



The evolution and determinants of Chinese inter-provincial green development efficiency: an MCSE-DEA-Tobit-based perspective

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Abstract

Continuous and rapid economic development has brought about excessive resource consumption and environmental pollution. Therefore, it is particularly essential to coordinate economic, resource, and environmental factors to achieve sustainable development. This paper develops a new data envelopment analysis (DEA) method that can be used for multi-level complex system evaluation (MCSE-DEA) to reveal the inter-provincial green development efficiency (GDE) in China from 2010 to 2018. Moreover, the Tobit model is applied to explore the influencing factors of GDE. We found that (i) the MCSE-DEA model tends to have lower efficiency scores than the traditional P-DEA (panel data envelopment analysis) model, and the top three provinces are Shanghai, Tianjin, and Fujian; (ii) the efficiency shows an increasing trend during the whole study period. The southeast region and the Middle Yangtze River region have the highest efficiency values, reaching 1.09, while the northwest region ranks last with an average efficiency value of 0.66. Shanghai performs the best, while Ningxia performs the worst, with efficiency values of 1.43 and 0.58, respectively; (iii) the provinces with lower efficiency values mainly come from economically underdeveloped remote regions, which can be attributed to issues of water consumption (WC) and energy consumption (EC). Moreover, there are much room for improvement in solid waste emissions (SW) and soot and industrial dust emissions (SD); (iv) the environmental investment, R&D investment, and economic development level can significantly improve GDE, while industrial structure, urbanization level, and energy consumption have inhibiting effects.

Keywords Sustainable development · Green development efficiency · Efficiency assessment · Data envelopment analysis · Multi-level complex system evaluation

Introduction

The economic development mode characterized by high consumption, high pollution, and high emissions leads to a large number of countries entering resource bottlenecks and ecological deterioration, causing increasingly fierce competition for energy and resources, and severe pressure on environmental protection (Deng et al. 2017; Wang et al.

2017). As an essential representative of emerging economies, China also faces a dilemma in unbalanced resource allocation, large energy consumption, and environmental severe pollution (Dong et al. 2021). Currently, China is the world's largest energy consumer (BP 2020). According to the data of the National Bureau of Statistics of China in 2021, the energy consumption of China reached the value of 4.98 billion tons of standard coal in 2020 (NBSC 2021). In addition, in terms of the environmental performance index released by Yale University, the environmental pollution of China ranks second in the world (Dong et al. 2020), and the ecological problems caused by the pursuit of economic development are exposed.

The United Nations (UN) Sustainable Development Goals (SDGs) aim to address economic, social, and environmental issues that hinder progress in global sustainable development (Gue et al. 2020). Nowadays, the SDGs are a recognized blueprint for global development by 2030 and are used by businesses, industry, governments, and regional

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organizations (Belmonte-Ureña et al. 2021). Nevertheless, resource-energy and economic-environmental constraints have become the obvious obstacles to sustainable industrial development in the future (Bai et al. 2017). The current resource and environmental problems faced by China have attracted significant attention, and therefore the government has set out to establish a green, low-carbon cycle economic development system, and launched a series of strategic decisions on “green development”. Moreover, the Fifth Plenary Session of the 19th CPC Central Committee also proposed to focus on improving the ecosystem quality and stability, so as to achieve sustainable and high-quality development. Overall, it is urgent to coordinate economic, resource, and environmental factors to promote green development.

Actually, the concept of green development has become an alternative to sustainable development (Liu et al. 2022), and its key lies in the construction of green development efficiency (GDE) for enhancing economic development quality (Rashidi and Farzipoor Saen 2015). Wang and Huang (2014) found that most studies considered the efficiency of environmental factors as environmental efficiency, while the concept of environmental efficiency was inconsistent. In this context, they proposed the concept of green development efficiency to reflect the efficiency level of increased economic output while reducing environmental pollution emissions with a given input. GDE takes into account both resource, environmental, and economic factors, and thus has been extensively studied. Zhao et al. (2016) applied the SBM model to calculate the GDE in China from 1997 to 2013, indicating that the GDE was generally low and the human capital and industrial structure interaction items had a positive effect. Zhu et al. (2020) adopted the ultra-efficiency SBM model to measure the GDE in China from 1999 to 2017, and analyzed the impact of the carbon trading mechanism on the GDE. They found that the GDE showed a *u*-shaped trend, and the carbon trading mechanism had a positive effect. Ding et al. (2022) employed a spatial econometric model to investigate the influencing factors of GDE and found that industrial collaborative agglomeration played a positive role in promoting regional green development. Overall, a scientific evaluation of China’s GDE is of practical importance to reveal the current situation and development direction of green development in China.

Data envelopment analysis (DEA) is a non-parametric method proposed by Charnes et al. (1979) to assess the relative effectiveness among decision-making units (DMUs). It can integrate inputs and outputs in different dimensions with objective weights emerging from the data to reflect the input–output efficiency. On this basis, scholars have proposed multiple DEA models for specific problems and have various applications in different performance evaluation problems (Färe et al. 1992; Tone 2001). GDE is a complex system including resource factors, economic factors,

and environmental factors. Therefore, the DEA method, as an efficiency evaluation method, is especially suitable for the evaluation problem of complex systems (Ma et al. 2018). Actually, the DEA method has been widely applied in analyzing GDE problems (Yang et al. 2020). However, the complexity of the indicator system makes the DEA method have the following shortcomings in evaluating the complex system. On the one hand, the traditional DEA model is mainly based on sectional data and measures the efficiency of DMUs by constructing different technology frontier surfaces. On the other hand, the traditional DEA model has the defects in the same status of indicators and the inability to distinguish effective DMU. Therefore, applying the traditional DEA model to evaluate GDE will suffer from bias.

In addition, there is significant heterogeneity across Chinese provinces in terms of technology level, resource endowment, and industrial structure, leading to regional variability in their GDE. Wang et al. (2021) applied the DEA-Theil model to measure the regional energy efficiency in China and found that the overall energy efficiency was low, accompanied by significant province differences. Yang et al. (2017) used the directional distance function to calculate the provincial green development efficiency from 2003 to 2012, noting that the southern and eastern areas performed the best, while the central and southwest Yangtze River regions performed relatively poorly. Therefore, it is necessary to accurately and reasonably examine GDE and its influencing factors to identify possible shortcomings.

In summary, the traditional DEA model has some defects in evaluating the complex system evaluation problems, and there are large inter-provincial differences in green development efficiency in China. Therefore, this paper has the following innovations: First, the P-SBM model based on the same technology frontier surface that can be used for dynamic efficiency analysis of panel data is developed to measure the efficiency of all DMUs. Second, the MCSE-DEA (multi-level complex system evaluation) model is proposed to address the problems of the same status of indicators and the inability to distinguish effective DMU of the P-DEA model in evaluating the efficiency of complex systems. Overall, in this paper, we firstly measure the GDE of 30 Chinese provinces from 2010 to 2018 based on the MCSE-DEA model. And then the Tobit model is adopted to investigate the influencing factors of GDE. Overall, an accurate and reasonable evaluation of the current situation and influencing factors of GDE in China can promote economic growth with low resource input and environmental impact, which is meant to promote green development in China.

This article consists of 6 sections. The “Introduction” section presents the introduction. The “Literature review” section presents the literature review of existing research. The “Methodology” section presents the MCSE-DEA model that can solve the shortcomings of the P-DEA model in

evaluating the efficiency of complex systems. The “Indicator system and descriptive statistics” section presents the indicator system and descriptive statistics. The “Results and discussion” section presents the current situation of inter-provincial green development in China and the influencing factors. The “Conclusion and policy recommendations” section presents the conclusion and policy recommendations.

Literature review

Green development efficiency, as a critical proxy for green development quality, has been extensively studied from different perspectives, such as the national-level analysis (Rashidi and Farzipoor Saen 2015; Shao et al. 2019; Yang and Ni 2022), regional-level analysis (Chen and Lin 2020; Matsumoto and Chen 2021; Yang and Zhang 2018), city-level analysis (Liu et al. 2020, 2021; Xiao et al. 2021), and industry-level analysis (Shao et al. 2019; Wang et al. 2019; Xing et al. 2018). Particularly, research on the efficiency evaluation of green development in China has become an essential topic and has progressed (Liu et al. 2022). For example, Shao et al. (2019) used the dynamic network DEA approach (DNDEA) to assess the two-stage eco-efficiency of the Chinese industry from 2007 to 2015. The study found that eastern China performed best, followed by central and western regions. Shuai and Fan (2020) explored the role of environmental regulations in the efficiency improvement of the regional green economy in China from 2007 to 2018, based on the DEA-Tobit model. The results show that the green economy efficiency level of China was on the rise during the study period, and environmental regulation influence on the efficiency of the green economy presented a “U” shaped curve. Zhao et al. (2022) examined the economic growth and intrinsic drivers of 286 prefecture-level cities in China from 2003 to 2018 based on the Metafrontier-global-SBM super-efficiency method. The empirical results show that green economy growth performed well, and the innovation effect was the main factor driving the growth. It can be seen that the DEA method has been widely used for energy economic and environmental efficiency evaluation.

In terms of GDE measurement methods, there are mainly the stochastic frontier approach (SFA) and DEA method, with the former being a parametric method and the latter being a non-parametric method. For the parametric approach, the SFA method can distinguish the random error term from the inefficiency term, making the measurement results more accurate and reasonable, and thus has been widely used. Song and Chen (2019) estimated China’s food production and eco-efficiency based on the water footprint SFA, finding that GDP per capita and water supply per capita had a positive effect on food production eco-efficiency. Koengkan et al. (2022) measured the performance

of economic efficiency in Latin America based on the SFA and DEA approaches, showing that Panama was the most economically efficient country in Latin America, followed by Chile. Haider and Mishra (2021) adopted the Bayesian SFA method to measure the corporate energy efficiency of 82 Indian steel companies from 2003 to 2017, indicating that most companies could reduce their energy consumption by half. It can be seen that the SFA method has a certain application in energy and environmental efficiency evaluation. However, the SFA method needs to assume a production function, which is susceptible to the effects of specifying the form of the production function and in turn causes computational errors.

As for the non-parametric method, the DEA method does not need to set the specific form of the production function in advance, which can effectively avoid the above problems of the SFA method, and thus has great advantages in terms of the efficiency measurement. Zhang and Chen (2022) evaluated energy efficiency in Regional Comprehensive Economic Partnership Agreement (RCEP) countries based on the SBM-DEA model, noting that the overall energy efficiency of RCEP was poor, and optimizing the industrial structure and energy consumption structure can improve energy efficiency. Peiro-Palomino and Picazo-Tadeo (2019) applied the DEA method to analyze GDE in EU countries and found that the main driver of environmental efficiency was economic development. In addition, the 2016 Research Frontiers report released by the Chinese Academy of Sciences also indicates that the DEA method has been the most popular method in energy and environmental efficiency evaluation in recent years. Hence, this paper applies the DEA method to measure the GDE in China.

However, the complexity of the indicator system makes the DEA method have the following shortcomings. First, there are different levels of indicators for the complex multi-level system. To be specific, the indicators used in the traditional DEA model have the same levels, leading to the evaluation results overemphasizing the role of secondary factors and biasing the measurement results. And if the weighted sum method is used to synthesize secondary indicators, it is difficult to detect the improved information on the original indicators. Second, multi-level complex systems can have an efficiency value of 1 for most of the DMUs, which is mainly caused by the high number of evaluation indicators and thus the inability to distinguish effective units (Ma et al. 2018). And the traditional DEA model based on sectional data does not allow for analysis of panel data. Therefore, the efficiency values measured by this model are not comparable.

In terms of the research on the influencing factors of green development efficiency, scholars at home and abroad have achieved fruitful results. Regarding the selection of influencing factors, researchers generally analyze the urbanization (Li et al. 2020), industrial

structure (Yang et al. 2022), environmental regulation (Passetti and Tenucci 2016), R&D investment (Zhang et al. 2021), and FDI (Zhang 2020). For example, some studies have shown that environmental regulation and technological progress have a driving effect on industrial green total factor productivity (Wang and Zhao 2021). Lin and Zhou (2022) indicated that urbanization might promote green economic growth, while population size and foreign direct investment might inhibit green economic growth. Zhu et al. (2019) found that industrial structure rationalization and advancement can positively affect green development efficiency.

Therefore, this paper will further carry out the following work given the shortcomings of existing research. First, the MCSE-DEA model proposed to address the problems of the same status of indicators and the inability to distinguish effective DMU of the P-DEA model. Second, this paper measures China’s inter-provincial GDE from 2010 to 2018 based on the MCSE-DEA model and compares the results with the P-DEA model. Finally, we apply the MCSE-DEA-Tobit model to analyze the status of inter-provincial GDE and its influencing factors. In summary, the research framework of this study is illustrated in Fig. 1.

Methodology

DEA model with undesirable outputs

Assuming that there are n DMUs, where $x_j = (x_{1j}, x_{2j}, \dots, x_{mj})^T$ is the input indicator value for the j th DMU, $y_j = (y_{1j}, y_{2j}, \dots, y_{sj})^T$ is the desirable output indicator value for the j th DMU, and $\bar{y}_j = (\bar{y}_{1j}, \bar{y}_{2j}, \dots, \bar{y}_{lj})^T$ is the undesirable output indicator value for the j th DMU,

and that the indicator values for each DMU are positive, Korhonen and Luptacik (2004) give the following DEA model considering the undesirable output can be formulated as follows:

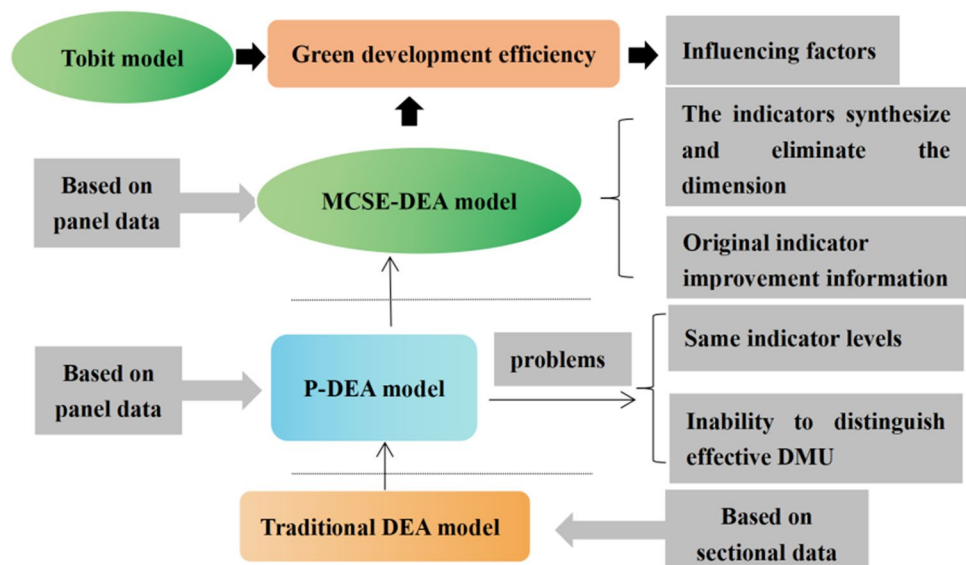
$$\left\{ \begin{array}{l} \max \varphi + \varepsilon (\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ + \sum_{k=1}^l \bar{s}_k^+) \\ \text{s.t. } \sum_{j=1}^n x_j \lambda_j + s^- = x_{j_0} \\ \sum_{j=1}^n y_j \lambda_j - s^+ = \varphi y_{j_0} \\ \sum_{j=1}^n \bar{y}_j \lambda_j + \bar{s}^+ = \bar{y}_{j_0} \\ \delta \sum_{j=1}^n \lambda_j = \delta \\ \lambda \geq 0, s^- \geq 0, s^+ \geq 0, \bar{s}^+ \geq 0. \end{array} \right. \quad (1)$$

P-DEA model used for energy and environmental efficiency evaluation

It is assumed that in the evaluation of GDE, there are n DMU with a total of T periods of data. The selected input indicators are capital stock (CS), total employment (TE), construction land area (CL), water consumption (WC), and energy consumption (EC). Gross domestic product (GDP) as a desirable output indicator, solid waste emissions (SW), domestic garbage removal volume (DG), CO₂ emissions (CO), SO₂ emissions (SO), NOx emissions (NO), soot and industrial dust emissions (SD), and total waste water emissions (WW) are undesirable output indicators. The input–output indicators for the j th DMU in period t are $x_j^t = (CS_j^t, TE_j^t, CL_j^t, WC_j^t, EC_j^t)$, $y_j^t = GDP_j^t$, $\bar{y}_j^t = (SW_j^t, DG_j^t, CO_j^t, SO_j^t, NO_j^t, SD_j^t, WW_j^t)$, and the values of each input and output indicator are positive.

The P-DEA model with undesirable outputs is based on panel data, where the efficiency model of the j_0 th DMU in period t with respect to period t_0 is as follows:

Fig. 1 The research framework of GDE measurement based on MCSE-DEA-Tobit model



$$\left\{ \begin{aligned} & \max \varphi_{j_0}^t + \varepsilon (\sum_{i=1}^5 s_i^- + s^+ + \sum_{r=1}^7 \bar{s}_r^+) \\ \text{s.t. } & \sum_{j=1}^n (CS_j^{t_0}, TE_j^{t_0}, CL_j^{t_0}, WC_j^{t_0}, EC_j^{t_0}) \lambda_j + s^- = (CS_{j_0}^t, TE_{j_0}^t, CL_{j_0}^t, WC_{j_0}^t, EC_{j_0}^t) \\ & \sum_{j=1}^n GDP_j^{t_0} \lambda_j - s^+ = \varphi_{j_0}^t GDP_{j_0}^t \\ & \sum_{j=1}^n (SW_j^{t_0}, DG_j^{t_0}, CO_j^{t_0}, SO_j^{t_0}, NO_j^{t_0}, SD_j^{t_0}, WW_j^{t_0}) \lambda_j + \bar{s}^+ = (SW_{j_0}^t, DG_{j_0}^t, CO_{j_0}^t, SO_{j_0}^t, NO_{j_0}^t, SD_{j_0}^t, WW_{j_0}^t) \\ & \delta \sum_{j=1}^n \lambda_j = \delta \\ & \lambda \geq 0, s^- \geq 0, s^+ \geq 0, \bar{s}^+ \geq 0. \end{aligned} \right. \tag{2}$$

where $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)$, $s^- = (s_1^-, s_2^-, \dots, s_5^-)$, $\bar{s}^+ = (\bar{s}_1^+, \bar{s}_2^+, \dots, \bar{s}_7^+)$, ε is a non-Archimedean infinitesimal quantity, and φ is the efficiency of the j_0 th DMU. δ is a parameter taking values 0, 1, when $\delta = 0$, the production activity satisfies constant returns to scale (CRS), and φ is the comprehensive efficiency value and measures the resource utilization and resource allocation ability in the green development process; when $\delta = 1$, the production activity satisfies variable returns to scale (VRS). φ is the pure technical efficiency value and measures the technical level of converting inputs into outputs.

Assuming that $\varphi^0, \lambda^0, s^{-0}, s^{+0}, \bar{s}^{+0}$ is the optimal solution of model (2) such that

$$\begin{aligned} \hat{x}_{j_0}^t &= (CS_{j_0}^t, TE_{j_0}^t, CL_{j_0}^t, WC_{j_0}^t, EC_{j_0}^t) - s^{-0} \hat{y}_{j_0}^t = \varphi_{j_0}^t GDP_{j_0}^t + s^{+0} \\ \hat{y}_{j_0}^t &= (SW_{j_0}^t, DG_{j_0}^t, CO_{j_0}^t, SO_{j_0}^t, NO_{j_0}^t, SD_{j_0}^t, WW_{j_0}^t) - \bar{s}^{+0} \end{aligned} \tag{3}$$

and call $(\hat{x}_{j_0}^t, \hat{y}_{j_0}^t, \hat{y}_{j_0}^t)$ as the projection of the j_0 th decision unit. Let

$$\Delta x_{j_0}^t = x_{j_0}^t - \hat{x}_{j_0}^t, \Delta y_{j_0}^t = \hat{y}_{j_0}^t - y_{j_0}^t, \Delta \bar{y}_{j_0}^t = \bar{y}_{j_0}^t - \hat{y}_{j_0}^t \tag{4}$$

then $(\Delta x_{j_0}^t, \Delta y_{j_0}^t, \Delta \bar{y}_{j_0}^t)$ reflects the deficiencies and improvement directions of the production of the j_0 th decision unit in period t relative to period t_0 .

MCSE-DEA model

In model (2), it is not reasonable to put GDP and CO₂, SO₂, and NO_x in equal position to measure the efficiency values. Therefore, the following combines construction land area (CL), water consumption (WC), and energy consumption (EC) into one indicator of resource utilization (RU), and the specific synthesis formula is as follows:

$$\begin{aligned} \overline{RU}_j &= \frac{CL_j^t}{3 \max_{1 \leq j \leq n} CL_j^t} + \frac{WC_j^t}{3 \max_{1 \leq j \leq n} WC_j^t} + \frac{EC_j^t}{3 \max_{1 \leq j \leq n} EC_j^t} \\ &= a_3 CL_j^t + a_4 WC_j^t + a_5 EC_j^t \end{aligned} \tag{5}$$

In addition, to eliminate the influence of the magnitude on each index, take

$$\begin{aligned} \overline{CS}_j^t &= \frac{CS_j^t}{\max_{1 \leq j \leq n} CS_j^t} = a_1 CS_j^t, \overline{TE}_j^t = \frac{TE_j^t}{\max_{1 \leq j \leq n} TE_j^t} \\ &= a_2 TE_j^t, \overline{GDP}_j^t = \frac{GDP_j^t}{\max_{1 \leq j \leq n} GDP_j^t} = b_0 GDP_j^t. \end{aligned} \tag{6}$$

This way $(\overline{CS}_j^t, \overline{TE}_j^t, \overline{RU}_j^t)$ gives a complete picture of the inputs in terms of money, people, and resources.

At the same time, the undesirable output $(SW_j^t, DG_j^t, CO_j^t, SO_j^t, NO_j^t, SD_j^t, WW_j^t)$ is synthesized into an indicator of the amount of waste output (WO) by the following formula:

$$\begin{aligned} \overline{WO}_j^t &= \frac{SW_j^t}{7 \max_{1 \leq j \leq n} SW_j^t} + \frac{DG_j^t}{7 \max_{1 \leq j \leq n} DG_j^t} + \frac{CO_j^t}{7 \max_{1 \leq j \leq n} CO_j^t} \\ &+ \frac{SO_j^t}{7 \max_{1 \leq j \leq n} SO_j^t} + \frac{NO_j^t}{7 \max_{1 \leq j \leq n} NO_j^t} + \frac{SD_j^t}{7 \max_{1 \leq j \leq n} SD_j^t} + \frac{WW_j^t}{7 \max_{1 \leq j \leq n} WW_j^t} \\ &= b_1 SW_j^t + b_2 DG_j^t + b_3 CO_j^t + b_4 SO_j^t + b_5 NO_j^t + b_6 SD_j^t + b_7 WW_j^t, \end{aligned} \tag{7}$$

The model can be expressed as follows:

$$\left\{ \begin{aligned} & \max \varphi_{j_0}^{ct} + \varepsilon (\sum_{i=1}^3 s_i^c + s^{cq} + s^{cw}) \\ \text{s.t. } & \sum_{j=1}^n (\overline{CS}_j^{t_0}, \overline{TE}_j^{t_0}, \overline{RU}_j^{t_0}) \lambda_j + s^c = (\overline{CS}_{j_0}^t, \overline{TE}_{j_0}^t, \overline{RU}_{j_0}^t) \\ & \sum_{j=1}^n \overline{GDP}_j^{t_0} \lambda_j - s^{cq} = \varphi_{j_0}^{ct} \overline{GDP}_{j_0}^t \\ & \sum_{j=1}^n \overline{WO}_j^{t_0} \lambda_j + s^{cw} = \overline{WO}_{j_0}^t \\ & \delta \sum_{j=1}^n \lambda_j = \delta \\ & \lambda \geq 0, s^c \geq 0, s^{cq} \geq 0, s^{cw} \geq 0 \end{aligned} \right. \tag{8}$$

Assuming that $\varphi^{c0}, \lambda^0, s^{c0}, s^{cq0}, s^{cw0}$ is the optimal solution of model (8), the projection formula for the j_0 th DMU given by model (8) is as follows:

$$\tilde{x}_j = (\overline{CS}_{j_0}^t, \overline{TE}_{j_0}^t, \overline{RU}_{j_0}^t) - s^{c0} \tilde{y}_j = \varphi_{j_0}^{ct0} \overline{GDP}_{j_0}^t + s^{cq0} \tilde{y}_j = \overline{WO}_{j_0}^t - s^{cw0} \tag{9}$$

According to Eq. (9), it can be seen that model (8) is difficult to find the improvement information against the original

indicators and etc. Therefore, this paper further gives the model that can reflect the improvement information against the original indicators as follows:

$$Y_{jt} = \begin{cases} Y_{jt}^* = \beta_0 + \sum_{t=1}^n \beta_t x_{jt} + \varepsilon_{jt}, Y_{jt}^* > 0 \\ 0, Y_{jt}^* \leq 0, \end{cases} \tag{13}$$

$$\left\{ \begin{aligned} & \max \varphi + \varepsilon(a_1 s_1^- + a_2 s_2^- + b_0 s^{q+} + \sum_{i=3}^5 a_i s_i^- + \sum_{r=1}^7 b_r s_r^{w+}) \\ \text{s.t. } & \sum_{j=1}^n (CS_j^{t_0}, TE_j^{t_0}, CL_j^{t_0}, WC_j^{t_0}, EC_j^{t_0}) \lambda_j + s^- = (CS_{j_0}^t, TE_{j_0}^t, CL_{j_0}^t, WC_{j_0}^t, EC_{j_0}^t) \\ & \sum_{j=1}^n GDP_j^{t_0} \lambda_j - s^{q+} = \varphi GDP_{j_0}^t \\ & \sum_{j=1}^n (SW_j^{t_0}, DG_j^{t_0}, CO_j^{t_0}, SO_j^{t_0}, NO_j^{t_0}, SD_j^{t_0}, WW_j^{t_0}) \lambda_j + s^{w+} = (SW_{j_0}^t, DG_{j_0}^t, CO_{j_0}^t, SO_{j_0}^t, NO_{j_0}^t, SD_{j_0}^t, WW_{j_0}^t) \\ & \delta \sum_{j=1}^n \lambda_j = \delta \\ & \sum_{i=3}^5 a_i s_i^- \geq 0, \sum_{r=1}^7 b_r s_r^{w+} \geq 0 \\ & \lambda \geq 0, s_1^-, s_2^-, s^{q+} \geq 0 \end{aligned} \right. \tag{10}$$

Assuming that $\bar{\varphi}, \bar{\lambda}, \bar{s}^-, \bar{s}^{q+}, \bar{s}^{w+}$ is the optimal solution to model (10), we define

$$\begin{aligned} \bar{x}_j &= (CS_{j_0}^t, RK_{j_0}^t, CL_{j_0}^t, WC_{j_0}^t, EC_{j_0}^t) - \bar{s}^-, \bar{y}_j = \bar{\varphi} GDP_{j_0}^t + \bar{s}^{q+} \\ \bar{y}_j^w &= (SW_{j_0}^t, DG_{j_0}^t, CO_{j_0}^t, SO_{j_0}^t, NO_{j_0}^t, SD_{j_0}^t, WW_{j_0}^t) - \bar{s}^{w+}, \end{aligned} \tag{11}$$

is the projection of the j_0 th DMU.

It can be verified by the empirical analysis section that model (10) and model (8) give equal values of the efficiency of the DMU. And Eq. (11) can decompose the projection given by Eq. (9) into the original indicators. Let

$$\Delta x_j = x_j - \bar{x}_j, \Delta y_j = \bar{y}_j - y_j, \Delta y_j^w = y_j^w - \bar{y}_j^w. \tag{12}$$

Unlike the projection given in model (1), in Eq. (12), if (or $\Delta x_{ij} \geq 0$ or $\Delta x_{ij} \leq 0$) indicates that the j th DMU is deficiencies (or more efficient) on the i th input indicator. If (or $\Delta y_j^w \geq 0$ or $\Delta y_j^w \leq 0$) means that the j th DMU is under-input (or more efficient) on the r th undesirable output indicator.

Tobit model

The GDE measured in this paper is greater than 0, which is a “restricted dependent variable,” and the Tobit model can solve the regression problem of “restricted dependent variable” well. Thus, the Tobit model is established to analyze the GDE empirically. The equation of the Tobit model is as follows:

where Y_{jt} is the dependent variable, x_{jt} is the independent variable, β_0 is the constant term, β_t is the estimated coefficient vector, ε_{jt} is the random error perturbation term, and $\varepsilon_{jt} \sim (0, \sigma^2)$.

Based on green development theory and drawing on existing research results (Ding et al. 2022; Xu et al. 2022), this paper selects the following six variables as the influencing factors of GDE (as shown in Table 1) and explores the influence of these factors on GDE.

Indicator system and descriptive statistics

Due to data availability, the DMUs in this paper are the 30 provinces, autonomous regions, and municipalities directly under the central government (referred to as provinces) except Tibet, Hong Kong, Macau, and Taiwan. The relevant data are obtained from the China Statistical Yearbooks (NBSC, 2011–2019), China Environmental Statistical Yearbooks (NBSC, 2011–2019), and China Energy Statistical Yearbooks (NBSC, 2011–2019). The indicators used in this paper are as follows.

- (1) The input indicators include capital, labor, and natural resources (as shown in Fig. 2). We use the estimation method proposed by Zhang et al. (2004) to calculate the capital stock. The calculation formula is $K_j^t = I_j^t + (1 - \delta)K_j^{t-1}$, where K_j^t and K_j^{t-1} represent the capital stock of province j in period t and $t - 1$, respectively. I_j^t is the total fixed asset investment in

Table 1 Indicators of influencing factors of green development efficiency

Variable name	Variable definition
Industrial structure (IS)	Share of the secondary industry in GDP
Environmental policy (EP)	Spending on environmental protection accounts for GDP
Urbanization level (UL)	The proportion of the urban population in the total population
R&D input (RD)	Share of R&D expenditure in GDP
Economic development (ED)	Per capita GDP
Energy consumption (EC2)	Per capita electricity consumption

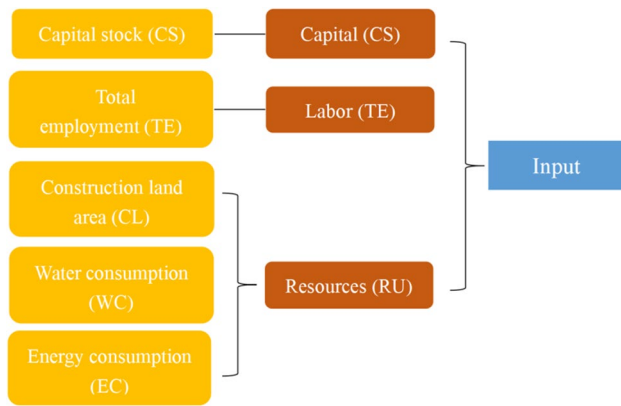


Fig. 2 Input indicators

period t , and δ is the depreciation rate. We convert the energy consumption in resource inputs into standard coal.

- (2) Output indicators include desirable output and undesirable output (as shown in Fig. 3), where desirable output is GDP, and undesirable output is waste pollutants. For desirable output, we treat GDP as constant 2000 prices. For undesirable output, we use the IPCC reference method (Paustian et al. 2006) to calculate energy-related CO₂ emissions.

Descriptive statistics are given in Table 2. It can be seen that the growth rates of construction land area, energy consumption, GDP, solid waste emissions, household refuse, CO₂ emissions, soot and industrial dust emissions, and total waste water emissions are 27.43%, 20.05%, 92.47%, 60.21%, 44.07%, 24.50%, 30.46%, and 2.53%, respectively, while SO₂ and NO_x emissions can be observed a negative growth of -70.11% and -26.19%, respectively. This indicates that rapid economic development

is accompanied by resource consumption. In terms of pollutant emissions, although some pollution emissions have increased, there are also reductions in emissions like SO₂ and NO_x, indicating an improvement in green development. In addition, there are significant differences in these indicators, showing that there are large differences among provinces in terms of various inputs, GDP, and pollutant emissions.

To better analyze the regional characteristics, we divide the 30 provinces into six regions: northeast, southeast, southwest, northwest, Middle Yangtze River, and Middle Yellow River (Tang et al. 2016). The northeast region includes the provinces of Heilongjiang, Jilin, and Liaoning, which are rich in resources such as coal and oil (Wang and Huang 2014). The southeast region includes Guangdong, Hainan, Fujian, and Guangxi, of which Fujian and Hainan have more developed coastal tourism economies (Yang et al. 2020). The southwest region consists of four provinces (Chongqing, Guizhou, Sichuan, and Yunnan), which are an essential base for developing China's non-ferrous metal industry and strategic reserves. The northwest region consists of five remote provinces (Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang), which are remote, harsh, and sparsely populated, but rich in resources (e.g., oil, coal, and natural gas) (Dong et al. 2021). The Middle Yangtze River (Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, and Hunan) is an essential base for grain, oil, and cotton production in China. They are also the most water-rich regions in China (Tang et al. 2016). Among them, Shanghai, Jiangsu, and Zhejiang have abundant physical and human capital and are three of the most powerful economic entities in China. The Middle Yellow River (Beijing, Tianjin, Hebei, Henan, Shandong, Shanxi, and Inner Mongolia) is rich in hydro energy, coal, oil, natural gas, and minerals, and occupies an essential position in the country with excellent development potential (Wang and He 2022). Among them, Beijing and Tianjin have a large economic capacity and advanced technology.

Fig. 3 Output indicators

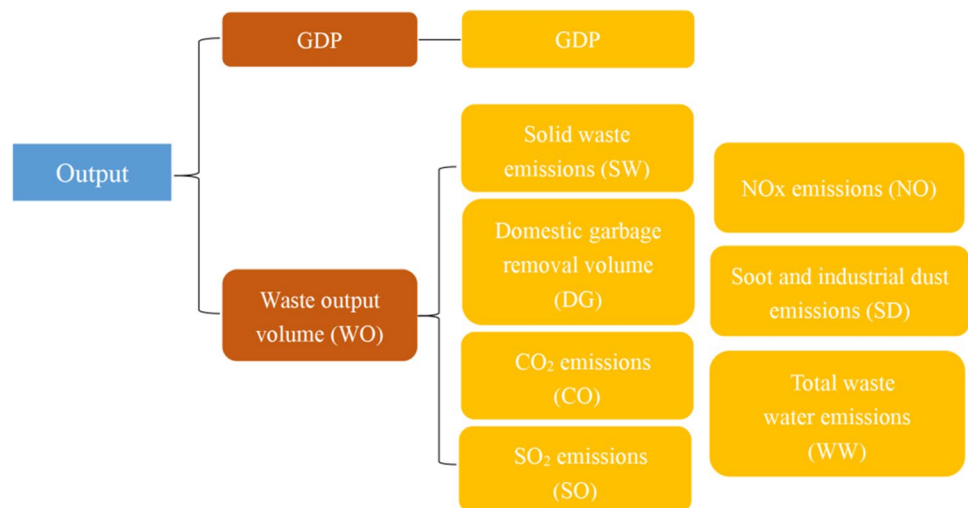


Table 2 Descriptive statistics of data used in this study (2010–2018, 30 provinces)

Indicators	Unit	Max	Min	Mean	Range	Growth rate
Input indicators						
Capital stock	Billion yuan	299,476.43	3721.00	70,817.62	295,755.42	258.84%
Total employment	Million persons	6766.00	307.65	2694.98	6458.35	3.70%
Construction land area	Square kilometers	5577.44	113.50	1651.98	5463.94	27.43%
Water consumption	Billion m ³	592.00	22.49	201.74	569.51	− 0.05%
Energy consumption	Million SCE	25,369.34	1073.83	8942.72	24,295.52	20.05%
Desirable output						
GDP	Billion yuan	57,793.94	806.08	15,090.70	56,987.86	92.47%
Undesirable outputs						
Solid waste emissions	Million tons	45,575.83	212.10	10,730.83	45,363.73	60.21%
Domestic garbage removal volume	Million tons	3035.38	66.25	621.90	2969.13	44.07%
CO ₂ emissions	Million tons	94,538.21	3025.57	31,369.39	91,512.64	24.50%
SO ₂ emissions	Thousand tons	182.74	0.47	55.65	182.27	− 70.11%
NOx emissions	Million tons	180.11	6.01	64.69	174.10	− 26.19%
Soot and industrial dust emissions	Thousand tons	179.77	1.50	43.76	178.27	30.46%
Total waste water emissions	Million tons	938,261.03	18,418.00	227,654.96	919,843.03	2.53%

Table 3 presents the average values of various indicators for six regions in China from 2010 to 2018. It can be seen that the developed regions (i.e., the Middle Yangtze River and Middle Yellow River regions) have much higher inputs than the less developed regions (i.e., the northwest and southwest regions), suggesting that the developed regions rely on using natural resources as inputs. However, from the perspective of pollution emissions, except for household waste and wastewater emissions, the developed regions do not have significantly higher pollution emissions than the less developed regions, meaning that some progress has been made in emission reduction techniques in the developed regions.

Results and discussion

Comparison of GDE based on the MCSE-DEA model and the P-DEA model

The P-SBM model is constructed based on the same technology frontier surface to measure the efficiency of all DMUs, and thus has longitudinal comparability and can be used for dynamic efficiency analysis of panel data. The MCSE-DEA model is proposed to address the problems of the same status of indicators and the inability to distinguish effective DMU of the P-DEA model. In this paper, we select the data of 2010

Table 3 Descriptive statistics by region (2010–2018, 30 provinces)

Indicators	Northeast	Southeast	Southwest	Northwest	Middle Yangtze River	Middle Yellow River
Input indicators						
Capital stock	64,498.06	66,128.44	58,976.92	30,304.94	93,603.88	89,123.03
Total employment	1942.13	3037.70	2831.01	1047.78	3426.31	3189.31
Construction land area	1847.55	1854.28	1210.61	659.02	2251.29	1814.72
Water consumption	206.57	246.73	145.34	173.77	291.36	136.55
Energy consumption	8701.44	7526.66	7250.12	4868.40	9938.65	12,736.81
Desirable output						
GDP	14,070.75	18,790.09	10,369.02	4097.26	21,338.70	17,716.43
Undesirable outputs						
Solid waste emissions	12,581.51	5007.60	9691.96	7623.41	7971.48	18,780.67
Domestic garbage removal volume	671.80	851.62	458.76	260.17	799.29	643.47
CO ₂ emissions	27,566.10	27,837.01	23,637.55	17,707.39	35,764.45	44,799.57
SO ₂ emissions	52.20	34.39	64.46	43.74	47.53	80.88
NOx emissions	67.20	50.08	46.11	43.55	65.16	97.19
Soot and industrial dust emissions	60.60	25.92	31.56	35.39	37.36	66.09
Total waste water emissions	169,643.44	344,127.31	176,559.33	71,376.55	322,170.26	232,271.06

as the reference surface and use the MAXDEA software to measure the GDE in China from 2010 to 2018 based on the MCSE-DEA model and the P-DEA model. We rank them by their efficiency value. Figure 4 compares the efficiency distribution of GDE based on the P-DEA model (Fig. 4a) and the MCSE-DEA model (Fig. 4b) during 2010–2018. There are significant differences in GDE between them. In general, the efficiency score of the MCSE-DEA model is lower than the P-DEA model (as shown in Fig. 5), and the efficiency ranking shows significant changes (as shown in Table 4). In terms of efficiency scores, the efficiency score based on the MCSE-DEA model is 0.93, while the efficiency value measured by the P-DEA model is 1.32. From the efficiency ranking of each province, the highest efficiency score under the MCSE-DEA model is Shanghai, with an efficiency value of 1.43, while Shanghai ranks second under the P-DEA model with an efficiency value of 3.69. We can see that the MCSE-DEA model has the same efficiency value calculated by model 10. The MCSE-DEA model can reflect only improved information on the integrated indicators, while model 10 can reveal improved information on the original indicators. From the efficiency distribution map (as shown in Fig. 4), most eastern provinces show higher efficiency scores, while the western provinces gain lower scores.

Spatial and temporal analysis of GDE

First, Fig. 6 presents the average trend of GDE from 2010 to 2018 in China, from which it can be seen that GDE experiences an increasing trend. The comprehensive efficiency ranges from 0.78 to 1.10, and the pure technical efficiency ranges from 0.81 to 1.28 in 9 years. The comprehensive efficiency and pure technical efficiency are in the efficiency

effective state from 2016 to 2018, reaching the technical frontier level of 2010.

Secondly, Fig. 7 illustrates the trend of regional efficiency changes and the results show that the average GDE of six regions exhibits an upward trend. It indicates that the regional efficiency in China has improved significantly during the study period. Figure 8 provides the regional GDE and growth rate status. Among them, the greatest improvements in average efficiency value appear in the Middle Yangtze River and southeast region, with growth rates of 58.67% and 38.80%, respectively. The next region is the Middle Yellow River, with an average efficiency value of 0.96 and a growth rate of 49.60%. The northeast region ranks fourth in terms of efficiency value, with an average efficiency value of 0.90 and a growth rate of 27.75%. In contrast, the northwest region gains the worst average efficiency value and growth rate, with the values of 0.66 and 15.31%, respectively. The southwest region, on the other hand, ranks medium with an efficiency value of 0.84 and a growth rate of 37.54%.

Figure 9 illustrates the inter-provincial green development status from 2010 to 2018. In the Middle Yangtze River, Shanghai and Jiangsu have higher efficiency values of 1.43 and 1.20, respectively, while Jiangxi performs worst, with the lowest efficiency value of 0.83. Fujian and Guangdong in the southeast have higher efficiency values of 1.24 and 1.18, respectively, while Guangxi has an efficiency value of only 0.88. In the Middle Yellow River, Tianjin gains the highest efficiency of 1.41, while Shanxi and Inner Mongolia have efficiency scores below 0.70. This may be due to serious energy consumption and environmental problems (Tang et al. 2016). The difference in efficiency values among the three provinces in the northeast is relatively small, with efficiency values ranging from 0.88 to 0.92. In contrast, the

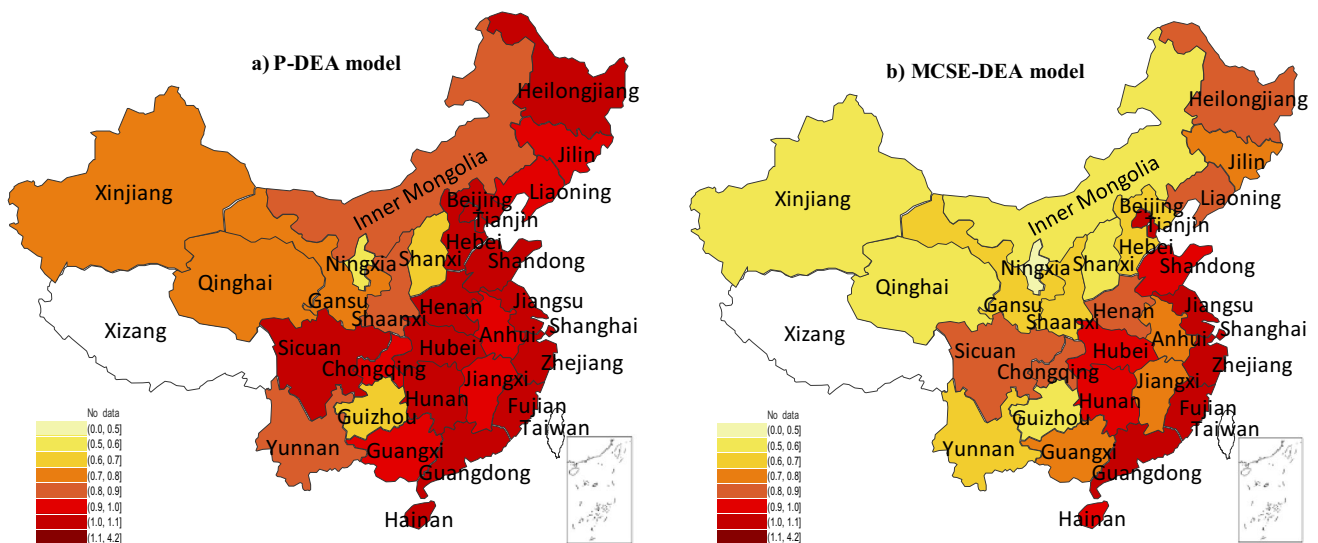


Fig. 4 Average scores of GDE under the P-DEA model and the MCSE-DEA model, 2010–2018

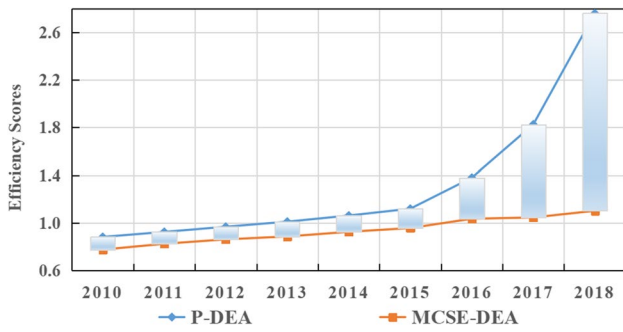


Fig. 5 GDE trends under the P-DEA model and the MCSE-DEA model (2010–2018, 30 provinces)

northwest region has low-efficiency values, with efficiency values ranging from 0.58 to 0.77. In the southwest region, Sichuan and Chongqing perform better, with average efficiency values above 0.94; however, the efficiency value of Guizhou is only 0.66.

Table 4 GDE scores of different models

Region	Province	P-DEA	MCSE-DEA	Model 10
Northeast	Heilongjiang	1.1384	0.9188	0.9188
	Jilin	1.0166	0.8810	0.8810
	Liaoning	1.0598	0.9046	0.9046
Southeast	Guangdong	1.5879	1.1773	1.1773
	Hainan	1.4199	1.0467	1.0467
	Fujian	1.6686	1.2417	1.2417
	Guangxi	1.0696	0.8801	0.8801
Southwest	Chongqing	1.0990	0.9443	0.9443
	Sichuan	1.1421	0.9795	0.9795
	Guizhou	0.7843	0.6592	0.6592
	Yunnan	0.9181	0.7669	0.7669
Northwest	Shanxi	0.9402	0.7680	0.7680
	Gansu	0.8722	0.7030	0.7030
	Qinghai	0.8472	0.6058	0.6058
	Ningxia	0.6747	0.5782	0.5782
	Xinjiang	0.8206	0.6552	0.6552
	Middle Yangtze River	Shanghai	3.6928	1.4303
Middle Yangtze River	Jiangsu	1.4250	1.1994	1.1994
	Zhejiang	1.5594	1.1631	1.1631
	Anhui	1.0862	0.8997	0.8997
	Jiangxi	1.0324	0.8306	0.8306
	Hubei	1.2578	1.0804	1.0804
	Hunan	1.2065	1.0128	1.0128
	Middle Yellow River	Beijing	4.1687	1.2194
Middle Yellow River	Tianjin	1.9456	1.4077	1.4077
	Hebei	1.1246	0.7758	0.7758
	Henan	1.2075	0.9411	0.9411
	Shandong	1.2217	1.0544	1.0544
	Shanxi	0.7807	0.6172	0.6172
	Inner Mongolia	0.9971	0.6970	0.6970

Overall, there are still considerable disparities in efficiency levels within and between regions, which may have a negative impact on the synergistic development of regional economies. It is noticeable that the provinces with higher efficiency values are mainly from three regions: the Middle Yangtze River (Shanghai, Jiangsu, and Zhejiang), the Middle Yellow River (Tianjin and Beijing), and the southeast region (Fujian and Guangdong), which are the economically developed coastal provinces. These provinces have actively adopted advanced technology, equipment, and management experience (Tang et al. 2016). Beijing receives a highly efficient ranking, primarily because of the significant reforms it had previously undergone for the 2008 Summer Olympics. The other provinces, Guizhou, Xinjiang, Shanxi, Qinghai, and Ningxia, gain lower efficiency values, with an average efficiency value of no more than 0.66. Among them, Xinjiang, Qinghai, and Ningxia belong to the northwest region. The lower efficiency values in the less developed western regions can be attributed to their relatively backward technology level, and limited capital investment. From the above analysis, it can be seen that although the GDE has improved significantly, there is still a large efficiency gap between different provinces, and therefore the further research of the inefficient provinces is essential.

Analysis of inefficient provinces

From the above analysis, it can be seen that the GDE of five provinces, namely Guizhou, Xinjiang, Shanxi, Qinghai, and Ningxia, is relatively low, and the average efficiency within 9 years does not exceed 0.66. Therefore, we carry out detailed analysis, including the efficiencies of inputs, desirable outputs, and undesirable outputs, respectively, on these provinces based on model 10, and the relevant results are shown in Fig. 10 ~ Fig. 12.

Figure 10 demonstrates the average proportion of each input factor that can be improved. A larger ratio indicates greater redundancy for these input indicators. Except for Guizhou, Shanxi, and Qinghai, which have negative improvement ratios in construction land area (CL), the

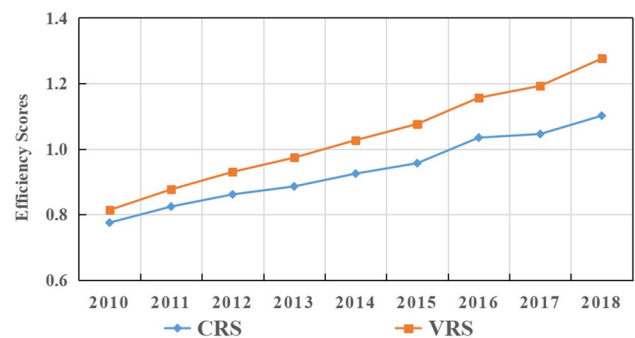
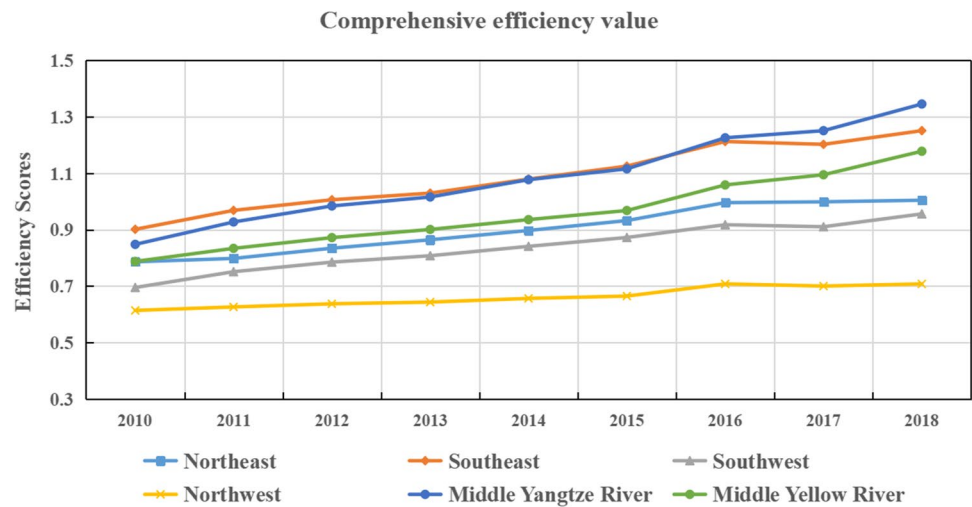


Fig. 6 Inter-provincial green development efficiency trends in China, 2010–2018

Fig. 7 GDE trends by region in China



five provinces have extensive redundancy in other input indicators and poorer ability to optimize resource allocation. The five provinces are most problematic in total water consumption (WC), with redundancy levels exceeding 44%. Among them, Xinjiang needs to optimize more than 94% in water consumption, which can be attributed to its large area and harsh natural conditions. Secondly, energy consumption (EC) needs to be optimized by more than 26% in five provinces to be effective, among which, the energy consumption of Ningxia should be optimized by 49%. Ningxia has abundant energy resources such as coal, oil, and natural gas, which provide a strong guarantee for its construction of an energy base. As can be seen, these five provinces have relatively high water and energy consumption due to their resource endowment and industrial structure. Xinjiang

and Ningxia also have 10% and 42% redundancy in construction land area (CL), respectively, and thus need to improve land use efficiency. In addition, the five provinces need some improvement in capital stock (CS) and total employment (TE). To be specific, they need to improve the efficiency of personnel work and capital use continuously. Overall, according to the above analysis, except for the construction land area, the five provinces have an enormous redundancy in input indicators for optimization, and further measures should be taken to optimize resource allocation, and improve the quality and efficiency of staff.

Second, regarding the desirable output, Fig. 11 presents the average ratio of desirable output indicator that can be improved. A larger ratio indicates a greater degree of deficiency in that output indicator. It can be observed that five

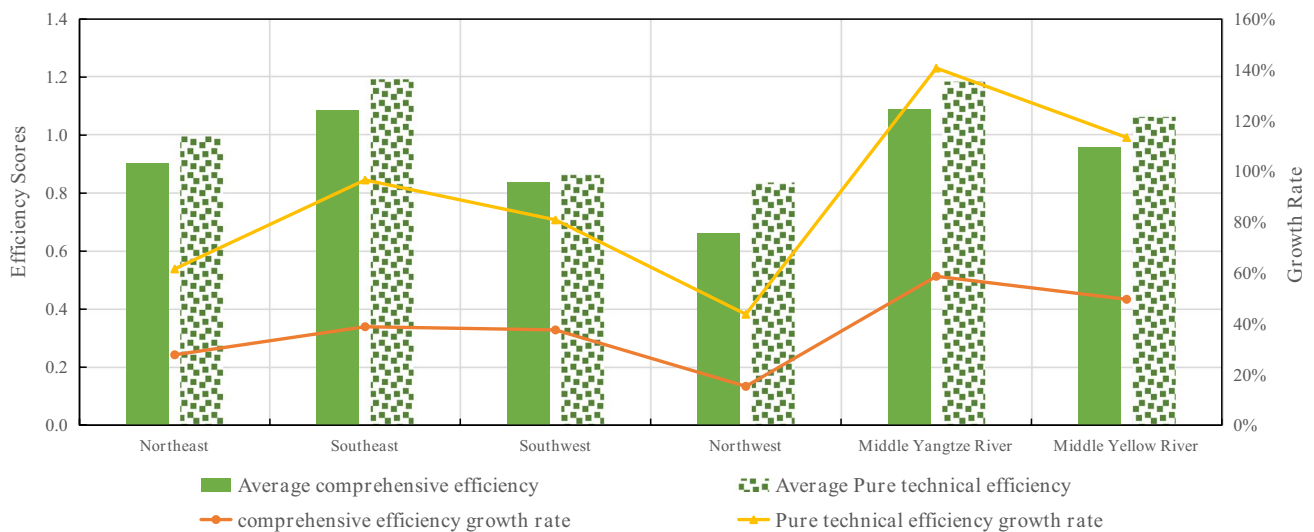
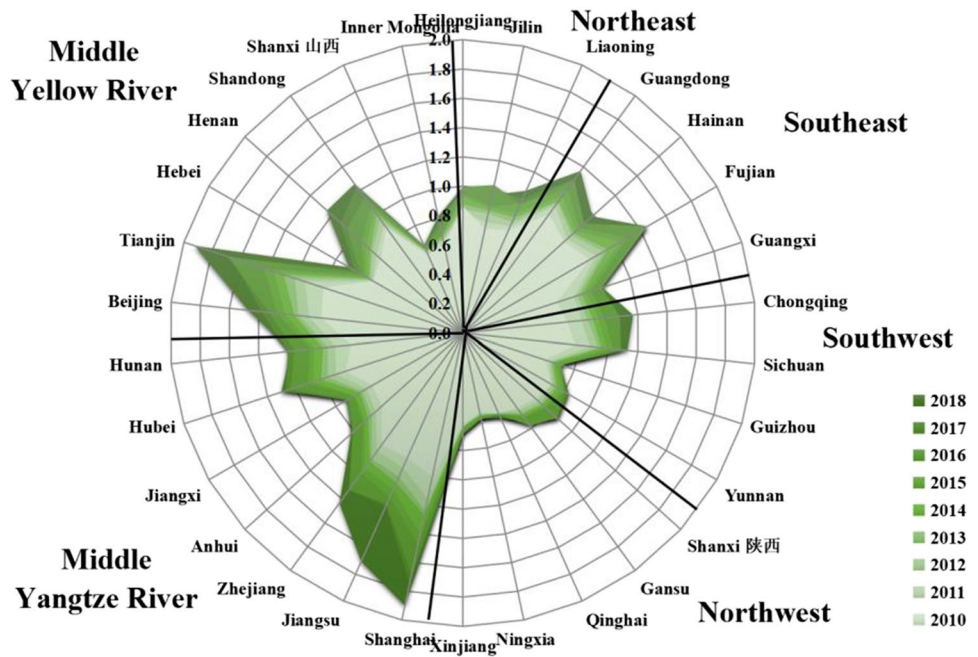


Fig. 8 GDE and growth rate by region

Fig. 9 Inter-provincial GDE in China, 2010–2018



provinces have a large deficit in GDP, and need to improve their average GDP by more than 52% to reach validity. Among them, the GDP of Ningxia needs to be optimized by more than 72% before it can reach validity. All in all, the five provinces mentioned above are generally lagging behind and need to promote their economic development.

Finally, from the perspective of undesirable output, Fig. 12 reports the proportion of each undesirable output indicator that can be improved, with a smaller ratio indicating that the province has better control over undesirable output. It can be found that except for Xinjiang performing better in total waste water emissions (WW), five provinces have certain

deficiencies in the rest of the undesirable output indicators. In particular, the problems in solid waste emissions (SW) and soot and industrial dust emissions (SD) are particularly prominent. In terms of the solid waste emissions, the improvement ratio of the five provinces is higher than 71%, with Ningxia and Shanxi needing to optimize more than 90%. In terms of soot and industrial dust emissions, five provinces need an improvement value greater than 74%, while four provinces, except Guizhou, need an improvement ratio of 84% or more. According to the above analysis, the shortcomings of these inefficient provinces can be identified, and constructive suggestions can be made for the next regulation step.

Fig. 10 Improvement strategies for input indicators in inefficient provinces (symbol: CS represents capital stock, TE represents total employment, CL represents construction land area, WC represents water consumption, EC represents energy consumption.)

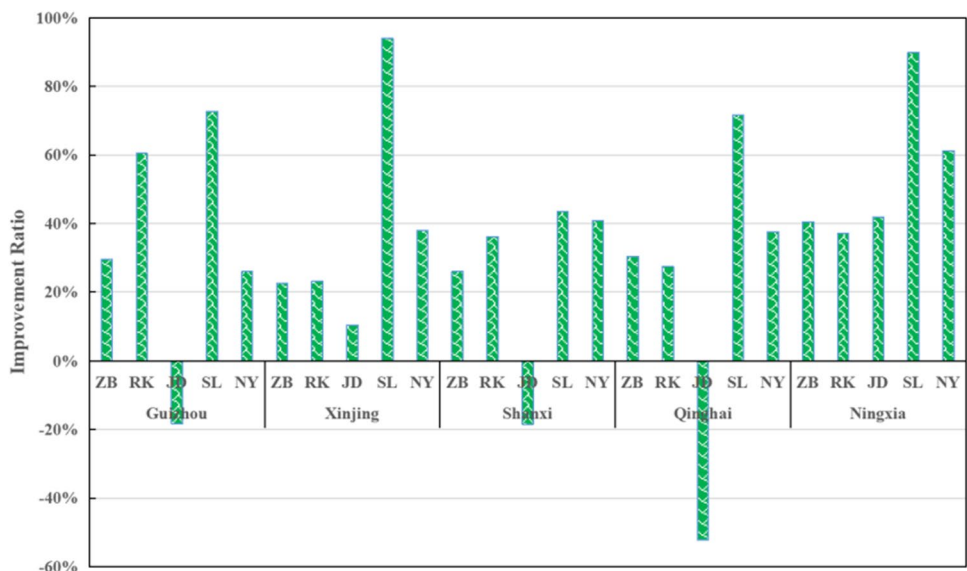
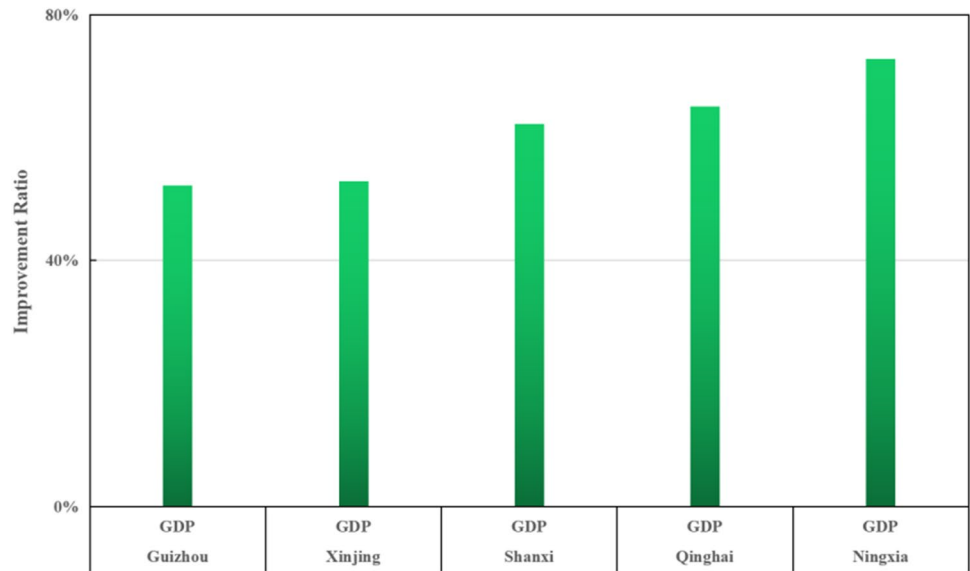


Fig. 11 Improvement strategies for desirable output indicators in inefficient provinces



Analysis of the Tobit model regression results

The following is the analysis of the influencing factors (as shown in Table 5), where a positive correlation means that the two phenomena change in the same direction and the dependent variable increases with the independent variable, i.e., there is a facilitative effect. A negative correlation means that the two phenomena change in opposite directions, and the dependent variable decreases with the increase of the independent variable, i.e., there is an inhibitory effect. ① Industrial structure (IS). The influence of the share of secondary industry on GDE is significantly negative. The secondary industry consumes more resources and emits more waste, so the increase in the proportion of the secondary industry will inhibit the improvement of GDE. ② Environmental policy

(EP). The percentage of environmental protection expenditure has significantly and positively correlated with GDE. Since the construction of ecological civilization has been proposed, it has effectively reduced the generation and emission of pollutants, and therefore environmental policies have contributed to improving GDE. ③ Urbanization level (UL). There is a negative correlation between the proportion of the urban population and GDE. At the early stage of urbanization, industries with low technology levels and high labor densities develop rapidly, and environmental pollution is serious, resulting in a low GDE. ④ R&D investment (RD). The proportion of R&D investment has positively correlated with GDE, indicating that improving science and technology level is conducive to the improvement in resource utilization rate and pollutant management, thereby contributing to the improvement of GDE.

Fig. 12 Improvement strategies for undesirable output indicators in inefficient provinces (symbol: SW represents solid waste emissions, DG represents domestic garbage removal volume, CO represents CO2 emissions, SO represents SO2 emissions, NO represents NOx emissions, SD represents soot and industrial dust emissions, WW represents total waste water emissions.)

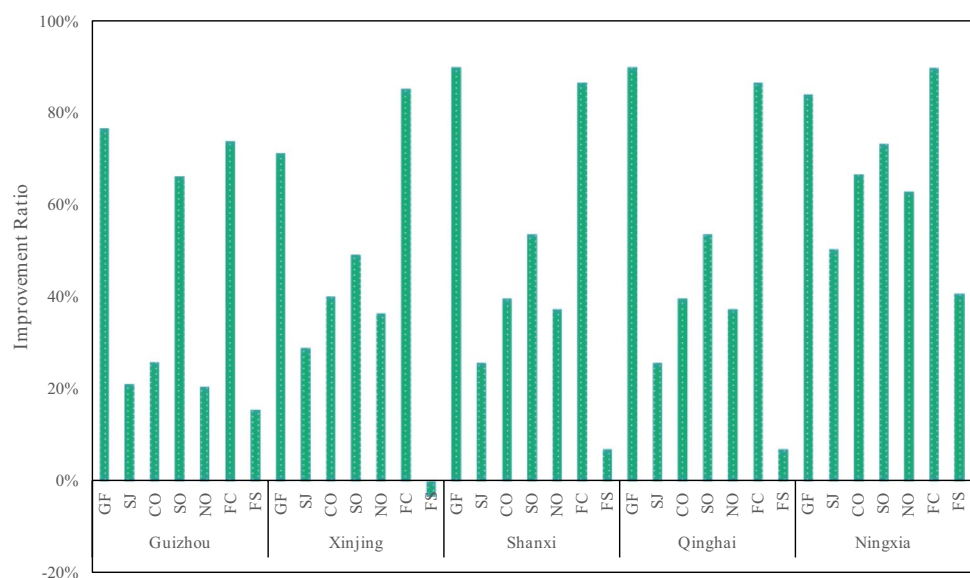


Table 5 The regression results of the Tobit model (symbol: IS represents the industrial structure, EP represents the environmental policy, UL represents urbanization level, RD represents R&D investment, ED represents the level of economic development, EC2 represents energy consumption)

GDE	Coef	St.Err	t-value	p-value	95% Conf
IS	−0.003**	0.001	−2.53	0.012	−0.006
EP	0.064***	0.023	2.77	0.006	0.019
UL	−0.022***	0.003	−7.25	0	−0.028
RD	0.166***	0.022	7.46	0	0.122
ED	1.798***	0.136	13.26	0	1.532
EC2	−0.384***	0.085	−4.52	0	−0.551

© The level of economic development (ED). GDP per capita has positively correlated with GDE, noting that the improvement of economic development level is conducive to improving residents' environmental protection awareness, thereby enhancing the GDE. © Energy consumption (EC2). Electricity consumption per capita has negatively correlated with GDE, showing that the increase in electricity consumption generates more pollutants. Thus, there is a suppressive effect on the improvement of GDE.

Conclusion and policy recommendations

The continuous and rapid economic development has brought about excessive resource consumption and environmental pollution. Therefore, it is essential to coordinate economic, resource, and environmental factors to achieve sustainable development. This paper develops the MCSE-DEA model to address the problems of the same status of indicators and the inability to distinguish effective DMU of the traditional P-DEA model. We employ the MCSE-DEA model to measure the inter-provincial green development efficiency (GDE) in China from 2010 to 2018. On this basis, the Tobit model is further applied to investigate the influencing factors of GDE. The results show that the average GDE shows an increasing trend during the study period, but there are significant disparities between and within regions. From a regional perspective, six regions show an upward trend in efficiency values, among which the Middle Yangtze River and the southeast region have the highest efficiency values, while the northwest region has the lowest efficiency values. From an inter-provincial perspective, more economically developed provinces, such as Shanghai, Tianjin, and Fujian, have higher efficiency values, while provinces in less developed regions like Shanxi, Qinghai, and Ningxia are less efficient. The study of the inefficient

provinces found significant redundancy in most indicators and a lack of optimal resource allocation. From the perspective of influencing factors, the environmental investment, R&D investment, and economic development level can significantly contribute to the improvement of GDE, while industrial structure, urbanization level, and energy consumption have inhibiting effects.

Based on the results obtained from our study, we propose some suggestions as follows. First, GDE has a large gap between and within regions. Studies on inefficient provinces found that water resource utilization in Xinjiang and energy consumption in Ningxia are large. Accordingly, Xinjiang should make great efforts in adjusting the industrial structure, strengthen the construction of water-saving facilities, and introduce advanced monitoring technology. Ningxia can reduce energy consumption by transforming the existing energy industry, utilizing new technologies, and improving the industrial structure. Second, Ningxia and Shanxi provinces have a large amount of waste production and soot and industrial dust emissions, and a high degree of dependence on natural resources. Therefore, in order to improve the efficiency of green development, there is an urgent need to focus on the optimal allocation of resources and improve the overall allocation of resources. Third, it is essential to change the economic development mode actively, reasonably plan the urban layout, effectively reduce the energy consumption intensity, and gradually increase the environmental protection efforts.

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Author contribution Lin Yang: conceptualization, methodology, validation, writing—reviewing and editing. Zhanxin Ma: supervision, validation, writing—reviewing and editing. Jie Yin, Yiming Li, Haodong Lv: data curation, software, visualization, writing—original draft preparation.

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Data availability No data was used for the research described in the article.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

- Bai Y, Deng X, Zhang Q, Wang Z (2017) Measuring environmental performance of industrial sub-sectors in China: a stochastic meta-frontier approach. *Phys Chem Earth A/B/C* 101:3–12
- Belmonte-Ureña LJ, Plaza-Úbeda JA, Vazquez-Brust D (2021) Circular economy, degrowth and green growth as pathways for research on sustainable development goals: a global analysis and future agenda. *Ecol Econ* 185:107050
- BP (2020) BP Statistical Review of World Energy Available at: <http://www.bp.com/statisticalreview>
- Charnes A, Cooper WW, Rhodes E (1979) Measuring the efficiency of decision-making units. *Eur J Oper Res* 3:339
- Chen X, Lin B (2020) Assessment of eco-efficiency change considering energy and environment: a study of China's non-ferrous metals industry. *J Clean Prod* 277:123388
- Deng X, Gibson J, Wang P (2017) Relationship between landscape diversity and crop production: a case study in the Hebei Province of China based on multi-source data integration. *J Clean Prod* 142:985–992
- Ding J, Liu B, Shao X (2022) Spatial effects of industrial synergistic agglomeration and regional green development efficiency: Evidence from China. *Energy Econ* 112:106156
- Dong F, Li Y, Qin C (2021) How industrial convergence affects regional green development efficiency: a spatial conditional process analysis. *J Environ Manag* 300:113738
- Dong F, Zhang YQ, Zhang XY (2020) Applying a data envelopment analysis game cross efficiency model to examining regional ecological efficiency: evidence from China. *J Clean Prod* 267:122031
- Färe R, Grosskopf S, Lindgren B, Roos P (1992) Productivity changes in Swedish pharmacies 1980–1989: a non-parametric Malmquist approach. *J Product Anal* 3:85–101
- Gue IHV, Ubando AT, Tseng ML, Tan RR (2020) Artificial neural networks for sustainable development: a critical review. *Clean Techn Environ Policy* 22(7):1449–65
- Haider S, Mishra PP (2021) Does innovative capability enhance the energy efficiency of Indian Iron and Steel firms? A Bayesian stochastic frontier analysis. *Energy Econ* 95:105128
- IPCC (2006) Greenhouse gas inventory: IPCC guidelines for National Greenhouse Gas Inventories. Bracknell, England: United Kingdom Meteorological Office
- Koengkan M, Fuinhas JA, Kazemzadeh E, Osmani F, Alavijeh NK, Auza A, Teixeira M (2022) Measuring the economic efficiency performance in Latin American and Caribbean countries: an empirical evidence from stochastic production frontier and data envelopment analysis. *Int Econ* 169:43–54
- Korhonen PJ, Luptacik M (2004) Eco-efficiency analysis of power plants: an extension of data envelopment analysis. *Eur J Oper Res* 154:437–446
- Li P, Tong LJ, Guo YH (2020) Spatial-temporal characteristics of green development efficiency and influencing factors in restricted development zones: a case study of Jilin Province, China. *Chin Geogr Sci* 30(4):736–48
- Lin B, Zhou Y (2022) Measuring the green economic growth in China: influencing factors and policy perspectives. *Energy* 241:122518
- Liu K-d, Shi D, Xiang W, Zhang W (2022) How has the efficiency of China's green development evolved? An improved non-radial directional distance function measurement. *Sci Total Environ* 815:152337
- Liu Q, Wang S, Li B, Zhang W (2020) Dynamics, differences, influencing factors of eco-efficiency in China: a spatiotemporal perspective analysis. *J Environ Manag* 264:110442
- Liu W, Zhan J, Zhao F, Wei X, Zhang F (2021) Exploring the coupling relationship between urbanization and energy eco-efficiency: a case study of 281 prefecture-level cities in China. *Sustain Cities Soc* 64:102563
- Ma Z, Cao L, Sg Bao (2018) A resource optimized allocation method of multi-level complex system. *Syst Eng-Theory Pract* 38:1802–1818
- Matsumoto K, Chen Y (2021) Industrial eco-efficiency and its determinants in China: a two-stage approach. *Ecol Indic* 130:108072
- NBSC (National Bureau of Statistics of China) (2011–2019) China Statistical Yearbooks 2011–2019. China Statistical Press, Beijing Available at: <https://data.cnki.net/yearBook/single?nav=&id=N2022110021>
- NBSC (National Bureau of Statistics of China) (2011–2019) China Environmental Statistical Yearbooks 2011–2019. China Statistics Press, Beijing Available at: <https://data.cnki.net/yearBook/single?id=N2022030234>
- NBSC (National Bureau of Statistics of China) (2011–2019) China Energy Statistical Yearbooks 2011–2019. China Statistics Press, Beijing Available at: <https://data.cnki.net/yearBook/single?id=N2022060061>
- NBSC (National Bureau of Statistics of China) (2021) China Statistical Yearbooks 2021. China Statistical Press, Beijing
- Passetti E, Tenucci A (2016) Eco-efficiency measurement and the influence of organisational factors: evidence from large Italian companies. *J Clean Prod* 122:228–39
- Peiro-Palomino J, Picazo-Tadeo AJ (2019) Is social capital green? Cultural features and environmental performance in the European Union. *Environ Resour Econ* 72:795–822
- Rashidi K, FarzipoorSaen R (2015) Measuring eco-efficiency based on green indicators and potentials in energy saving and undesirable output abatement. *Energy Econ* 50:18–26
- Shao L, Yu X, Feng C (2019) Evaluating the eco-efficiency of China's industrial sectors: a two-stage network data envelopment analysis. *J Environ Manag* 247:551–560
- Shuai S, Fan Z (2020) Modeling the role of environmental regulations in regional green economy efficiency of China: empirical evidence from super efficiency DEA-Tobit model. *J Environ Manag* 261:110227
- Song J, Chen X (2019) Eco-efficiency of grain production in China based on water footprints: a stochastic frontier approach. *J Clean Prod* 236:117685
- Tang K, Yang L, Zhang JW (2016) Estimating the regional total factor efficiency and pollutants' marginal abatement costs in China: a parametric approach. *Appl Energy* 184:230–240
- Tone K (2001) A slacks-based measure of efficiency in data envelopment analysis. *Eur J Oper Res* 130:498–509
- Wang Y, He L (2022) Can China's carbon emissions trading scheme promote balanced green development? A consideration of efficiency and fairness. *J Clean Prod* 367:132916
- Wang B, Huang R (2014) Regional green development efficiency and green total productivity growth in China: 2000–2010—base on parametric metafrontier analysis. *Ind Econ Rev* 5:16–35
- Wang D, Wan K, Yang J (2019) Measurement and evolution of eco-efficiency of coal industry ecosystem in China. *J Clean Prod* 209:803–818
- Wang Q, Zhao C (2021) Dynamic evolution and influencing factors of industrial green total factor energy efficiency in China. *Alexandria Eng J* 60:1929–1937
- Wang R, Wang Q, Yao S (2021) Evaluation and difference analysis of regional energy efficiency in China under the carbon neutrality targets: Insights from DEA and Theil models. *J Environ Manag* 293:112958
- Wang Z, Deng X, Wang P, Chen J (2017) Ecological intercorrelation in urban–rural development: an eco-city of China. *J Clean Prod* 163:S28–S41
- Xiao H, Wang D, Qi Y, Shao S, Zhou Y, Shan Y (2021) The governance-production nexus of eco-efficiency in Chinese resource-based cities: a two-stage network DEA approach. *Energy Econ* 101:105408

- Xing L, Xue M, Wang X (2018) Spatial correction of ecosystem service value and the evaluation of eco-efficiency: a case for China's provincial level. *Ecol Indic* 95:841–850
- Xu J-J, Wang H-J, Tang K (2022) The sustainability of industrial structure on green eco-efficiency in the Yellow River Basin. *Econ Anal Policy* 74:775–788
- Yang L, Tang K, Wang Z, An H, Fang W (2017) Regional eco-efficiency and pollutants' marginal abatement costs in China: a parametric approach. *J Clean Prod* 167:619–629
- Yang L, Ma C, Yang Y, Zhang E, Lv H (2020) Estimating the regional eco-efficiency in China based on bootstrapping by-production technologies. *J Clean Prod* 243:118550
- Yang L, Zhang X (2018) Assessing regional eco-efficiency from the perspective of resource, environmental and economic performance in China: a bootstrapping approach in global data envelopment analysis. *J Clean Prod* 173:100–111
- Yang L, Ni M (2022) Is financial development beneficial to improve the efficiency of green development? Evidence from the “Belt and Road” countries. *Energy Econ* 105:105734
- Yang Q, Sun ZG, Zhang HBA (2022) Assessment of urban green development efficiency based on three-stage DEA: a case study from China's Yangtze River Delta. *Sustainability* 14(19):12076
- Zhang C, Chen P (2022) Applying the three-stage SBM-DEA model to evaluate energy efficiency and impact factors in RCEP countries. *Energy* 241:122917
- Zhang JF, Liu JX, Li J (2021) Green development efficiency and its influencing factors in China's iron and steel industry. *Sustainability* 13(2):510
- Zhang J, Wu G, Zhang J (2004) The estimation of China's provincial capital stock: 1952–2000. *Econ Res J* (10):35–44
- Zhao L, Zhang L, Xu L, Hu M (2016) Mechanism of human capital, industrial structure adjustment and green development efficiency. *China Popul Resour Environ* 26:106–114
- Zhang XL (2020) Estimation of eco-efficiency and identification of its influencing factors in China's Yangtze River Delta urban agglomerations. *Growth and Change* 51(2):792–808
- Zhao X, Ma X, Shang Y, Yang Z, Shahzad U (2022) Green economic growth and its inherent driving factors in Chinese cities: based on the Metafrontier-global-SBM super-efficiency DEA model. *Gondwana Res* 106:315–328
- Zhu B, Zhang M, Zhou Y, Wang P, Sheng J, He K, Wei Y-M, Xie R (2019) Exploring the effect of industrial structure adjustment on interprovincial green development efficiency in China: a novel integrated approach. *Energy Policy* 134:110946
- Zhu B, Zhang M, Huang L, Wang P, Su B, Wei Y-M (2020) Exploring the effect of carbon trading mechanism on China's green development efficiency: a novel integrated approach. *Energy Econ* 85:104601

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