted into standard coal		
Labor input indicators	The sum of the employed persons in urban areas, private enterprises, and individual employees	Due to lacking of educational level data, the labor force is assumed to be no difference in quality	
Capital input indicators	Investment in fixed assets	Carry out constant price reduction taking year 2011 as for the base period	
Output indicators	Desirable output	Gross regional domestic product	Regional GDP (carry out constant price reduction taking year 2011 as for the base period)
Undesired output	The “three industrial waste” emissions	Waste water, waste gas, solid waste	

On the other hand, when analyzing the influential factors and influence degree on eco-efficiency, this paper uses the explanatory index (the explanatory variable of regression) as the economic scale and chooses economic scale, industrial structure (structure effects and technology effects are the fundamental factors that affect the dynamics of eco-efficiency indicators (Yu et al. 2013)), degree of opening to the outside world, scientific research, urbanization, energy consumption, environmental governance, household consumption, and industrial pollution control (as shown in the following table).

Index selection of influencing factors of ecological efficiency

basically in a good state, and the problem of a deteriorating ecological environment has been relatively effectively contained, but problems between the two still exist and are at times prominent.

In previous studies, some researchers have already found that the spatial distribution of ecological efficiency in various regions shows some characteristics of spatial agglomeration (Yang et al. 2014) and the findings of Li et al. (2016) on eco-efficiency from 2004 to 2012 also show that spatial distribution pattern of regional differences in eco-efficiency of China is a generally positive spatial correlation and the pattern of spatial aggregation is relatively stable. As also seen from Fig. 1, the spatial distribution of

Explanatory index (variable)	Abbreviation	Remarks
Economic scale	<i>GR</i>	The regional GDP of each province as the proportion of the national GDP
	$\ln(GP)$	The per capita GDP of each province
Industrial structure	<i>PI</i>	The ratio of industrial added value to the regional GDP in each province
Degree of opening to the outside	<i>DT</i>	The proportion of the total import and export trade in each province to the regional GDP
Scientific research devotion	<i>RD</i>	The intensity of R&D expenditure in each province
Degree of urbanization	<i>UR</i>	The urbanization rate of resident population in each province
Energy consumption level	<i>EC</i>	The proportion of energy consumption in each province in the country
Environmental governance level	<i>MI</i>	The proportion of investment in environmental pollution control in each province
Household consumption	<i>CPI</i>	Consumer Price Index
Industrial pollution control	<i>IPC</i>	Completed investment of industrial pollution control

Results of empirical analysis and discussion

Estimation of ecological efficiency in China

The scale pay of ecological efficiency of the provinces, municipalities, and autonomous regions is generally considered to be variable and we actively seek to minimize the input and undesirable output to achieve higher efficiency based on the existing desirable output. Therefore, the super-efficient SBM model under the condition of VRS is used for comprehensive analysis; the results obtained using MaxDea6.3 Professional Edition software are presented in Table 1.

As seen from Table 1, 17 provinces, nearly 60% of the total, have long-term ecological efficiency (with ecological efficiency exceeding 1). The top five provinces in average efficiency are Qinghai, Tianjin, Hainan, Beijing, and Shanxi, respectively. At the same time, 13 provinces (over 40%) have long been ineffective in eco-efficiency, with Chongqing, Hubei, Sichuan, Hunan, and Gansu the most ineffective. Globally, the overall eco-efficiency of China is at an upper moderate level. The relationship between ecological environment and economic development is

ecological efficiency has obvious cluster effect, and the ecological efficiency of all North China, represented by Beijing and Tianjin, and some of East China, represented by Shandong and Shanghai, remained in an effective state during the study period and was at the frontier of production. This shows that ecological and economic coordination as well as sustainable development has begun to take effect, and now, there is relatively good ecological and economic quality. In relatively developed regions, provinces usually have more modern industries, advanced technology, higher management levels, and better human resources, which undoubtedly will use resources more efficiently and discharge fewer pollutants (Zhang et al. 2008). In addition, certain achievements have been made in transforming the economy of eastern region into an intensive economic growth mode of “low consumption, low pollution, and high efficiency” (Yang 2009). However, the calculated ecological efficiency of SBM is a relative efficiency, and there is still room for improvement and development between ecology and economy even in a relatively effective state. At the same time, part of the central and southern regions represented by Hubei and Hunan, and some southwestern regions represented by Sichuan and Chongqing, have been ineffective for many consecutive years, and the development of

Table 1 The ecological efficiency values of SBM for 30 provinces in China from 2011 to 2015

Administrative divisions	Province (rank)	Year 2011	Year 2012	Year 2013	Year 2014	Year 2015	Average value
North China	Tianjin (2)	1.3325	1.3481	1.3388	1.3765	1.3688	1.3529
	Beijing (4)	1.2833	1.2436	1.2626	1.2813	1.2936	1.2729
	Shanxi (5)	1.2678	1.2592	1.2584	1.2889	1.2865	1.2722
	Hebei (7)	1.2472	1.2533	1.2766	1.2503	1.1611	1.2377
	Inner Mongolia (11)	1.1083	1.1106	1.0617	1.0458	1.0999	1.0853
North China average value		1.2478	1.2429	1.2396	1.2486	1.2420	1.2442
South China	Hainan (3)	1.3338	1.3422	1.3543	1.3677	1.3440	1.3484
	Guangdong (6)	1.2323	1.2646	1.2669	1.2617	1.2377	1.2526
	Guangxi (15)	1.0283	1.0447	1.0343	1.0278	1.0208	1.0312
South China average value		1.1981	1.2172	1.2185	1.2191	1.2009	1.2107
Northwest region	Qinghai (1)	1.7023	1.7954	1.8410	1.8824	1.9521	1.8347
	Ningxia (9)	1.2578	1.2248	1.2075	1.1409	1.0986	1.1859
	Shaanxi (13)	1.0713	1.0656	1.0586	1.0503	1.0344	1.0560
	Xinjiang (22)	0.5251	1.0034	1.0292	1.0151	0.4565	0.8059
	Gansu (26)	0.7138	0.6670	0.6080	0.6118	0.6010	0.6403
Northwest region average value		1.0541	1.1513	1.1488	1.1401	1.0285	1.1046
East China	Shandong (8)	1.1744	1.1741	1.1716	1.1960	1.2234	1.1879
	Shanghai (10)	1.0814	1.0956	1.1088	1.1143	1.1326	1.1065
	Jiangsu (16)	1.0242	1.0186	1.0047	1.0093	1.0107	1.0135
	Anhui (17)	1.0213	1.0132	0.9342	1.0148	1.0175	1.0002
	Zhejiang (20)	1.0375	1.0200	0.7461	0.7547	0.7243	0.8565
	Fujian (23)	1.0228	0.7705	0.8395	0.6406	0.5744	0.7696
	Jiangxi (12)	1.0779	1.0774	1.0772	1.0609	1.0741	1.0735
East China average value		1.0628	1.0242	0.9832	0.9701	0.9653	1.0011
Central China	Henan (14)	1.0203	1.0198	1.0536	1.0395	1.0464	1.0359
	Hunan (27)	0.5951	0.5785	0.6832	0.6230	0.6929	0.6346
	Hubei (29)	0.5633	0.4984	0.5740	0.5611	0.5235	0.5441
Central China average value		0.7262	0.6989	0.7703	0.7412	0.7543	0.7382
Northeast region	Liaoning (18)	0.8594	0.8603	1.0001	1.0213	1.0976	0.9677
	Jilin (24)	0.6342	0.5608	0.6563	0.8179	1.0143	0.7367
	Heilongjiang (25)	0.5066	0.5168	0.5701	1.0088	1.0522	0.7308
Northeast region average value		0.6666	0.6459	0.7422	0.9493	1.0547	0.8117
Southwest region	Yunnan (19)	1.0286	0.8352	0.9064	0.7781	0.8111	0.8719
	Guizhou (21)	0.7983	0.7684	1.0100	0.8649	0.6298	0.8143
	Sichuan (28)	0.6158	0.5979	0.6484	0.6795	0.6116	0.6306
	Chongqing (30)	0.4831	0.4424	0.7256	0.5355	0.4574	0.5288
Southwest region average value		0.7314	0.6610	0.8226	0.7145	0.6275	0.7114
National average value		0.9883	0.9823	1.0103	1.0107	0.9883	–

the ecological environment still faces arduous challenges. The ecological efficiency of these regions has been invalid for five consecutive years, which shows that the ecological environment related to economic development has experienced a serious “deficit” and the economic development has already seriously threatened or even destroyed the self-cycle of ecological

environment. Through local economic construction and social development planning, all the above-mentioned regions were faced with tremendous tasks of development and transformation during the measurement period. Taking Hubei province as an example, the provincial government clearly puts forward the concept of “accelerating the construction of resource-saving,

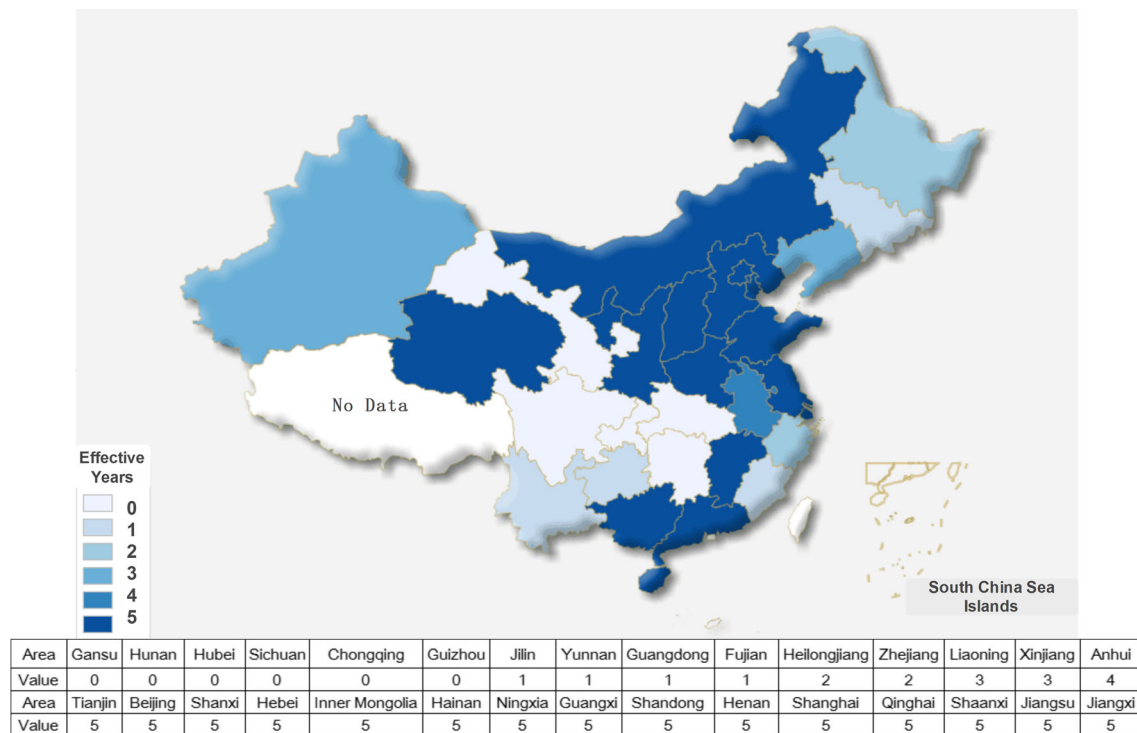


Fig. 1 The frequency chart of eco-efficiency in China from 2011 to 2015

environment-friendly production methods and consumption patterns, while constantly raising the level of ecological civilization” at the beginning of the “12th Five-Year Plan² (2011–2015)”. However, as the development center of the central region, Hubei province plays a decisive strategic role in the national development pattern and is given the heavy responsibility in a new round of industrialization and urbanization; therefore, there is the possibility that the ecological environment will give way to economic development and the ecological efficiency will be ineffective for successive years. There is an urgent need to improve the development model between ecology and economy.

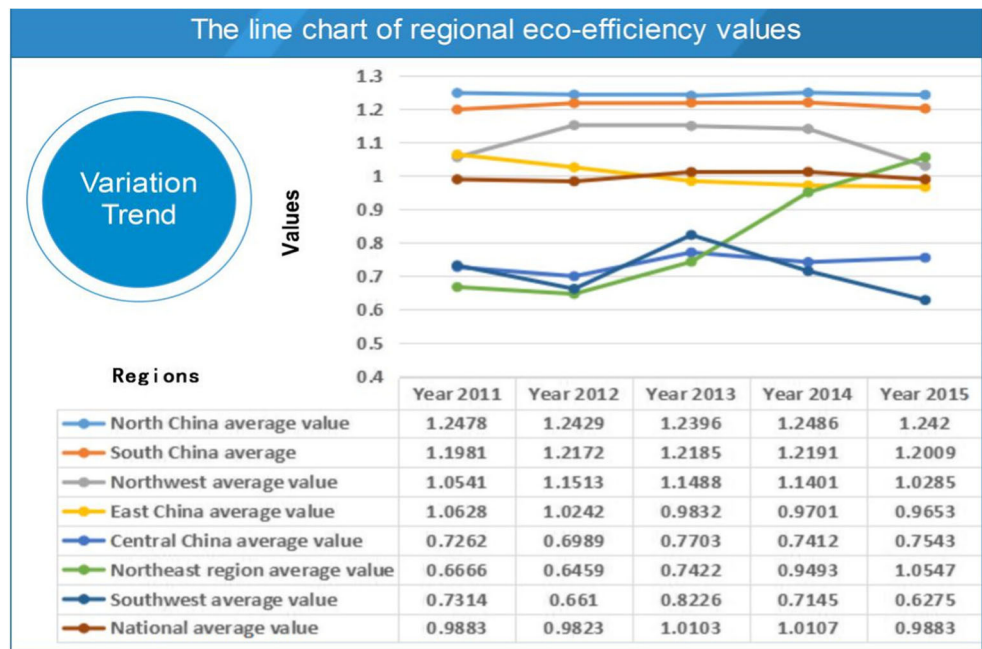
As seen from Fig. 2, among the eco-efficiency values for the seven geographic regions in China, each year, the average values in North China, South China, and Northwest China are above the national average. However, compared to the national average, the values in Central China, Southwest China, and Northeast China are lower and the value in East China is slightly lower. These results indicate that a clear imbalance

is present in the spatial distribution of China’s ecological efficiency and show a “high around the middle of the lower” distribution pattern. The difference of regional ecological efficiency in our country is more significant. The study finds that in the process of carrying the industrial transfer in the Eastern region, the Central and Western regions will face extremely severe ecological pressure. If not properly handled, the transfer of industries with low-tech, high-energy-consuming, and high-pollution industries will make the ecological environment fragile or even worse (Chen and Lu 2009). After the central government took over the industrial transfer in the east, it remained a kind of “high-input and high-emission growth model”, which limited the improvement of environmental efficiency in the central region (Zeng 2011). Therefore, undertaking industrial transfer should be coordinated with the building of a resource-saving and environment-friendly society (Chen and Lu 2009).

The ecological efficiency values in North China and South China have been relatively stable. Northwest China experienced a process of “first rising, then falling”. However, the ecological efficiency of the three regions has been in an effective situation. The relationship between ecological environment and economic development has basically stabilized, and the ecological environment in the economic development has been effectively solved. The reasons for the state in North and South China lie mainly in gathering a large amount of high-quality resources, and at the same time, the policy support for the two regions is the earliest and the largest, enabling the traditional

² The Twelfth Five-Year Plan (2011–2015) of the People’s Republic of China for National Economic and Social Development is referred to as the Twelfth Five-Year Plan. According to the “Proposal for the CPC Central Committee on Formulating the Twelfth Five-Year Plan for National Economic and Social Development,” it is mainly formulated to state the country’s strategic intentions, define the key government tasks, and guide the behavior of market players. This is a grand blueprint for China’s economic and social development in the next 5 years. It is a common program of action for people of all nationalities in the country and an important basis for the government to fulfill its duties of economic regulation, market supervision, social management, and public service.

Fig. 2 The regional eco-efficiency values of SBM in China from 2011 to 2015



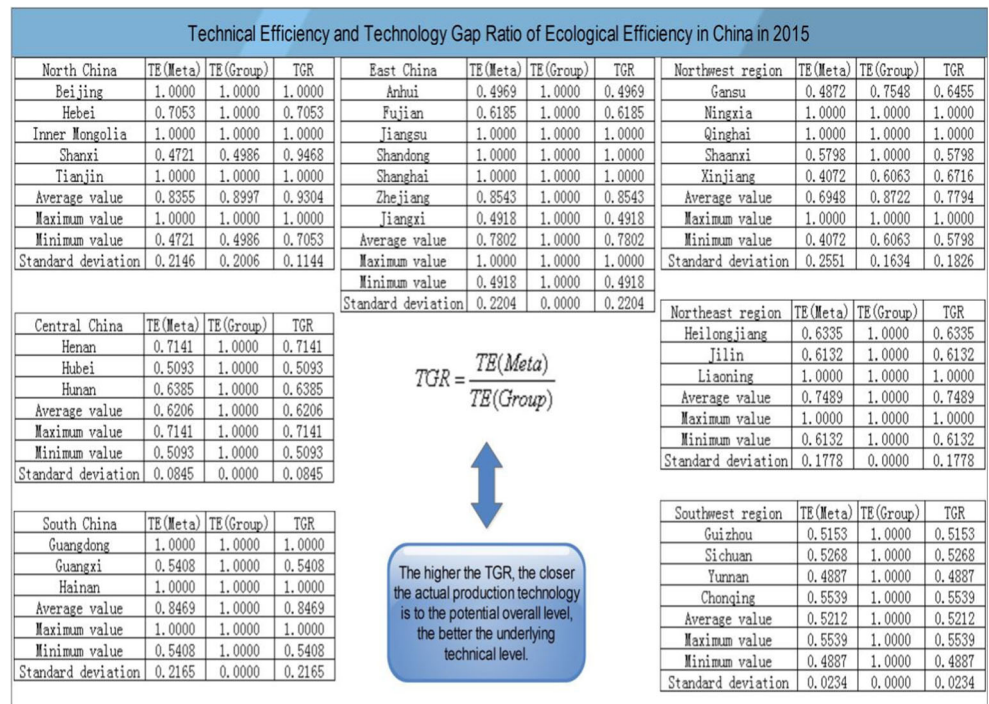
economy to meet the needs of green and low carbon transition and transformation. Although the ecological environment in Northwest China is bad, due to the long-term environmental protection policy supported by the state, and a large amount of the labor force shifting to the eastern coastal regions, the ecological carrying capacity of the region can be restored, and its eco-efficiency is also high. The ecological efficiency in East China has been declining year by year, gradually sliding from effective to ineffective, which is closely related to its increasing permanent population. Increasing population will inevitably increase the amount of resources used, which is bound to further aggravate excessive development of the ecological environment, and then create a vicious cycle. Thus, with the economy developing, the eco-efficiency is decreasing. In Northeast China, the ecological efficiency shows an upward trend from “ineffective to effective”. The ecological efficiency in Central and Southwest China has been at an ineffective level, but the fluctuations in Central China are relatively stable, whereas the changes in the southwest are rather violent and irregular. The continuous improvement of eco-efficiency in Northeast China is inseparable from the “Northeast Revival” strategy during the “Twelfth Five-Year Plan” (2011–2015). It focuses on solving the institutional and institutional contradictions that have constrained economic development in Northeast China, and accelerating the transformation of old industrial bases. The ability of scientific and technological innovation has a great effect on the restoration and protection of the local ecological environment. The central and southwestern regions are due for tremendous development and construction projects, so the ecological environment is still facing a huge cycle of development and government departments should give due attention.

Malmquist index

In this paper, the traditional Malmquist index and the metafrontier-Malmquist index are used to calculate the trends of ecological efficiency cutting-edge technical efficiency TE^M (meta), cluster frontier technical efficiency TE^G (group) and technological gap ratios TGR in the seven geographical divisions. The results are shown in Figs. 3, 4, and 5.

As seen from Fig. 4, the Malmquist index under the traditional idea is approximately 0.9579 and less than 1 for most provinces, indicating that the ecological efficiency of most provinces is not moving in a good direction. The regional differences in dynamic changes are relatively small; the largest intertemporal dynamic change index is that of Qinghai, whereas that of Xinjiang is smallest. The Malmquist index under the common front idea is approximately 0.9848, and there are more provinces with values greater than 1, indicating that the ecological efficiency in some provinces is developing well in this measurement. However, the overall average is still less than 1 and needs more and better direction of development. The difference between the two indicators is that the latter measures the technical gap between production units under different technological fronts, and the metafrontier-Malmquist index obtained at this time is more meaningful and has more in-depth spatial analysis, considering the differences in technical levels among regions. Overall, the improvement of eco-efficiency in 30 provinces of China is still under tremendous pressure and does not have the policy and technological advantages in terms of environmental remediation and pollution control.

Fig. 3 Technical efficiency and technology gap ratio of ecological efficiency in China in 2015



As seen from Fig. 3, the overall technical efficiency of eco-efficiency under the common frontier is at the upper middle level, and the development of each region is not balanced. The efficiency levels are higher in southern China, northern China, eastern China, and northeastern China and are, respectively, 0.8469, 0.8355, 0.7802, and 0.7489; however, the lower efficiency levels in Northwest China, Central China, and Southwest China are 0.6948, 0.6206, and 0.5212, respectively. If we compare the potential best production technologies across the country, there will be 15.31, 16.45, 21.98, 25.11, 30.52, 37.94, and 47.88% of the technological upgrading potentials in all regions in a sustained manner, so we can conclude that the central and southwestern parts of the country urgently need to upgrade their technical level to ensure the improvement of regional ecological efficiency. Under the group frontier, the technical efficiency is one in five of the seven regions, 0.8997 in North China, and 0.8722 in Northwest China. The value of the technical efficiency is very close to or even consistent with the optimal technical level of the cluster, indicating that development within the region is being integrated. The conclusion shows that at the regional level and the provincial level, the technical efficiency is lower under the common frontier than that of frontier of the group, and there is a certain gap because the two are based on different standards—there is a difference between the potential best technical level in the country technical level and the region’s own potential level at its best technical.

With continuous observation of the dynamic changes of TGR in conjunction in Fig. 5, the declining trend in North China, East China, Central China, South China, and Southwest China during the 5-year period from 2011 to 2015 means that the proportion of

potential optimal production technologies in the country is declining. This has had a negative impact on eco-efficiency, with the largest decline in southern China from 0.9789 in 2011 to 0.8469 in 2015. The above five regions are at the forefront of economic development. Their geographical position is superior, and they have perfect infrastructure, but the blind pursuit of high-speed and low efficiency economic benefits is not desirable. We need to promote economic growth and at the same time pay more attention to raising the technological level. The northeast and northwest regions showed a slowly rising trend, but the geographical locations of these two regions are relatively remote and the economic environment is relatively poor. However, with the support and active promotion of the strategy of “rejuvenating the Northeast” and “continuing the great development of the western region,” the two regions have firmly established the concept of “green development” at an early stage of economic development and have comprehensive consideration of the conditions and constraints in various aspects to make good achievements in the virtuous circle of economic, technological, and ecological environment.

We can see from the results that the static analysis of the individual and group technical level and the dynamic analysis of the technology gap ratio further reveal the group effect of economic development. On the one hand, technological progress among different regions reflects more differences, so the government needs to formulate economic development policies according to local conditions and introduce advanced science and technology; on the other hand, technological progress in the same region is relatively homogeneous, and the government needs to grasp commonality, actively replicate, and promote advanced

Fig. 4 Dynamic changes of environmental efficiency of China's 30 provinces between 2011 and 2015 (ML and MML)

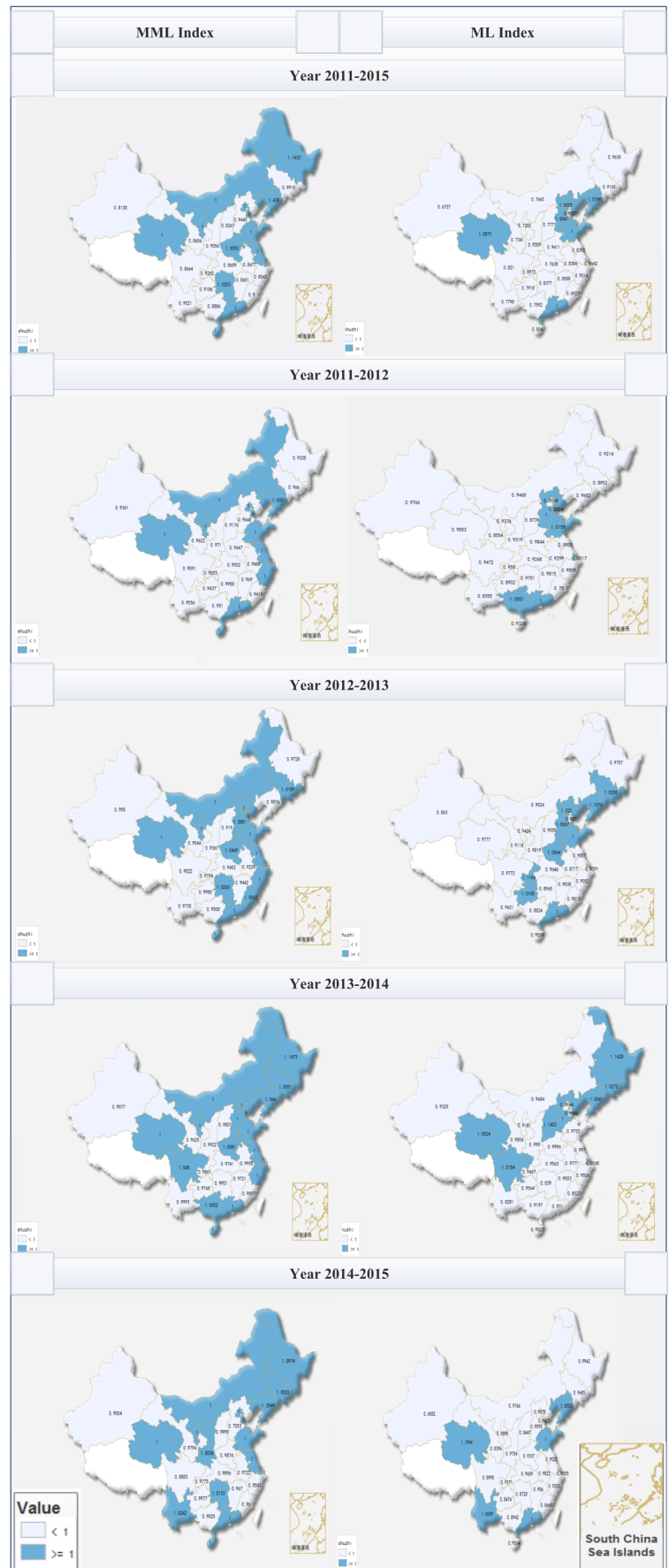
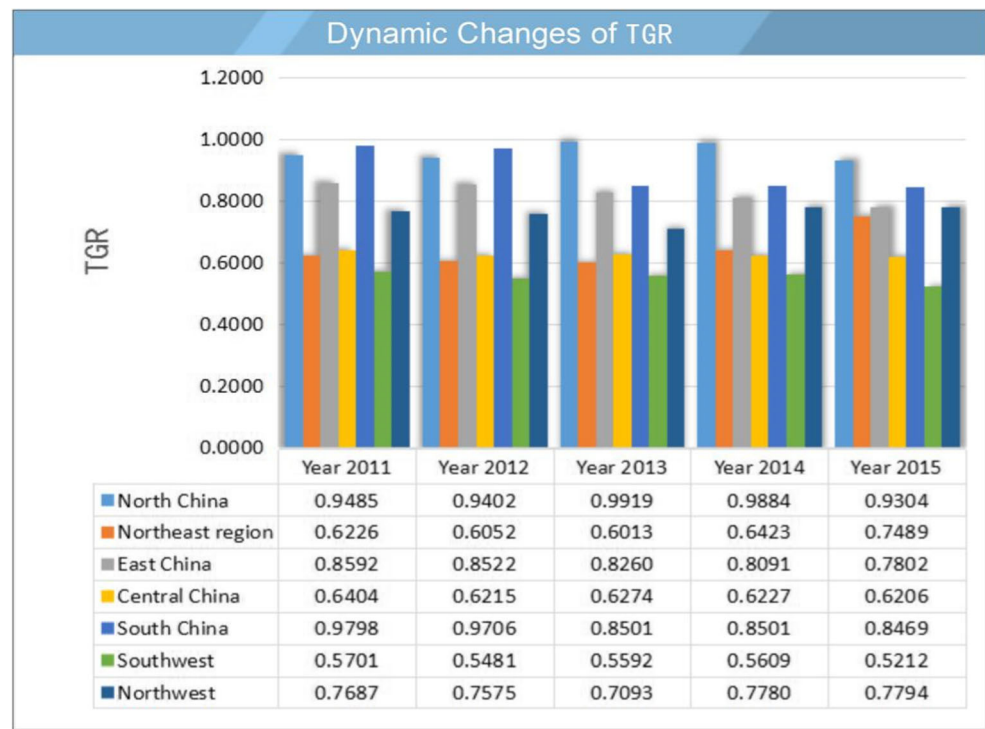


Fig. 5 Dynamic changes of the technology gap ratio of the across regions between 2011 and 2015



economic development experience. At the same time, government needs to handle fine differences and coordinate the advancement of the two to achieve better coordination and balanced development within and between regions.

Analysis of influencing factors of ecological efficiency

According to the environmental Kuznets curve (EKC) theory, environmental effects can be decomposed into several categories such as economies of scale, structural effects, technological effects, environmental policies, and regulatory factors (Hu et al. 2004). Based on the above theories, the existing literature, and the availability and applicability of data, this paper selects some indicators as follows.

First, we can set up the Tobit regression equation is as follows:

$$EEI_{it} = \beta_0 + \beta_1 GR_{it} + \beta_2 \ln(GP_{it}) + \beta_3 PI_{it} + \beta_4 DT_{it} + \beta_5 RD_{it} + \beta_6 UR_{it} + \beta_7 EC_{it} + \beta_8 MI_{it} + \beta_9 CPI + \beta_{10} IPC + \varepsilon_{it} \quad (12)$$

where β_i is the coefficient to be determined, ε_{it} is the random error term, and the specific explanation of the indicators can be found in the data introduction section. The results calculated using Eviews 8.0 software are shown in Table 2.

The Tobit regression results in Table 2 show that only the economic scale and industrial structure passed the significance test of 1%. Among them, the per capita GDP belonging to the economic scale has a positive effect on the ecological

efficiency values, the increase of the per capita level causes environmental pollution control funds to receive multiple-inputs, and with the expansion of economy, the economy of agglomeration gradually emerges. Also, the improvement of income level has also increased people's demand for high-quality "environmental quality" (Wang et al. 2010); the improvement of this financing environment contributes to the improvement of ecological efficiency. The increase in the proportion of industrial structure has a negative impact on the improvement of ecological efficiency, indicating that each province failed to properly consider its ecological impact while focusing on industrial development. The increase in the proportion of industrial output was accompanied by a decrease in ecological efficiency. Improvement in resource efficiency can be achieved by improving levels of technology in production sectors and shifting the economic structure from energy and resource-intensive industries to light industries (Yu et al. 2013). Industrial development still follows the extensive mode of development based on resource consumption and environmental pollution. The transformation of large-scale structures for energy conservation, emission reduction, and upgrading has yet to arrive.

Multiple collinearities exist between different influencing factors, so PCA method is needed to reduce the dimension of the data. The correlation test results indicate that there may be some correlation between the various variables. However, among them, the relevance between PI, the province of industrial added value accounted for the proportion of regional GDP and that of the other variables is very small, so we

Table 2 The results of ecological efficiency influencing factors regression analysis

Explanatory variable	Abbreviation	Coefficient	Z statistics
Economic scale	<i>GR</i>	7.047937	1.071910
	$\ln(GP)$	0.810488***	3.044232
Industrial structure	<i>PI</i>	-0.030336***	-1.980703
Degree of opening to the outside	<i>DT</i>	0.664645	0.337945
Scientific research devotion	<i>RD</i>	1.737471	0.197930
Degree of urbanization	<i>UR</i>	-1.278037	-0.857675
Energy consumption level	<i>EC</i>	-14.12044	-1.724895
Environmental governance level	<i>MI</i>	0.175533	0.030698
Consumer Price Index	<i>CPI</i>	0.045190	0.199178
Completed investment of industrial pollution control	<i>IPC</i>	0.002104	0.487062

*** is significant at 1% level; ** is significant at 5% level; and * is significant at 10% level

removed it and then proceeded with the principal component analysis. The KMO test value is greater than 0.7 and Bartlett sphericity test’s *P* value is less than 0.05. These two indicators again verify the correlation between variables, thus the principal component analysis is possible. The principal component analysis and the gravel map show that components 1, 2, and 3 can account for 82.493% of the variance and their eigenvalues are both above 1, so that components 1, 2, and 3 contain large amounts of raw data and they can be used as the main component.

According to the component coefficient matrix, we can write expressions for the common factor *F1*, *F2*, and *F3*:

$$F1 = -0.006*GR + 0.085*LN(GP) + 0.199*DT + 0.263*RD + 0.312*UR - 0.106*EC - 0.033*MI + 0.298*CPI - 0.061*IPC \tag{13}$$

$$F2 = 0.314*GR + 0.099*LN(GP) + 0.038*DT - 0.062*RD - 0.093*UR + 0.382*EC - 0.071*MI - 0.068*CPI + 0.346*IPC \tag{14}$$

$$F3 = 0.214*GR + 0.670*LN(GP) - 0.228*DT + 0.002*RD + 0.164*UR + 0.002*EC + 0.553*MI + 0.070*CPI + 0.162*IPC \tag{15}$$

According to the above expression, the Tobit regression equation is re-established as follows:

$$EEI_{it} = \beta_{11}F1 + \beta_{12}F2 + \beta_{13}F3 + \varepsilon_{it} \tag{16}$$

where *F1*, *F2*, and *F3* are three common factors, β_i is the coefficient to be determined, and ε_{it} is the error term.

From Table 3, we know the three common factors sorted by principal component analysis: *F1* and *F2* have a negative effect on the development of ecological efficiency, whereas *F3* has a positive effect. The common factor *F1* passed the significance test of 10%, which represents the “regional development” indicator; integrated

by the province’s total import and export trade accounting for the proportion of regional GDP, provincial R&D spending intensity, the province’s urbanization rate of resident population and the provincial Consumer Price Index. The increase of the proportion of provincial total import and export trade in the GDP of the region indicates that in recent years, the opening of various provinces in China has expanded. On the one hand, the international division of labor and specialization brought by this opening has increased economic efficiency, which has promoted ecological efficiency. However, on the other hand, many pollution-related enterprises will also be introduced and developed in China, which in turn will cause environment damage. The increased intensity of R&D expenditure in the provinces means that local governments will begin to attach importance to the development of science and technology. This can promote the efficient and healthy development of a region and have a positive effect on ecological efficiency. However, the proportion of R&D can only reflect the government’s investment in scientific research, not the measure of the level of technological progress better (Zeng 2011). The increase of the urbanization rate of the resident population in the provinces means an increase in the urban population and an increase in the urban load, which is not conducive to the improvement of ecological efficiency. The improvement of urbanization will constantly require improvement of urban functions, adjustment of industrial structure, optimization of spatial distribution, and sharing. It should be noted that the increasing population density will continue to require adaptive changes in urban functions, industrial structure, and spatial distribution. Once the per capita energy and resource consumption reach the bottom, the impact of population density on environmental efficiency is likely to turn into a negative effect (Zeng 2011). On the whole, the “regional development” indicator, which is

Table 3 Tobit regression analysis

Explanatory variables	Abbreviation	Coefficient	Z statistics
Regional development	Common factor $F1$	-0.040353*	-0.173285
Economic structure	Common factor $F2$	-0.288809***	-2.774176
Per capita development	Common factor $F3$	0.594077***	4.371155

*** is significant at 1% level; ** is significant at 5% level; * is significant at 10% level

represented by the common factor $F1$, has a negative effect on the promotion of ecological efficiency.

The common factor $F2$ has passed the significance test of 1%, which represents the “economic structure” indicator. The greater the proportion of GDP in each province, the better the economy has developed. Although local economy continues to grow, the impact on ecological efficiency is negative. Therefore, continuing to follow the traditional development model and blindly pursuing short-term economic benefits will not only promote the negative development of the economy, but also will make the environmental pollution and ecological destruction more serious. The greater the proportion of energy consumption in each province, the greater the cost of natural resource (energy) consumption to drive regional economic development. Without changing the energy supply structure and energy utilization technology, the impact on ecological efficiency is negative. The greater the value of completed investment in industrial pollution governance, the more financial resources the government has spent on pollution caused by industrial pollution, and the negative impact on ecological efficiency is significant. The link between the above three is precisely the relationship between input and output in the framework of economic structure. The former is the output, and the latter two are inputs. The impact of the common factor $F2$ on ecological efficiency is negative, indicating that China’s current economic structure and rapid economic development based on this structure will still cause a certain degree of negative impact on ecological environment. It is necessary for the national and local governments to constantly improve and optimize the economic structure and promote the common sustainable development of the economy and the environment.

The common factor $F3$ passed the significance test of 1% and has a strong correlation with the increase of GDP per capita in each province, which represents the indicator of “per capita development.” The increase in per capita GDP represents an improvement of living standards. When people’s living conditions are superior, they will begin to attach importance to other aspects of life, such as the living environment experience, which has a positive effect on the development of ecological efficiency.

Conclusions and policy recommendations

Conclusions

There are differences between regions regarding the level of development of a circular economy. There is a serious imbalance between interprovincial and provincial ecological efficiency. In nearly 60% of China’s 30 provinces, ecological efficiency is effective and in more than 40%, it is ineffective; overall, ecological efficiency is at the intermediate level. The ecological efficiencies of Qinghai, Tianjin, Hainan, Beijing, and Shanxi provinces are effective in the long run, mainly in North China and South China. Chongqing, Hubei, Sichuan, Hunan, and Gansu provinces have the most ineffective ecological efficiency, mainly concentrated in the southwest and central China. There is a clear cluster effect in the spatial distribution of ecological efficiency. The provinces with effective eco-efficiency are concentrated in North China, South China, and Northwest China, whereas provinces with ineffective eco-efficiency are concentrated in central and southwestern China. Eastern China and the northeastern region have undergone relatively large changes in ecological efficiency, but the ecological efficiency of the northeastern region is increasing annually, whereas the ecological efficiency in east China has changed from effective to ineffective.

The ecological efficiency of most provinces did not develop in a good direction, and these provinces did not have policy and technical advantages in environmental remediation and pollution control, and so on. Under the common forefront, the technical efficiency of eco-efficiency is at a mid to upper level, and the regional development is not balanced. The development within the frontier of the group is being integrated. The dynamic changes of TGR show that in the 5 years from 2011 to 2015, there was a downward trend in North China, East China, Central China, South China, and Southwest China. The blind pursuit of rapid development has neglected improvement at the technical level. The northeast and northwest regions showed a slowly rising trend. In recent years, with the support and active promotion of state policies, economic and technological development has achieved good results. Overall development of overall planning has a positive

effect on the optimization of ecological efficiency; on the contrary, it will have a negative impact.

In recent years, the increase of per capita GDP, increase of R&D investment in provinces, and increase of the proportion of provincial imports and exports in regional GDP has promoted efficient and healthy regional development and has had a positive effect on ecological efficiency. On the other hand, an increase in the urbanization rate of the resident population in a province means an increase in the urban load and an overload of population over the environmental capacity. The higher the consumer price index is, the greater the degree of resource consumption and environmental damage will be. Each province accounted for a larger proportion of the GDP, a higher proportion of energy consumption, more industrial pollution control completed investment, and increase in the proportion of the industrial structure. These all have a negative impact on eco-efficiency improvement. An increase is usually accompanied by a decline in ecological efficiency. China's economic development is still basically following the extensive mode of development at the expense of resource consumption and environmental pollution. Energy-saving emission reduction and upgrading of the large-scale structural transformation has yet to occur.

Policy recommendations

We should continue to adhere to the supply-side structural reforms and transform the “end of the pipe” to “the source of prevention and control,” and gradually eliminate the backward and excess capacity of “high input, high pollution, high energy consumption, low efficiency”. We ought to focus on improving the quality and efficiency of the supply system, enhance the momentum of sustained economic growth, and promote the level of social productivity in China to achieve the overall leap, the ecological environment of a virtuous circle, circular economy for healthy development.

We should continue to adhere to the “innovation-driven-development” strategy and promote the concept of development gradually changing from “win by quantity” to “win by quality”; improve the technology gap ratio (TGR) gradually, leverage structural adjustment, stimulate the development mode transformation and upgrade with the power of innovation; then, gradually reverse the serious situation of China's resource consumption, environmental pollution, and severe degradation of ecosystems by institutional and technological innovation, development pattern innovation, and other means.

We need to improve the use efficiency of government funds for improving the ecosystem and develop a more scientific capital use plan to ensure the optimum use of government spending and minimize the negative effects of improper use of funds.

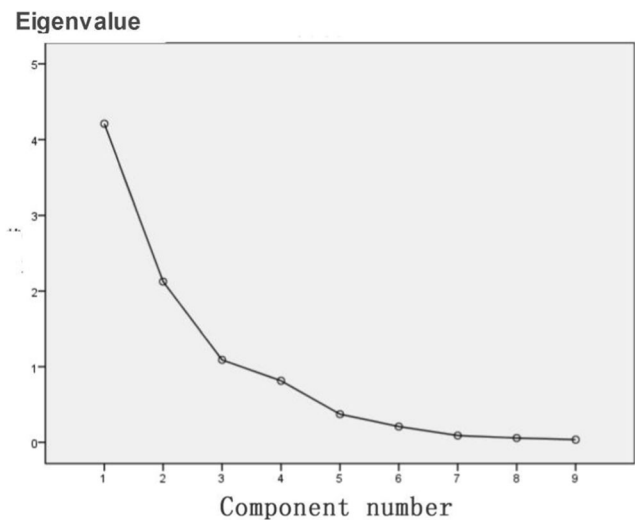
We need to strengthen the introduction of quality management of foreign-funded enterprises in opening up to the outside world, improve the introduction and absorption efficiency of high-tech industries, and optimize and upgrade the industrial structure, meanwhile strengthen the cultivation of output power of local enterprises in opening to the outside world and create an industrial cluster with international competitiveness, and eventually achieve ecological and economic sustainable development.

We need to strengthen interprovincial and provincial collaborative development and common governance, gradually establish a cross-administrative regional joint control coordination mechanism of key regions, river basin environmental pollution, and ecological damage, and then implement unified planning, unified standards, unified monitoring, and unified prevention and control measures and finally establish and improve a better, stronger ecological monitoring system.

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Appendix:

Gravel map



The results of principle component analysis

Correlation coefficient matrix											
		GR	LN GP	PI	DT	RD	UR	EC	MI	CPI	IPC
Correlation	GR	1	0.167	0.011	0.588	0.408	0.317	0.851	-0.378	0.404	0.731
coefficient	LN GP	0.167	1	-0.197	0.09	0.105	0.358	0.293	-0.046	0.228	0.374
	PI	0.011	-0.197	1	-0.134	-0.198	-0.359	-0.082	0.073	-0.294	0.047
	DT	0.588	0.09	-0.134	1	0.58	0.728	0.277	-0.406	0.795	0.281
	RD	0.408	0.105	-0.198	0.58	1	0.803	0.115	-0.218	0.822	0.166
	UR	0.317	0.358	-0.359	0.728	0.803	1	0.044	-0.257	0.944	0.143
	EC	0.851	0.293	-0.082	0.277	0.115	0.044	1	-0.152	0.101	0.814
	MI	-0.378	-0.046	0.073	-0.406	-0.218	-0.257	-0.152	1	-0.231	-0.085
	CPI	0.404	0.228	-0.294	0.795	0.822	0.944	0.101	-0.231	1	0.207
	IPC	0.731	0.374	0.047	0.281	0.166	0.143	0.814	-0.085	0.207	1

KMO and Bartlett test		
KMO Sampling adequacy measure κ		0.708
Bartlett's	Last read card side	229.31
Sphericity test	Degree of freedom	36
	Significance	0

Total variance explained									
Component	Initial eigenvalue			Extract the square sum of loads			Rotate the sum of the squares of the load		
	total	percentage	percentage	total	percentage	percentage	total	percentage	percentage
1	3.276	40.944	40.944	3.276	40.944	40.944	2.624	32.794	32.794
2	1.524	19.046	59.99	1.524	19.046	59.99	1.959	24.483	57.278
3	1.166	14.57	74.56	1.166	14.57	74.56	1.383	17.283	74.56
4	0.82	10.251	84.811						
5	0.738	9.223	94.034						
6	0.366	4.571	98.605						
7	0.066	0.82	99.425						
8	0.046	0.575	100						

Rotated composition matrix a			
	Component		
	1	2	3
GR	0.329	0.874	-0.245
LN GP	0.257	0.344	0.724
DT	0.786	0.305	-0.296
RD	0.865	0.084	-0.051
UR	0.973	0.04	0.12
EC	-0.002	0.962	0.015
MI	-0.3	-0.243	0.623
CPI	0.968	0.099	0.017
IPC	0.089	0.901	0.184

Component Score Coefficient Matrix			
	Component		
	1	2	3
GR	-0.006	0.314	-0.214
LN GP	0.085	0.099	0.67
DT	0.199	0.038	-0.228
RD	0.263	-0.062	0.002
UR	0.312	-0.093	0.164
EC	-0.106	0.382	0.002
MI	-0.033	-0.071	0.553
CPI	0.298	-0.068	0.07
IPC	-0.061	0.346	0.162

Brief author introduction

Xiaojun Ma (1978–) is an associate professor and doctor from Liaoning Fushun and her research focus is macroeconomic statistics. She has presided over two national social science fund projects and four provincial and ministerial level projects. She won second prize for the Liaoning Province Philosophy and Social Science Achievement Award (the fifth provincial government award) in 2015 and first prize for the Liaoning Province Natural Science Achievement Award in 2017. She has published two national monographs and more than 30 papers in “management of the world”, “People’s daily (theoretical)”, “China’s environmental science”, “system science and mathematics” as well as other core journals.

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