



# Understanding Chinese energy-environmental efficiency: performance, decomposition, and strategy

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## Abstract

Understanding energy-environmental efficiency is important for coordinating economic development and eco-environment protection through energy use; however, vague definitions and conflicting results confuse researchers and policymakers and impact China's high-quality development. After delimiting energy-environmental efficiency, this study employed the intermediate adjustment situation three-stage Slacks-Based Model Data Envelopment Analysis model to explore Chinese provincial energy-environmental efficiencies from 1995 to 2018, and discussed their impacts by regional strategies. The results illustrated that Chinese energy-environmental efficiencies were overestimated, and their national average value dropped from 0.573 to 0.361 after removing the influence of external environmental factors and random interference. Moreover, energy-environmental efficiencies in East China performed significantly better than other regions, with expanding gaps between regions existed. Moreover, China maintained low-scale efficiency and high pure energy-environmental efficiency, and the low-scale efficiency led to the worrisome energy-environmental efficiency. Fortunately, pure energy-environmental efficiencies were promising, but their downward trends that started in 2002 should be a warning. Unexpectedly, the regional strategies held various impacts, they benefitted overall energy-environmental efficiency and scale efficiency, but not help pure energy-environmental efficiency, and the impacts were weak and short time. Policymakers should improve scale efficiency and formulate regional strategies in a timely manner to maintain energy-environmental efficiency improvement.

**Keywords** Energy-environmental efficiency · IAS three-stage SBM-DEA · Efficiency decomposition · Regional strategy

## Introduction

Energy has played a crucial role in China's economic expansion. In 2018, China consumed 23.56% of the total initial energy (BP 2020) worldwide while producing 16.07% of global GDP, and its energy efficiency (GDP/energy consumption) was 47.57% and 38.90% of the USA and Japan (IBRD-IDA 2019), respectively. The energy-saving potential in mainland China was 59.22% of its current consumption (Feng et al. 2018), and energy consumption engendered over 10 billion tons of CO<sub>2</sub> emissions (IEA 2019), approximately 28.56% of the 2018 global emissions. Moreover, Chinese economic restructuring requires a sufficient and steady energy supply; however, the dependence on oil and natural gas imports has reached 70% and 43%, respectively, and escalating trade disputes could impact energy security. The challenges of low economic expansion efficiency, massive energy waste, colossal pollution emissions, and low energy supply due to the low energy efficiency have disturbed China's high-quality development and have indicated a need to

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## Highlights

- China's provincial energy-environmental efficiencies were overestimated and performed terribly with regional gaps.
- High pure energy-environmental efficiency and low-scale efficiency were the main characteristics in China.
- The regional strategies were beneficial to energy-environmental efficiency and scale efficiency but harmful to pure energy-environmental efficiency.

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transform China's traditional energy using patterns. Organically measuring the synergistic performance of energy, eco-environment, and the economy is the premise to improve its performance.

Correspondingly, energy-environmental efficiency (EEE) is redefined by energy efficiency under ecological constraints, and previous researches on generalized energy-environmental efficiency have been conducted in China with some disputes. Even though the index evaluation system is similar, the EEE is defined by various names, such as eco-efficiency (Liu et al. 2020), environmental efficiency (Chen et al. 2017), green economic efficiency (Zhuo and Deng 2020), total-factor energy efficiency (Huang and Wang 2017), and ecological total-factor energy efficiency (Zhang et al. 2015). Moreover, the calculation results are inconsistent; Zhang et al. (2015) and Wang and Feng (2015) report a sharp contradiction between China's economics and eco-environment. Conversely, Chen et al. (2020) and Zhong et al. (2020) reported the opposite. Unfortunately, ambiguous definitions and inconsistent results are unfavorable for improving efficiency. Therefore, after clarifying the meaning of the efficiency, choosing suitable eco-environmental expense indicators, and streamlining the measurement framework, we construct the improved three-stage SBM-DEA model to re-calculate China's real provincial EEE.

Additionally, China has implemented the national regional development strategy in the twenty-first century includes several regional strategies to rectify the economic imbalance that should have had extensive and lasting impacts on EEE. The impacts of these strategies on the economy and ecology separately, such as the impact of the Western Development Strategy on green economic efficiency (Zhuo and Deng 2020), the effects of the Strategy for Revitalizing the Old Industrial Base in Northeast China on regional economic growth and social development (Ren et al. 2020), and the impact of the First Development Strategy of the Eastern Region in China on total factor productivity (Zhang et al. 2017a), have been investigated. However, the roles of these regional strategies in energy efficiency are vague or unknown; therefore, we aimed to clarify them.

To address these gaps, we applied the adjusted three-stage SBM-DEA model to re-calculate China's provincial EEE after weakening the influences of the above three parts, which offered an adjusted model to remove the impacts of external environmental factors and interference under general adjustment, and provided actual efficiencies under accurate meaning and a new measurement framework. Furthermore, the impacts of four regional strategies on EEE, pure energy-environmental efficiency (PEEE), and scale efficiency (SE) were discussed, which expanded the research on the factors influencing these efficiencies. Therefore, this study provides a clear understanding of EEE and its impacts by regional strategies. The results showed that

the new model is valid for neutralizing the adverse effects of the traditional three-stage SBM-DEA. China's poor real EEE indicate that GDP expansion and eco-environment cost by energy use are poorly coordinated, and SE is crucial to prompting its improvement. These regional strategies are beneficial to SE but not to PEEE.

The paper is organized as follows: the "Literature review" section presents a literature review; the "Methodology" section describes the methodology; the "Variables, data, and empirical result" section presents the variables, data, and empirical results; the "Discussion" section discusses the impact of state strategies on energy-environmental efficiency; and the "Conclusion and policy implications" section presents the conclusions and policy implications.

## Literature review

### The energy-environmental efficiency and its measurement

EEE is defined by various names under a similar evaluation system that missed the organic connections among energy, eco-environment, and economy. Examples include efficiency evaluation (Bian et al. 2015), eco-efficiency (Liu et al. 2020; Zhang et al. 2017b; Zhou et al. 2020), environmental efficiency (Chen et al. 2017), and green economic efficiency (Zhuo and Deng 2020), which overlook the critical role of energy in production activities. Conversely, total-factor energy efficiency (Huang and Wang 2017), total-factor carbon emission efficiency (Zhang and Wei 2015), ecological total-factor energy efficiency (Zhang et al. 2015), green total-factor energy efficiency (Wu et al. 2020), and total-factor CO<sub>2</sub> emission performance (Wang et al. 2016) comprehensively measure all elements' contributions rather than the primary connections of the above three parts. These various definitions blur our understanding of efficiency.

Fortunately, compared with the above indicators, energy and environmental efficiency (Wang et al. 2013) or energy-environmental efficiency (EEE) (Wang and Zhao 2017; Chen et al. 2019, 2020; Zhong et al. 2020) is the efficiency in assessing the quality of economic development, and labor and capital elements are included in the connotation framework. EEE could be digestible and straightforward, including the three aspects of energy utilization, eco-environmental costs, and economic achievements, which is recognized in this study.

Measurements have been performed in China regarding wide EEE. Apart from the research on firms (Zhang et al. 2020; Chen and Ma 2021), industries (Liu et al. 2020; Wang and Zhao 2017; Zhang et al. 2017b; Zhou et al. 2020), sectors (Song et al. 2013; Zhang and Wei 2015; Chen et al. 2019, 2021), and cities (Chen et al. 2017; Huang and Wang

2017; An et al. 2019; Wang et al. 2021), regional studies were also the focus.

For example, studies from regional perspective of East China, Central China, and West China (Hu and Wang 2006; Bian et al. 2015; Zhang et al. 2015, 2017b, 2020; Cui et al. 2015; Chen et al. 2020); Northeast China, East China, Central China, and West China (Li and Hu 2012; Wang et al. 2013; Huang and Wang 2017; Liu et al. 2020; Chen et al. 2021); North China, Northeast China, East China, South-Central China, Southwest China, and Northwest China (Zhang et al. 2018; Feng and Li 2020); North China, Northeast China, East China, Central China, South China, Northwest China, and Southwest China (Zhao et al. 2019); Northeast Area, North Coast Area, East Coast Area, South Coast Area, Middle Yellow River Area, Middle Yangtze River Area, Southwest Area, and Northwest Area (Wang and Zhao 2017); Circum-Bohai Sea, Yangtze River Delta, Pan-Pearl River Delta, Coastal Areas (Qin et al. 2017); Urban Agglomerations in Eastern China (Qin et al. 2021); Yangtze River Economic Zone (Chen et al. 2017; Zhong et al. 2020); Xiangjiang River Basin (An et al. 2019); Oil and Gas Resource-based Area (Wang et al. 2021); High Regulated Regions and Low Regulated Regions (Zhang et al. 2018). These studies provide a detailed description of China's regional energy efficiency.

However, the opposite results happened in the macro-level studies. For one thing, some papers believe that China's EEE performed much to be desired. Song et al. (2013) indicated an essentially declining trend coexisting with distinct differences in provincial environmental efficiency in China from 1998 to 2009. Zhang et al. (2015) demonstrated that most provinces were not exhibiting high ecological total-factor energy efficiency and significant regional technology gaps existed from 2001 to 2010. Similarly, Wang and Feng (2015) also showed that China's economics and environment by energy use were contradictory from 2002 to 2011. Besides, Zhuo and Deng (2020) added that the green economic efficiency in coastal areas of China was generally higher than that of western China from 1995 to 2016. For another thing, some other studies disagree with the above points. For example, Chen et al. (2020) indicated that China's EEE improved from 1999 to 2017, and the study of Zhong et al. (2020) illustrated that the EEE in the Yangtze River urban agglomeration increased, and the regional differences narrowed from 2008 to 2017. The opposite results were mainly caused by ambiguous definitions, undesirable output selection, and the inclusion of unrelated factors.

First, the various EEE definitions correspond to contradictory results. For instance, environmental efficiency in Song et al. (2013) and ecological total-factor energy efficiency in Zhang et al. (2015) showed that China's EEE performed poorly. Conversely, the EEE of Chen et al. (2020) and Zhong et al. (2020) disagreed with the above points.

Second, differences in the selection of eco-environmental costs inevitably lead to inconsistent EEE results. For example, regarding wastewater, solid waste, and waste gas as eco-environmental costs, Song et al. (2013) and Zhuo and Deng (2020) obtained similar EEE results, whereas Chen et al. (2020) and Zhong et al. (2020) chose CO<sub>2</sub> and SO<sub>2</sub> emissions and obtained opposite results. As solid waste is easier to handle or recycle, we chose waste gas and wastewater as the eco-environmental costs in this study.

Third, including unrelated factors disturbs the EEE measurement. The above indicators measure, but are not limited to, EEE because of redundant factors, such as labor and capital. However, the defects are represented in the EEE estimation, and the EEE measurement could only be more straightforward and fitting when including energy utilization, eco-environmental costs, and economic achievements.

These vague definitions and conflicting results indicate that China's real EEE remain unknown and are unable to propose related promotion policies. After clarifying the meaning of EEE, choosing suitable ecological expense indicators, and streamlining the measurement framework, we re-evaluated Chinese EEE. Moreover, the regional EEE analysis is followed the division (Li and Hu 2012; Wang et al. 2013; Huang and Wang 2017; Liu et al. 2020; Chen et al. 2021). Besides, the error caused by the calculation method cannot be ignored.

### The IAS three-stage SBM-DEA model

Two types of indicators were constructed to measure energy efficiency. One single-factor indicator of energy efficiency is the ratio between GDP and energy consumption, such as energy intensity, which is simple and straightforward. However, it neglects the substitution between energy and other inputs and may lead to biased results that gradually reduce use by related fields. Another type of multiple-factor indicator integrating the contributions of other elements and Data Envelopment Analysis (DEA) (Farrell 1957) and Stochastic Frontier Analysis (SFA) (Kumbhakar and Lovell 2000) are measurement methods. The disadvantage of corresponding to one output limits the application of SFA. Conversely, DEA (Farrell 1957), CCR-DEA (Charnes et al. 1978), and BCC-DEA (Banker et al. 1984) are well established for evaluating the relative efficiencies of comparable entities with multiple inputs and outputs. These DEA models were introduced by Hu and Wang (2006) for energy efficiency analyses. Nevertheless, efficiency is impractical when undesirable outputs are not considered. Tone (2001) proposed that the Slacks-Based Model (SBM) overcomes this defect and is widely accepted.

However, their impacts of external environmental factors and random disturbances are neglected, and the bootstrapping estimate set (Simar and Wilson 1998) and stochastic

DEA (Olesen and Petersen 2016) weaken these effects to a certain degree. However, they assume that efficiency divergence arises from the heterogeneity of decision-making units (DMU). Instead, the three-stage DEA model proposed by Fried et al. (2002) was verified to eliminate the impacts of external environmental factors and random errors. This model was used in three modes: (1) closely following the practices of Fried et al. (2002), such as energy efficiency (Zhao et al. 2019) and industrial environmental regulation efficiency (Feng and Li 2020). (2) Adjusting the model to calculate efficiency, for example, environmental efficiency (Xie et al. 2017). (3) Combining the three-stage DEA with others to estimate efficiency, such as regional coal resource efficiency (Cui et al. 2015), total-factor energy efficiency (Huang and Wang 2017), and agricultural total factor productivity (Chen et al. 2021).

Unfortunately, these three-stage DEA models consider the worst situation to adjust the external environmental impacts on the inputs or outputs, which weakens the representativeness and interpretive force of the results. Because after distinguishing the impacts of external environmental factors and random disturbances on the input or output slacks, the adjustments generally refer to the worst situation in the current period. Although all DMU are adjusted to a unified external environment and random interference, this treatment may misestimate efficiency scores. To address this, the best-case scenario is used to neutralize the impacts of the most terrible adjustment by the intermediate adjustment situation three-stage DEA (IAS three-stage DEA), which offers efficiency that reflects the general state better than the traditional three-stage DEA does.

When incorporating environmental costs, combining the three-stage DEA and SBM provides an exemplary method for measuring efficiency, which researchers have tried. For example, Huang and Wang (2017) evaluated and analyzed the total-factor energy efficiency of Chinese 276 cities from 2000 to 2012, and Chen et al. (2021) explored the real agricultural total factor productivity of 30 Chinese provinces from 2000 to 2017. However, defects remain in their three-stage DEA models. Therefore, we applied the IAS three-stage DEA model with the SBM method to re-calculate veritable EEE in 31 Chinese provinces.

### The impacts of regional strategies

Multiple policies are required to meet energy efficiency targets (Wiese et al. 2018); however, the functions of energy policies are controversial. Bertoldi and Mosconi (2020) alluded that energy consumption in Europe in 2013 would have been approximately 12% higher without the implementation of energy efficiency policies. Li and Solaymani (2021) also summarized that efficiency improvement policies effectively reduced the rebound

effect and led to greater energy savings in the economy. Instead, the guidelines presented by Patt et al. (2019) suggested that energy efficiency could be counterproductive to limiting climate change to 1.5 °C global warming from pre-industrial times.

Likewise, to leverage regional development, the Chinese government has proposed the national regional development strategy in the twenty-first century and consists of the Western Development Strategy (including Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Inner Mongolia, and Guangxi, and started in 2000), the Strategy for Revitalizing the Old Industrial Base in Northeast China (including Heilongjiang, Jilin, and Liaoning, and started in 2003), the Strategy of Rising of Central China (including Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan, and started in 2006), and the First Development Strategy of the Eastern Region in China (including Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan, and started in 2006). These strategies should have worked differently in terms of energy efficiency.

Previous studies have investigated the impact of these strategies on the economy and ecology separately. For example, Zhuo and Deng (2020) proposed that the Western Development Strategy enhanced regional green economic efficiency. Ren et al. (2020) suggested that the Strategy for Revitalizing the Old Industrial Base in Northeast China significantly increased its GDP and GDP per capita by 25.70% and 46.00%, respectively. Zhang et al. (2017a) found the First Development Strategy of the Eastern Region in China contributed to total factor productivity. However, these studies are insufficient to infer whether the strategies have played the same role in EEE, making it impossible to summarize these impacts and provide suggestions. Therefore, the functions of strategies on EEE and their decompositions require a more in-depth discussion.

### Methodology

This study employs the IAS three-stage SBM-DEA model to evaluate real provincial EEE. The contents of the model are as follows: In the first stage, the initial EEE was used to obtain an input-oriented SBM-DEA model with three inputs and one desirable output. In the second stage, the input slacks and undesirable output slacks in the first stage were divided into environmental effects, managerial inefficiency, and random errors, after which they were adjusted to refer to the intermediate adjustment situation. The revised data of the second step and real GDP were used in the SBM-DEA model to re-measure the EEE in the third stage.

### The first stage: the input-oriented SBM-DEA model

Various pollutants are by-products that are harmful to production activities, and incorporating these pollutants under a DEA framework is mainly classified into five categories (Bian et al. 2015). In this study, we treat undesirable outputs as eco-environmental cost inputs. The input-oriented SBM-DEA under constant returns to scale is written as follows:

$$\rho = \min_{\lambda, s^-} \left( 1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}} \right) \tag{1}$$

$$s.t. \begin{cases} x_o = X\lambda + s_i^- \\ y_o = Y\lambda \\ \lambda \geq 0, s_i^- \geq 0 \\ i = 1, 2, 3, m = 3 \end{cases}$$

$\rho$  is called comprehensive EEE for DMU, driven by three inputs of energy consumption, exhaust emissions, and wastewater discharge, and is represented by  $X$  when  $i = 1, 2,$  and  $3,$  respectively; and  $m$  is the input types; and  $i$  corresponding to the  $i$  kind input. Moreover,  $s_1^-, s_2^-, s_3^-$  are slacks of the three inputs that demonstrate how much the DMUo should reduce its three inputs to achieve the best practical level. One output of  $Y$  displays by real GDP, and  $\lambda$  is the optimal weight calculated using linear programming.  $\rho = 1$  when  $s_1^- = s_2^- = s_3^- = 0$  and DMU is efficient. Otherwise, the DMU is inefficient.

### The second stage: adjusting inputs refer to the intermediate adjustment situation

Managerial inefficiency, environmental effects, and stochastic disturbances (Feng and Li 2020) affect the comprehensive efficiencies. To distinguish these needless effects, an SFA model is built using the external environmental variables as explanatory variables, and the slacks of each input are received from the first stage as interpreted variables:

$$s_{in}^- = f^i(z_n; \beta^i) + v_{in} + \mu_{in}; i = 1, \dots, m, n = 1, \dots, N \tag{2}$$

$s_{in}^-$  represents the slack of  $i$  input in DMU  $n$ , and  $z_n$  implies the vector of external environmental variables that influence the provincial EEE; hence,  $f^i(z_n; \beta^i)$  is a deterministic feasible slack frontier, and  $\beta^i$  is a parameter vector of the external environmental variables estimated from  $i$  input slack.  $f^i(z_n; \beta^i) = \beta_0^i + \sum \beta_k^i Z_{ik}$  is the interpretation of external environmental factors, and  $v_{in} \sim N(0, \sigma_{vi}^2)$  and  $\mu_{in} \sim N^+(\mu^n, \sigma_{\mu i}^2)$  express statistical noise and managerial inefficiency to the corresponding  $i$  input of DMU  $n$ . Set  $\gamma = \sigma_{\mu i}^2 / (\sigma_{\mu i}^2 + \sigma_{vi}^2)$ , assuming that  $v_{in}$  and  $\mu_{in}$  are distribute independently,  $\gamma$  approaching 1 signifies that the impacts of managerial inefficiency dominate the energy inefficiencies of DMU, and the SFA method could be utilized (Zhao et al.

2019). The ordinary least squares approach can be applied when  $\gamma$  approaches 0.

Based on Jondrow et al. (1982), the estimator of the conditional expected value of the administration inefficiency term  $\mu_{in}$  of input variables for each DMU can be obtained by the following method:

$$\hat{E}[\mu_{in}/(v_{in} + \mu_{in})] = \frac{\hat{\lambda}_i \hat{\sigma}_i \left[ \frac{\phi(\frac{\hat{\epsilon}_{in} \hat{\lambda}_i}{\hat{\sigma}_i})}{\Phi(\frac{\hat{\epsilon}_{in} \hat{\lambda}_i}{\hat{\sigma}_i})} + \frac{\hat{\epsilon}_{in} \hat{\lambda}_i}{\hat{\sigma}_i} \right]}{1 + \hat{\lambda}_i^2} \tag{3}$$

where  $\hat{E}[\mu_{in}/(v_{in} + \mu_{in})], \hat{\epsilon}_{in}, \hat{\lambda}_i,$  and  $\hat{\sigma}_i$  represent the evaluated values of  $E[\mu_{in}/(v_{in} + \mu_{in})], \epsilon_{in}, \lambda_i,$  and  $\sigma_i,$  respectively.  $\lambda_i = \frac{\sigma_{\mu i}}{\sigma_{vi}}, \sigma_i^2 = \sigma_{\mu i}^2 + \sigma_{vi}^2$ . The density function and distribution function of the standard normal distribution are  $\phi(\cdot)$  and  $\Phi(\cdot),$  respectively. The elaborated mathematical procedure can be set and referred to Ref Fried et al. (2002), Zhang et al. (2017b), and Zhao et al. (2019). Then,  $v_{in}$  is estimated.

$$\hat{E}[v_{in}/(v_{in} + \mu_{in})] = s_{in}^- - z_n \hat{\beta}^i - \hat{E}[\mu_{in}/(v_{in} + \mu_{in})]; i = 1, \dots, m, n = 1, \dots, N \tag{4}$$

Unlike in the traditional three-stage DEA model, the inputs are rectified to an intermediate situation. Specifically, we used the scenario of the best in the current period multiplied by the worst state adjustment and got their geometric average to replace the formula in Fried et al. (2002), and the new operation is as follows:

$$x_{in}^A = x_{in} + \sqrt{\left[ (\max_t(z_n \hat{\beta}^i) - z_n \hat{\beta}^i) + (\max_t(v_{in}) - v_{in}) \right]} \tag{5}$$

$$* \sqrt{\left[ (z_n \hat{\beta}^i - \min_t(z_n \hat{\beta}^i)) + (v_{in} - \min_t(v_{in})) \right]}$$

As shown in Eq. (5),  $x_{in}^A$  and  $x_{in}$  are adjusted, and the initial inputs of  $i$  input in DMU  $n, \max_t(z_n \hat{\beta}^i)$  and  $\min_t(z_n \hat{\beta}^i)$  are the upper and lower boundaries of the  $i$  input affected by external environmental factors in  $t$  period; hence,  $(\max_t(z_n \hat{\beta}^i) - z_n \hat{\beta}^i)$  and  $(z_n \hat{\beta}^i - \min_t(z_n \hat{\beta}^i))$  are the worst and best circumstances under the impacts of external environmental factors. Similarly,  $\max_t(v_{in})$  and  $\min_t(v_{in})$  are the maximum and minimum values that are affected by random errors in  $t$  period, respectively; therefore,  $(\max_t(v_{in}) - v_{in})$  and  $(v_{in} - \min_t(v_{in}))$  are the maximal and minimal uncertainty circumstances in  $t$  period, respectively.

$(\max_t(z_n \hat{\beta}^i) - z_n \hat{\beta}^i) + (\max_t(v_{in}) - v_{in})$  is the adjustment content in Fried et al. (2002), representing that DMU  $n$  suffers the worst external environment and the most accidental cases of  $i$  input in  $t$  period. Specifically, adjusting the inputs refers to the worst situation. Inversely,  $(z_n \hat{\beta}^i - \min_t(z_n \hat{\beta}^i)) + (v_{in} - \min_t(v_{in}))$  is the opposite of the above part, which means that DMU  $n$  suffers the best external

environment and the least accidental cases of  $i$  input in  $t$  period. It is then used to multiply the adjustment content in the traditional three-stage DEA model and obtain their geometric mean to replace the typical part. The IAS part is given by (6).

$$\sqrt{\left[ \frac{\max(z_n \hat{\beta}^i) - z_n \hat{\beta}^i}{\max(z_n \hat{\beta}^i) + z_n \hat{\beta}^i} + \frac{\max(v_{in}) - v_{in}}{\max(v_{in}) + v_{in}} \right]} * \sqrt{\left[ \frac{z_n \hat{\beta}^i - \min(z_n \hat{\beta}^i)}{z_n \hat{\beta}^i + \min(z_n \hat{\beta}^i)} + \frac{v_{in} - \min(v_{in})}{v_{in} + \min(v_{in})} \right]} \tag{6}$$

Therefore, it neutralizes and weakens the adverse effects of operations in the traditional three-stage DEA model, which is changed to an IAS three-stage DEA model to obtain meaningful efficiency values.

### The third stage: the input-oriented IAS SBM-DEA model

Compared with the first stage of EEE, the third stage’s efficiency gauged by the adjusted inputs and real GDP are used in formula (7) which is reliable (Cui et al. 2015; Zhang et al. 2017b; Xie et al. 2017; Feng and Li 2020), which is called real EEE for the impacts by external environmental factors, and random errors are adjusted.

$$\rho^* = \min_{\lambda^*, s_1^{-*}, s_2^{-*}, s_3^{-*}} \left( 1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^{-*}}{x_{io}^A} \right)$$

$$s.t. \begin{cases} x_o^* = X^A \lambda^* + s_i^{-*} \\ y_o^* = Y \lambda^* \\ \lambda^* \geq 0, s_i^{-*} \geq 0 \\ i = 1, 2, 3, m = 3 \end{cases} \tag{7}$$

$\rho^*$  is the real EEE for the impacts of external environmental factors and random errors are removed, and it is driven by adjusted energy consumption, exhaust emissions, and wastewater discharge, represented by  $X^A$  when  $i = 1, 2$ , and 3, respectively.  $s_1^{-*}, s_2^{-*}, s_3^{-*}$  are the slacks of the three adjusted inputs, and  $Y$  is displayed by the real GDP.  $\lambda^*$  is a new optimal weight that is calculated using linear programming. A DMU is efficient when  $\rho^* = 1$ ; otherwise, the DMU is inefficient.

Furthermore, efficiency decomposition provides available information for further analysis of EEE aspects. Banker et al. (1984) suggested decomposing the overall technical efficiency in Charnes et al. (1978) into pure technical efficiency and scale efficiency. Following this method, the decomposition of EEE is as follows:

$$\rho^* = EEE = PEEE * SE \tag{8}$$

Hence, EEE is decomposed into PEEE and SE using formula (8). PEEE reflects how the production technology is applied to maximize economic achievements with fixed energy consumption and eco-environmental costs, and its high value indicates high management ability. SE reflects

the scale effectiveness and rationality of resource allocation in a regional economy. Its better performance signifies that the economy of scale effect is achieved and is advisable in the scale and allocation of factors.

## Variables, data, and empirical result

### Inputs, output, and external environmental factors

We chose energy consumption, real GDP, and exhaust emissions and wastewater discharge as the input, output, and undesirable outputs, respectively, under the new EEE measurement framework (Table 1). Furthermore, we regarded undesirable outputs as the eco-environmental expenses (inputs).

Notably, various energy consumptions are translated into standard coal according to the standard coal conversion coefficient (Coal Equivalent-ENS 2019). Unlike Zhao et al. (2019), we divide external environmental factors into natural environmental factors (forest land area and energy self-sufficiency rate) and social environmental factors (population density, industrial structure, and traffic conditions) to classify the impacts.

### Data source

All data were obtained from the *National Bureau of Statistics of China* (1995–2018) and *China Statistical Yearbook* (1996–2019), and missing data were supplemented from the *Statistical Bulletin of National Economic and Social Development of Provinces* (1996–2019) and *China Environmental Statistics Yearbook* (1996–2019). According to the consistency and availability of the data, 31 Chinese provinces (except Taiwan, Hong Kong, and Macao) from 1995 to 2018 were collected as samples. In order to analyze regional EEE gaps and explore the impact of corresponding regional strategy, we further divide the sample into Northeast China (Heilongjiang, Jilin, and Liaoning), East China (Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan), Central China (Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan), and West China (Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Inner Mongolia, and Guangxi) (follow the Ref Li and Hu 2012; Wang et al. 2013; Huang and Wang 2017; Liu et al. 2020; Chen et al. 2021).

### Empirical result

#### The comprehensive energy-environmental efficiency (stage I)

In this phase, the input-oriented SBM-DEA model under constant returns to scale in the DEA-SOLVER Pro software (5.0) was used to calculate the initial provincial comprehensive EEE

**Table 1** The factors in the new energy-environmental efficiency measurement framework

Stage	Variable category	Variable	Unit	Variable description
SBM stage (the first and third stage)	Input	Energy consumption	10 thousand tons	It is summarized after converting electricity, coke, coal, kerosene, gasoline, fuel oil, natural gas, crude oil, and diesel consumption into standard coal
	Undesirable output	Exhaust emissions	10 thousand tons	The sum of CO <sub>2</sub> and SO <sub>2</sub> emissions
		Wastewater discharge	10 thousand tons	Industrial Wastewater Discharge
	Desirable output	Real GDP	100 million CNY	The GDP data is adjusted by the multiply price index based on the period of 1995
SFA stage (the second stage)	Slacks	Energy consumption slacks	10 thousand tons	Identical to the corresponding variable
		Exhaust emissions slacks	10 thousand tons	Identical to the corresponding variable
		Wastewater discharge slacks	10 thousand tons	Identical to the corresponding variable
	Natural environmental factors	Forest land area	Million ha	The sum of forest area and crop planting area
		Energy self-sufficiency rate	%	Energy consumption/energy production
	Social environmental factors	Population density	Thousand people	The percentage of the total permanent population at the end of the year to the corresponding province area
		Industrial structure	%	The proportion of secondary industry GDP in the total
Traffic conditions		km/km <sup>2</sup>	A rate of the sum of roads, waterways, and railways to the area of corresponding provinces	

in 31 provinces in China from 1995 to 2018, without considering the impacts of environmental factors and random errors.

The initial provincial EEE is shown in Fig. 1. Firstly, Shandong, Fujian, Guangdong, Hainan, Shaanxi, Chongqing, and Tibet with EEE equaled 1 in 1995 accounted for 22.58% of the total. However, some changes happened in 2018; only four provinces, Beijing, Tianjin, Chongqing, and Tibet, remained on the optimal production frontier in 2018. Other disappeared benchmark provinces, such as Shandong, Fujian, Guangdong, Hainan, Shaanxi, and Inner Mongolia, may have reduced their GDP expansion quality for the persistent pollutants.

Secondly, China's EEE first increased from 0.550 to 0.654 during 1995–2001, then fluctuated and decreased to 0.479 in 2018, showing an inverted U shape rather than an upward trend (Chen et al. 2020).

Thirdly, the differences were noticeable regionally. East China had the highest efficiency, followed by West China, and Northeast China had the lowest scores. Additionally, the top eight EEE provinces, Beijing, Tianjin, Shandong, Chongqing, Jiangsu, Fujian, Guangdong, and Tibet were located in East China and West China. Instead, the five bottom EEE provinces, Shanxi, Ningxia, Qinghai, Guizhou, and Gansu, were in Central China and West China. However, the impact of external environmental factors on EEE was not considered.

### The impact of external environmental factors on energy-environmental efficiency (stage II)

In this part, we seen the slacks of input as independent variables and selected five external environmental factors as

dependent variables in the SFA model and estimated them by the software Frontier 4.1.

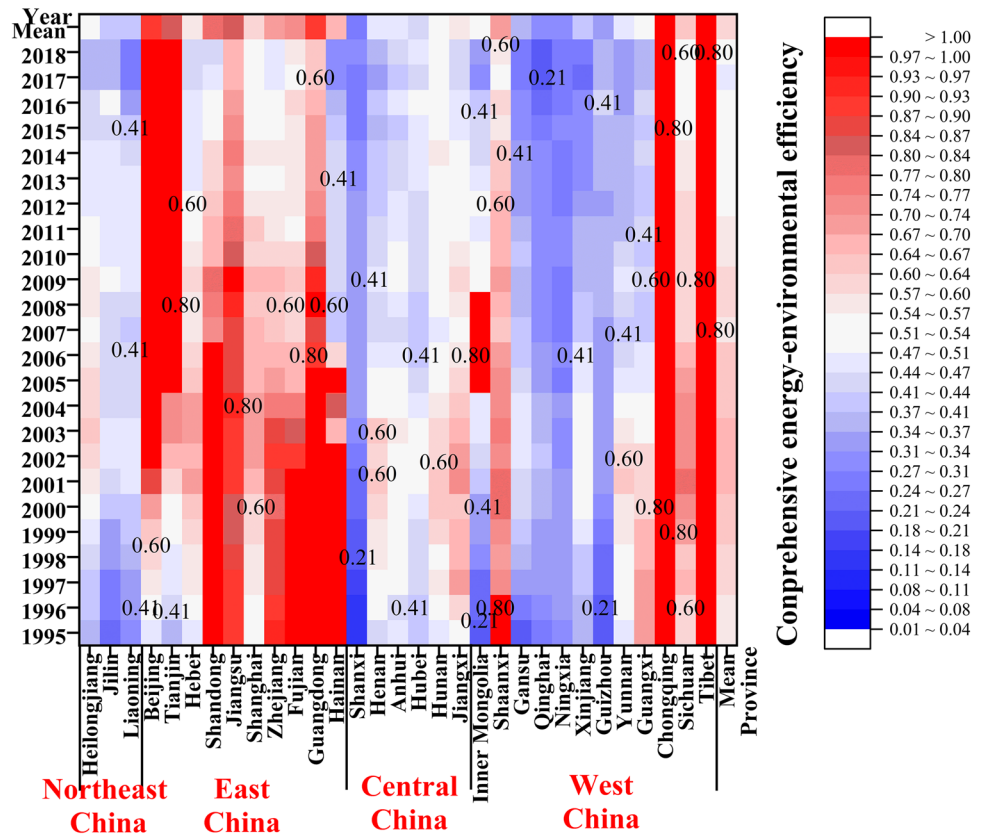
As shown in Table 2, the SFA models' robustness was validated by the  $\gamma$  and the LR examination results of the three models. That is, the managerial inefficiency dominates baneful EEE performance. Thus, disturbances caused by environmental factors and random errors must be avoided. If the regression coefficient of an external environmental factor is positive, an increase in the variable will lead to resource-wasting, negatively influencing EEE, and vice versa. The estimation results are as follows.

The forest land area represents each province's absorption capacity to the pollutants (especially waste gas) aroused by energy consumption. The larger the value is, the stronger ability to deal with the pollutants. The results hint at the index positively impacting energy consumption, exhaust emissions, and wastewater discharge at the significance of 1%, 10%, and 1%. The provincial forest land area significantly negatively affected EEE. The stronger the self-purification capacity of the natural environment, the more energy is consumed by the provinces, resulting in a decreased EEE.

The population density reflects economic activeness. The higher this indicator implies the province keens to consume more energy. The population density coefficients are all positive. The effects of the population density on input slacks are positive; therefore, they negatively influence EEE. That is, high population density could reverse the direction of EEE.

The traffic conditions denote the economic basis of a region. Under significant of 1%, the regression results depict

**Fig. 1** The comprehensive energy-environmental efficiency (in the first stage)



**Table 2** SFA estimation results

Explanatory variable (input slacks)	Energy consumption	Exhaust emissions	Wastewater discharge
Constant term	6187.48*** (15.188)	46,298.24*** (499.848)	268,399.62*** (268.061)
Forest land area	15.83*** (16.145)	3.34* (1.734)	121.23*** (8.641)
Population density	0.98 (-0.656)	11.24** (3.616)	77.95** (3.4830)
Traffic conditions	7248.75*** (7.798)	14,758.37*** (9.519)	-62,737.95*** (-53.531)
Energy self-sufficiency rate	-12,402.90*** (-9.84)	-18,186.55*** (-24.284)	-146,205.22*** (-14.61)
Industrial structure	15,335.40*** (21.458)	-24,995.82*** (-34.730)	451,089.64*** (45.102)
$\sigma^2$	189,366,780	614,327,660	67,662,071,000
$\gamma$	0.79	0.77	0.89
LR test	544.388	424.423	873.611

\*\*\*, \*\*, and \* indicate the 1%, 5%, and 10% significance level of the *t*-statistics of the coefficients

the traffic conditions holding positive impacts on energy consumption and exhaust emissions but negatively affected wastewater discharge, which means that the impact of traffic conditions on EEE are weak and complicated. The EEE in provinces with good traffic conditions may perform better,

which could also mean consuming more energy and pollution simultaneously.

The energy self-sufficiency rate reflects a region’s resource endowment. The larger the value means the more sufficient energy the province supplies. The energy



self-sufficiency rate plays negative roles in energy consumption, wastewater discharge, and exhaust emissions at the level of 1%. A high energy self-sufficiency rate hints at the potency of energy production, which significantly increases the EEE of the region.

The industrial structure determines the way resources use. The higher the indicator implies the province depend more heavily on the secondary industry expansion. The industrial structure affects the slacks negatively. Unlike Cui et al. (2015), the aggregation of industrial structure espouses EEE augmentation, resulting from the increasingly intensive use of energy and other resources that lead to the shrinking of polluting industries. Most external environmental variables are ineffective in improving EEE, particularly natural environmental factors. The rewarding environmental factors require strengthening, while unhelpful aspects should be restricted.

**The real energy-environmental efficiency (stage III)**

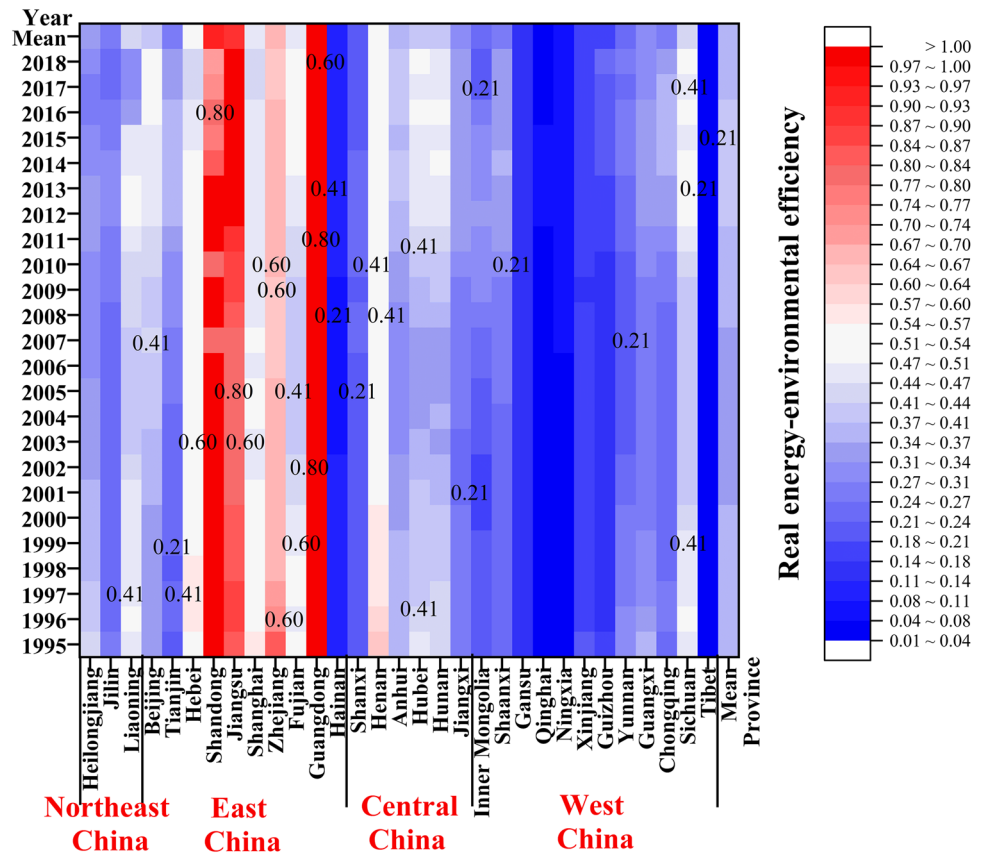
To re-calculate real EEE, the original and adjusted inputs were input into model (7). The results are shown in Fig. 2.

Figure 2 presents the real EEE of 31 Chinese provinces. The real EEE was between 0.250 and 0.500 in most provinces during 1995–2018, and the average value was 0.361.

The top and bottom three provinces were Guangdong, Shandong, and Jiangsu in East China, and Tibet, Qinghai, and Ningxia in West China (with fragile natural eco-environment and weak economic and social development), respectively. Similar to Zhang et al. (2015), 50% of the provinces mainly distributed in West China had decreasing EEE, indicating a worsening contradiction in these areas.

The fundamental EEE differences between provinces were expanded, similar to the views of Zhang et al. (2015) and Chen et al. (2020). For example, Tianjin, Shandong, Shanghai, Zhejiang, and Fujian in East China were far away from the frontier because these provinces rely too heavily on high energy consumption and polluting industries, which has brought related eco-environmental issues and has decreased EEE. Similarly, Shanxi, Inner Mongolia, Tibet, Qinghai, Xinjiang, and Gansu in West China moved away from the national average and were sliding to a lower level because of low-efficiency resource utilization and severe environmental pollution disturbing their EEE improvement. Instead, Beijing, Jiangsu, Hubei, Hunan, Chongqing, and Sichuan provinces have increased their EEE tremendously. Guangdong and Jiangsu, with a mean EEE = 1, have become the learning model for other provinces. In conclusion, the low EEE in China indicate that the economic achievements and eco-environmental costs due to energy use were not coordinated.

**Fig. 2** The real energy-environmental efficiency (in the third stage)



### Comparison of comprehensive and real energy-environmental efficiency

A comparison of Figs. 1 and 2 shows declining real EEE of the 31 provinces. The national average EEE dropped from 0.573 to 0.361, which is different from the point of Zhao et al. (2019). The number of provinces at the EEE frontier decreased from four in 1995 (Beijing, Tianjin, Chongqing, and Tibet) to two in 2018 (Jiangsu and Guangdong). Moreover, the 4 regions were originally at the EEE frontier, but vanished later, indicating that these regions experienced more helpful external environments than others. Conversely, Shandong, Jiangsu, and Guangdong had the highest EEE after adjusting, which indicate that external environments hinder their high-quality development.

Figure 3 compares the comprehensive and real provincial EEE of 31 provinces during 1995–2018. As illustrated, EEE in most provinces decreased, indicating that China’s internal environment was helpful to their EEE. The average EEE after adjusting for Tibet, Chongqing, Hainan, Beijing, Tianjin, Shaanxi, Inner Mongolia, and Shanxi decreased by 0.981, 0.733, 0.575, 0.487, 0.535, 0.428, 0.254, and 0.056, respectively. Beijing, Tianjin, Tibet, and Chongqing cultivated a sustainable environment to improve technological innovation and urbanization and promote EEE improvement. For example, the Zhongguancun Science Park in Beijing in 2014 topped state-level high-technology zones (Zhao et al. 2019). For Hainan, several eco-environmental protection laws and regulations implemented since 2007 have created

a friendly external environment to improve EEE (Zhang et al. 2017b).

With abundant coal resources, Shaanxi, Inner Mongolia, and Shanxi are built as fossil energy bases for China’s economic development, and these regions benefited from whole economic and energy consumption structures to improve EEE. Xinjiang, Qinghai, Gansu, Ningxia, Guizhou, and Yunnan with lower real EEE than other provinces, but higher R&D investment, changed external environmental factors to improve their EEE. Similarly, Jilin’s local government devoted efforts to developing green industry and strengthening the supervision of the polluting industry, which significantly increased in the nation.

Conversely, Liaoning, Shandong, Jiangsu, Guangdong, and Henan experienced increases of 0.024, 0.130, 0.050, 0.131, and 0.045 in their average real EEE, respectively. Guangdong, Shandong, and Jiangsu have heavily depended on energy-intensive and polluting industries, such as iron and steel smelting and the textile industry; therefore, external environmental factors have led to decreased EEE in these provinces. Liaoning is an essential traditional industrial base in China; however, its industries face transformation difficulties that negatively affect EEE. The weak implementation of regulations and relatively low levels of economic development comprise Henan’s unfavorable external environment (Zhang et al. 2017b; Zhao et al. 2019), and its real EEE increased after the above adjustment. Furthermore, slight changes occurred in Heilongjiang, Anhui, Jiangxi, Hunan, Hubei, Sichuan, and Guangxi.

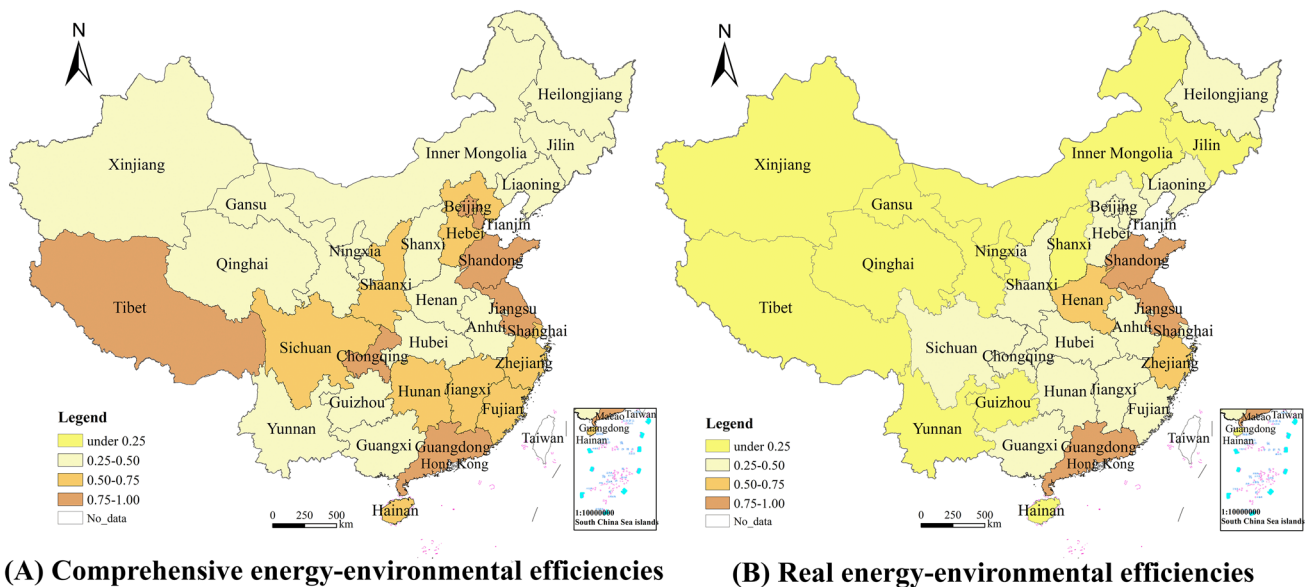


Fig. 3 The comprehensive and real energy-environmental efficiencies

The regional spatiotemporal characteristics are shown in Fig. 4. The comprehensive EEE were significantly higher than the real EEE, and the average values decreased by 37.00%, 21.96%, 22.90%, 19.21%, and 64.74% in 31 province, Northeast China, East China, Central China, and West China, respectively, which differs from Zhao et al. (2019). That is, the external environment is generally beneficial to EEE. In particular, the regions that benefited the most and least are West China and Central and Northeast China, respectively. These gaps may be caused by their locations' and policies' differences.

Notably, East China maintained the best comprehensive and real EEE, whereas West China achieved the worst performances. The comprehensive EEE presents an inverted U-shaped trend, while the real EEE presents more features, such as the U-shape in Central and East China and fluctuations in West China.

### Decompositions of the real energy-environmental efficiency

Learning from Banker et al. (1984), EEE is decomposed into two parts: PEEE and SE. The average EEE, PEEE, and SE among regions are shown in Fig. 5.

Figure 5 illustrates the average real EEE, PEEE, and SE of 31 provinces from 1995 to 2018. As illustrated, for all the provinces, PEEE are remarkably higher than EEE and SE,

which indicates that the managers have effectively utilized under given energy consumption and eco-environmental costs to maximize output. Compared with PEEE, the SE are as problematic as EEE, which means that energy consumption with pollutants and GDP matched unreasonably. Enterprises in West China, Central China, and Northeast China can expand their economic scale. Qin et al. (2017) indicated that pure efficiency was the most vital part of energy efficiency; however, we agree with Chen et al. (2019) and assert that SE is the main obstacle to improving EEE in China, for the variation of EEE is mainly determined by SE.

Moreover, the EEE, PEEE, and SE in the East China of Jiangsu, Shandong, and Guangdong provinces were over 0.80; they have become learning models owing to their excellent performances. Conversely, these efficiencies in the Shanxi, Guangxi, Hainan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Tibet, Qinghai, Ningxia, and Xinjiang located in West China need more support and helpful policies to improve.

The spatiotemporal features of the real EEE and its decomposition are shown in Fig. 6A–C. Regional PEEE are ranked first, followed by SE and EEE. The best PEEE, SE, and EEE were in East China, whereas the worst PEEE, SE, and EEE were in Central and Northeast China and West China, respectively. The SE and EEE were similar, and their morphologies were consistent, indicating that the SE played a decisive role in the change in EEE. Notably, PEEE in all

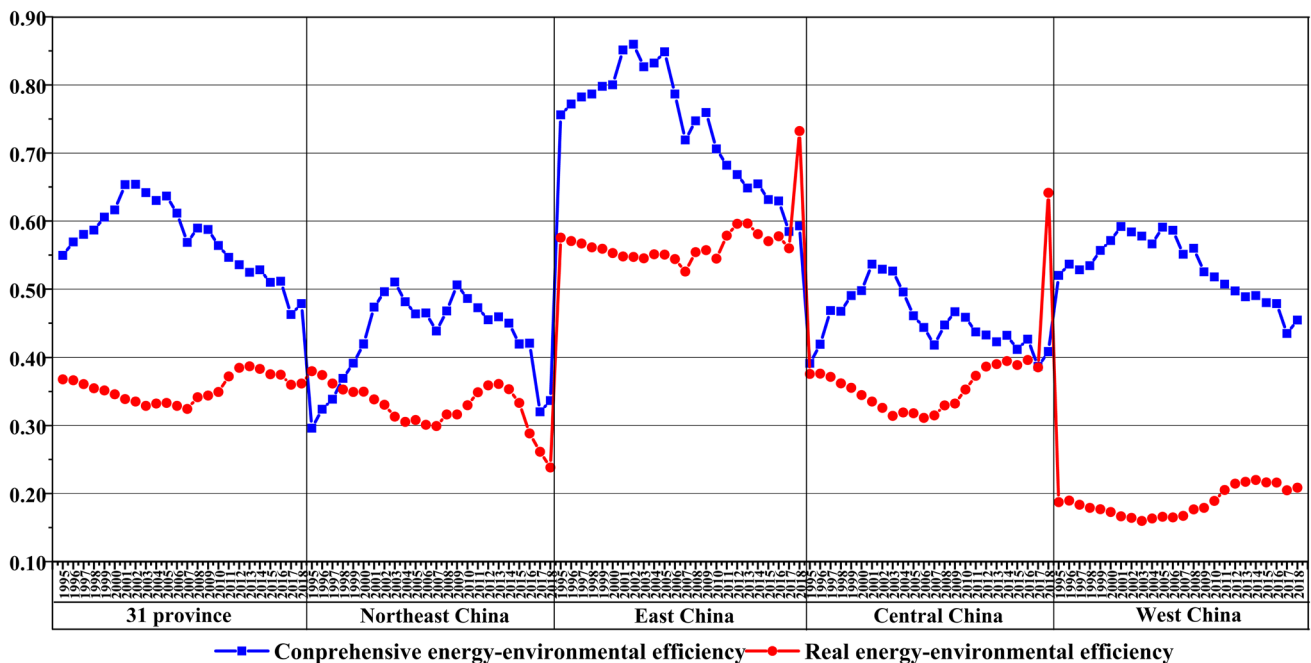
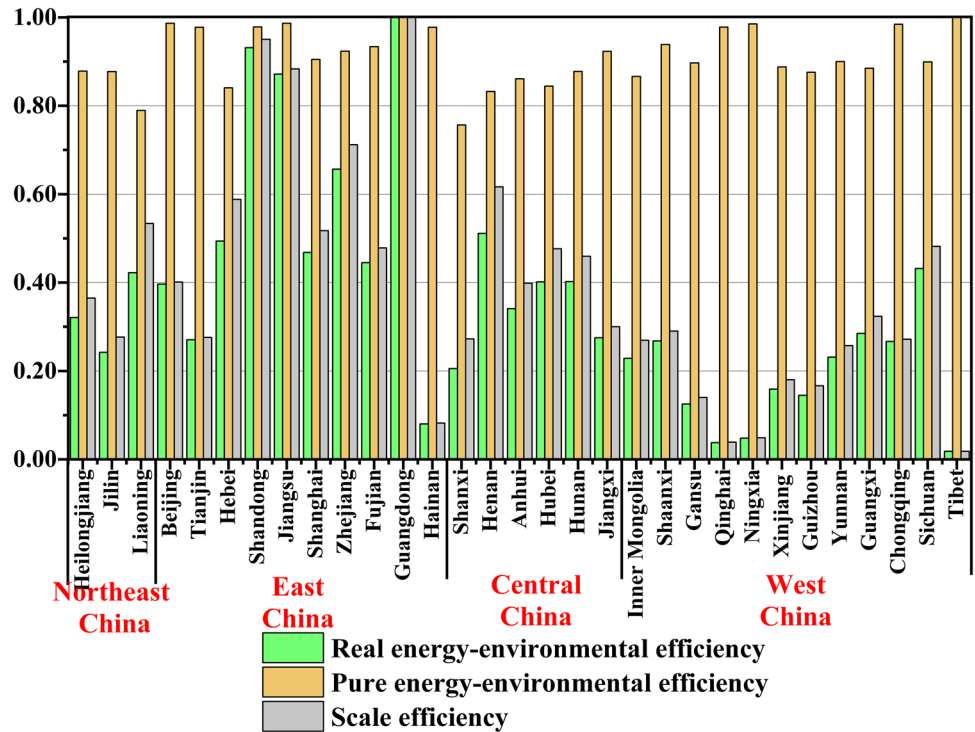


Fig. 4 The spatiotemporal features of comprehensive and real energy-environmental efficiency

**Fig. 5** The real energy-environmental efficiency and its decompositions



regions have shown significant fluctuations and decreasing tendencies since 2002. This is likely caused by China joining the WTO in 2001, which triggered fierce competition in GDP expansion and pressured the eco-environment that negatively impacted their PEEE.

**Statistical features of the energy-environmental efficiency and its decompositions in three adjustment situations.**

Comparisons between the worst, intermediate, and best cases were performed based on the unified data to verify model credibility. First, compared to EEE, PEEE, and SE in the worst adjustment state, the changes in the intermediate adjustment scenario were  $-0.005$ ,  $0.067$ , and  $-0.039$ , respectively. A similar worst adjustment case result in an intermediate adjustment scenario, indicating that best case indeed plays a neutralization role, but has a weak impact on the calculation results and does not affect the conclusion.

Second, the three reference cases maintain the same evolution trends (Fig. 7A1–C1), which are U-shaped with a rising tendency, slight decrease, and U-shaped with a rising tendency in EEE, PEEE, and SE, respectively, and those in the intermediate adjustment case are between the other two extreme cases. The neutralization makes EEE, PEEE, and SE change smoothly rather than dramatically, as in the worst-case and best-case scenarios, and does not change the trend of EEE, PEEE, and SE in the worst adjustment case.

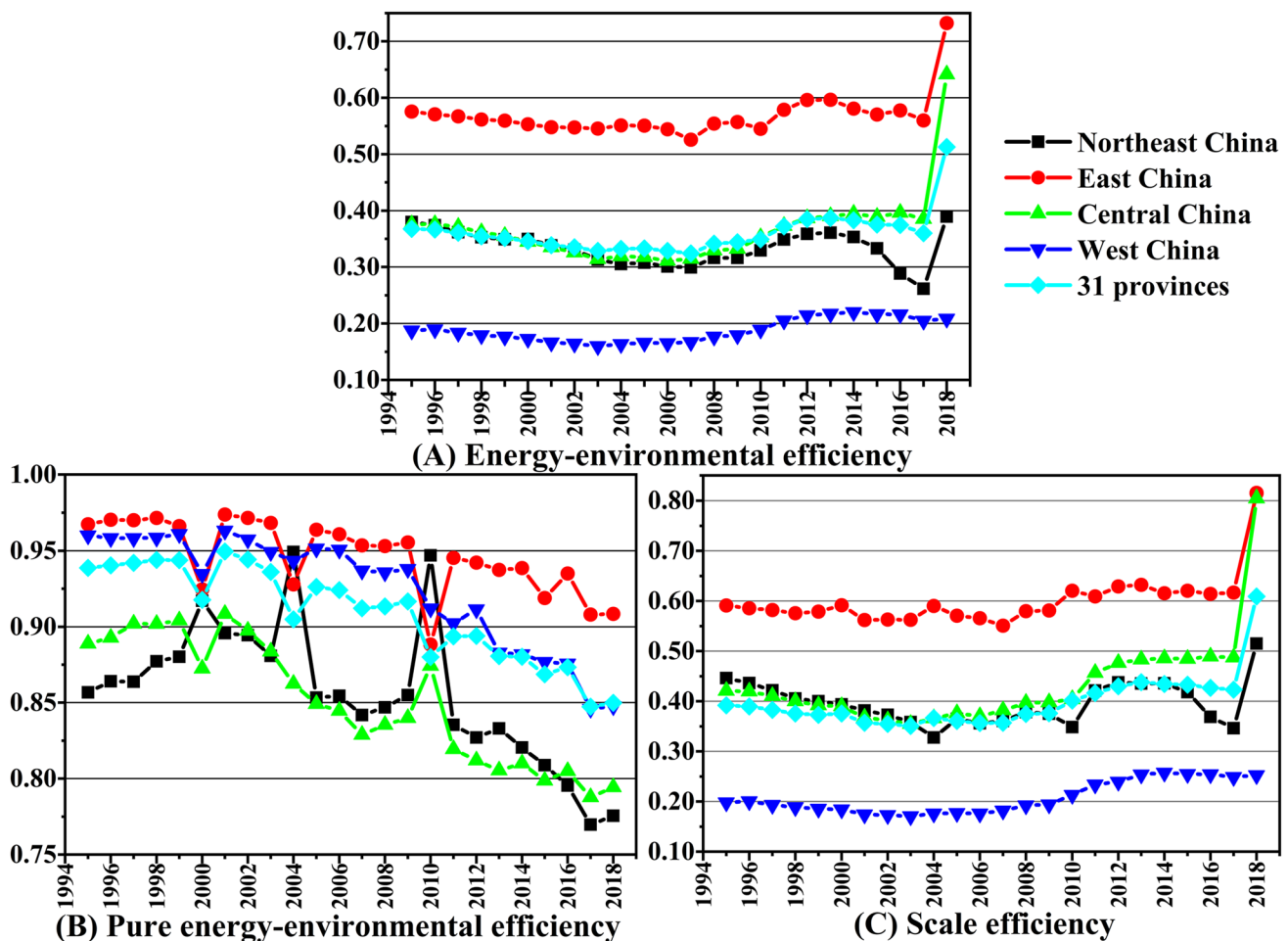
Third, after neutralization by the ideal adjustment case, the 25–75% concentrations of intermediate adjusted EEE, PEEE, and SE are similar and slightly less than that in the worst adjustment state (Fig. 7A2–C2). Additionally, their fluctuation ranges changed by  $0.39\%$ ,  $-37.45\%$ , and  $0.39\%$  compared with the worst adjustment state. That is, the neutralization effect in the best adjustment situation will not affect the distribution range of EEE and SE but will narrow the gaps in PEEE.

The IAS three-stage SBM-DEA model reduces EEE and SE while increasing PEEE and narrowing PEEE differences among provinces, without changing the overall conclusion. Although the change is simple, more reliable results compared with the traditional three-stage SBM-DEA were achieved. Before more actions are conducted into practice to improve EEE, the situations faced by each province need specific analysis.

**Grouping according to pure energy-environmental efficiency and scale efficiency**

According to the average real PEEE and SE, the 31 Chinese provinces were divided into high-high, high-low, low-high, and low-low groups (Fig. 8).

The “high-high” group comprises Guangdong, Jiangsu, Shandong, Beijing, Fujian, and Zhejiang that all located in East China and topped the EEE ranking list. These



**Fig. 6** The regional spatiotemporal features of real energy-environmental efficiency and its decompositions

provinces have similar PEEE values, ranging from 0.900 to 0.990, but vary in SE. Guangdong, Shandong, and Jiangsu are 60% higher than Beijing and Fujian, and the scale economy has promotion potential.

The “high-low” group displays that the provinces obtained high SE and low PEEE, and Shanghai, Sichuan, Hunan, Anhui, Hubei, Hebei, Henan, and Liaoning are classified in the category. For these provinces, excepting to achieve economies of scale, advanced technology and experience must be introduced to maximize economic output and coordinate their relationships with the eco-environment.

The “low-high” group with low SE and high PEEE includes Tibet, Ningxia, Hainan, Qinghai, Chongqing, Tianjin, Shaanxi, and Jiangxi. These provinces have similar PEEE, between 0.900 and 1.000, but obviously different SE. SE in Chongqing, Tianjin, Shaanxi, and Jiangxi are about 0.300 higher than those in Tibet, Qinghai, Ningxia, and Hainan. Reducing pollutant emissions, promoting resource efficiency, and appropriately matching resources

are the primarily measures to improve SE. Besides, promoting PEEE improvement in these provinces is also essential.

The “low-low” group comprises the provinces of Yunnan, Gansu, Guangxi, Xinjiang, Heilongjiang, Jilin, Guizhou, Inner Mongolia, and Shanxi, whose PEEE and SE are both low. High dependence on resource endowments and short industry chains that are unable to form a favorable technological innovation system are the main reasons (Zhang et al. 2017b; Zhao et al. 2019). Hence, both PEEE and SE should be improved by improving innovation capabilities and expanding industry chains to enhance EEE. Additionally, more environmental protection policies are needed to foster their economies.

## Discussion

The Chinese government has formulated multiple regional strategies to narrow economic gaps, and the impact of these strategies has been extensively studied. However, no

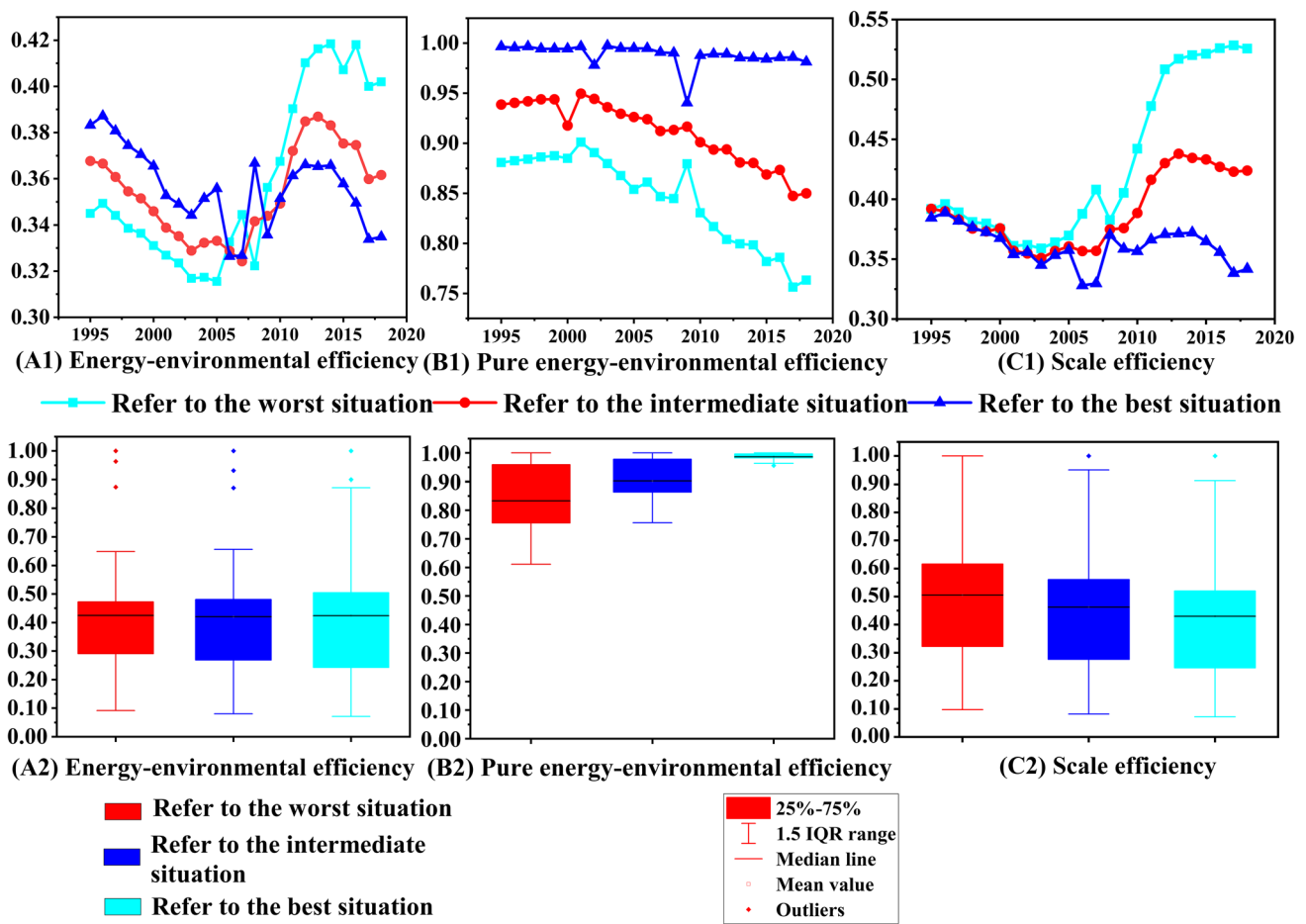


Fig. 7 Statistical features of the energy-environmental efficiency and its decompositions in three adjustments scenarios

comparison was presented, and the commonalities of these effects could not be summarized. We discuss the impact of these strategies on EEE and their decompositions below.

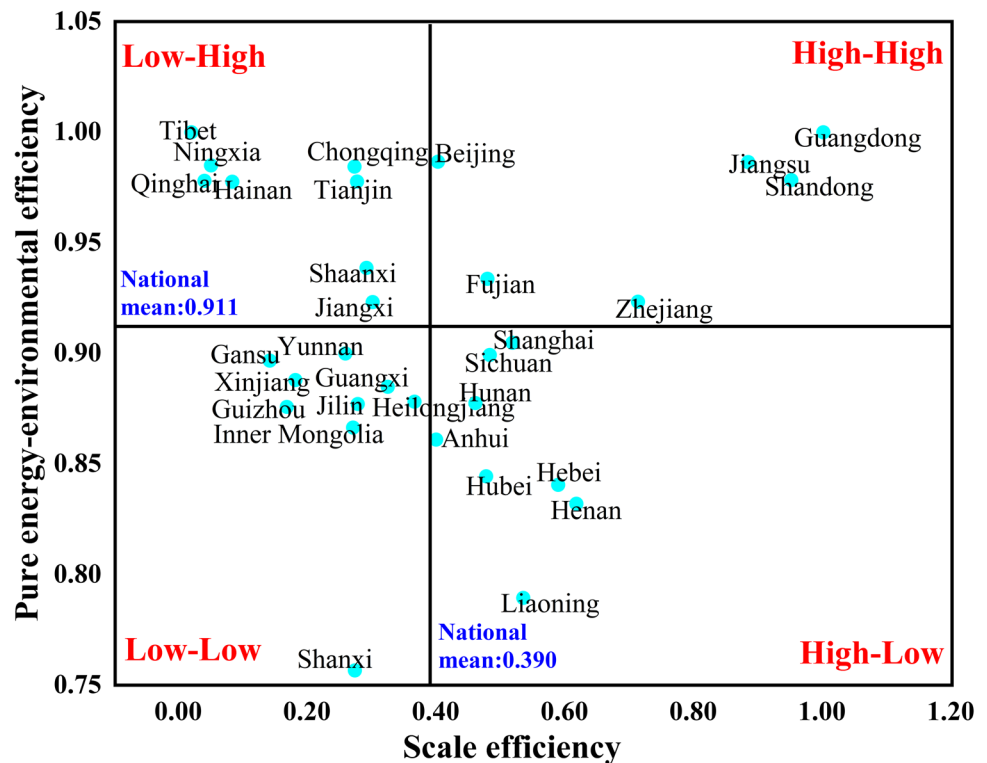
First, Fig. 9A shows that before and after 2000, slight changes occurred in the EEE, PEEE, and SE curves; in particular, PEEE rose after that period, demonstrating the impacts of Western Development Strategy. It has positively worked on PEEE, and the effect disappeared 2 years later, whereas it weakly and negatively affected EEE and SE, in contrast to Zhuo and Deng (2020). This is because the strategy stimulated western provinces to strengthen the economy and attract various investments that promote PEEE improvement. However, this strategy did not reduce the carbon intensity or improve the soft environment. Moreover, the weak economic foundation and incomplete industrial support limited the strategy’s role in improving the EEE and SE.

Second, compared with other areas, Northeast China is the old industrial base and has abundant qualified labor and rich land. However, the PEEE curve was almost unchanged, while the EEE and SE curves rose after 2003, implying that the Strategy for Revitalizing the Old Industrial Base in

Northeast China had a weak and positive effect on EEE and SE, but negative impacts on PEEE (Fig. 9B). The explanation is that, with a solid economic and industrial foundation, the strategy brought about advanced technology, eased eco-environmental costs, and improved EEE and SE. Nevertheless, the strategy did not improve infrastructural roads and education investment (Ren et al. 2020), and the strategy depended the dependence on traditional industries that conflicted with the energy conservation policy and threatened PEEE.

Third, raising development in Central China with a large population, intensive traditional cultures, and an agriculture-based economy is problematic. Figure 9C shows that the EEE and SE curves changed before and after 2006, whereas PEEE did not, demonstrating that the Strategy of Rising of Central China is conducive to affecting EEE and SE but ineffective in supporting PEEE. This is because the industries transferring from the coastal areas coexist with the strategy to bring advanced technology and resources to these provinces, improving their EEE and SE. However, an unreasonable economic structure and inefficient cooperation disturbed the strategy to improve PEEE. Additionally, the outflow of

**Fig. 8** Groups according to pure energy-environmental and scale efficiencies



various resources to East China from central provinces did not change, weakening the strategic functions.

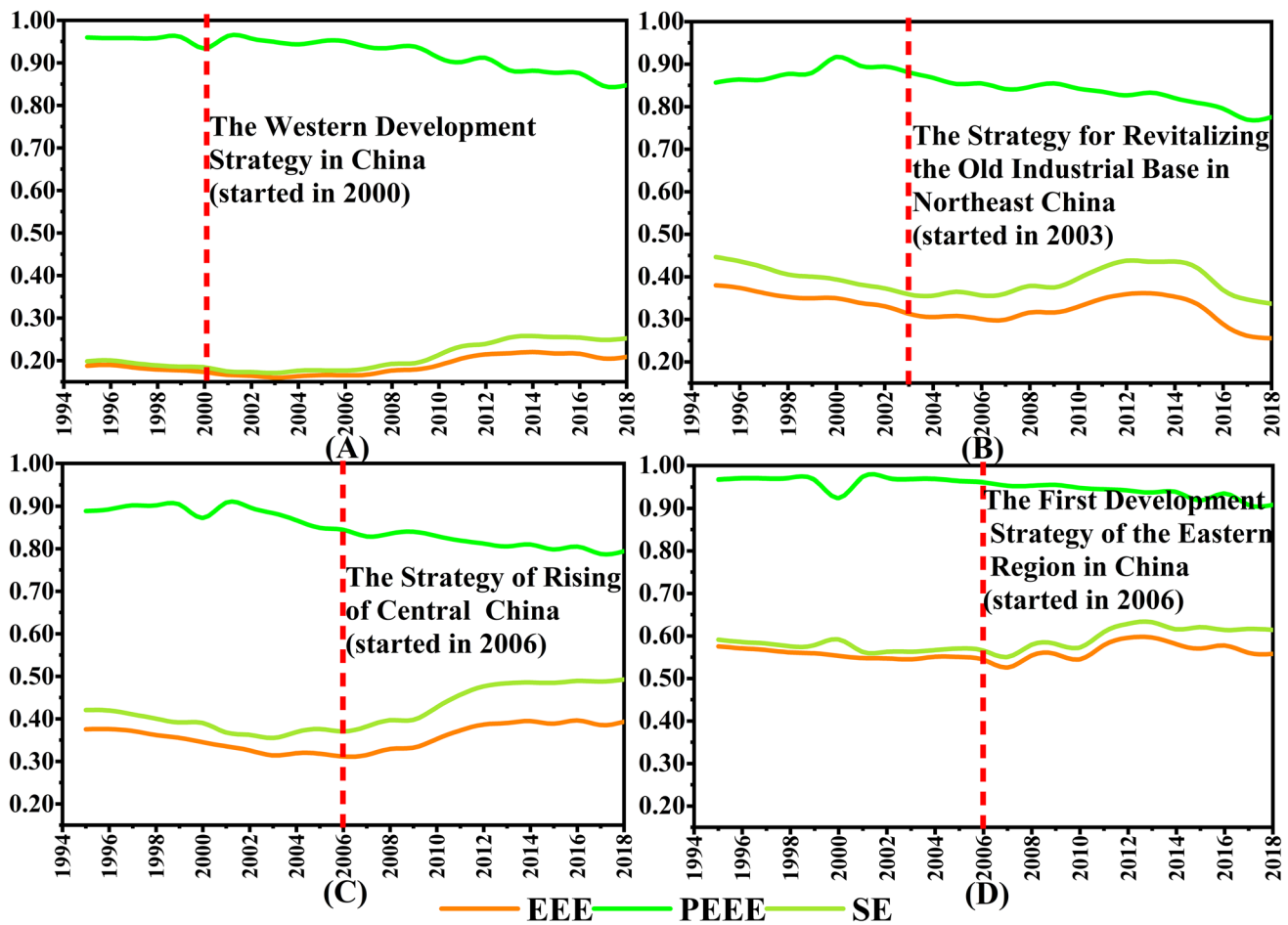
Fourth, the First Development Strategy of the Eastern Region in China expects East China to develop sustainably. Figure 9D shows that the EEE and SE curves decreased in 2007 but increased rapidly after 2007, demonstrating that the First Development Strategy of the Eastern Region in China is helpful to EEE and SE, similar to Zhang et al. (2017a). However, the strategy is ineffective in supporting PEEE because the declining PEEE unchanged. A possible explanation for this is that this strategy promoted that East China enhanced its innovation capabilities and reconstructed the economic structure thereby decreased EEE and SE first and then improved them. Nevertheless, the responses the 2008 financial crisis reactivated the outdated industries; therefore, they intensified pressure on the environment and decreased EEE, PEEE, and SE.

In summary, these strategies benefit EEE and SE because they bring resources, advanced technology, and policy support to the corresponding areas; however, they are ineffective for improving the ability to manage and operate established resources. Second, a strategy can be more effective if hardware conditions support it. For instance, with the help of solid economic and industrial foundations in Northeast China and East China, the strategy promoted their green GDP expansion. Conversely, the outdated economy supported the Western Development Strategy and the Strategy of Rising Central China's function on EEE, PEEE, and

SE. Third, the targeted strategy (fewer areas covered) was accompanied by pronounced impacts. For example, the impacts were significant in the Strategy for Revitalizing the Old Industrial Base in Northeast China, the Strategy of Rising of Central China, and the First Development Strategy of the Eastern Region in China compared to the Western Development Strategy, because they implement fewer provinces. Furthermore, all impacts are weak and short.

## Conclusion and policy implications

In recent decades, the increasing contradiction between economic development and environmental damage triggered by energy use has forced China to transform its mode of development. However, EEE is inconsistently estimated by ambiguous definitions, undesirable output selection, and unrelated factors, which are ineffective for high-quality Chinese development. Moreover, the functions of regional strategies on efficiencies have not been concluded. This study employed the IAS three-stage SBM-DEA model to re-measure EEE from 1995 to 2018, after controlling for the above factors. Additionally, we discuss and summarize the effects of these strategies on EEE, PEEE, and SE. The results are as follows: (1) The IAS three-stage SBM-DEA model reduced EEE and SE while increasing PEEE and narrowing its differences among provinces without changing the overall conclusion,



**Fig. 9** The impacts on real provincial energy-environmental efficiency and its decompositions by regional strategies

indicating that the adjustment in the model is feasible and valuable. (2) China’s EEE are low and overestimated. East China performed better than the other regions, and the gaps among the regions were expanding. (3) EEE are decomposed into PEEE and SE. High PEEE with low SE are the main characteristics in China, and the poor SE led to worrisome EEE. Notably, the downward tendency that started in 2002 in PEEE should be vigilant. (4) These strategies promoted EEE and SE, but were ineffective for improving PEEE. A strategy could effectively function on efficiencies with the support of a solid economic and industrial base and a clear target range.

Controlling the adverse effects of external environmental factors by evolving more suitable models to measure EEE is necessary. Moreover, the current external environment is generally conducive to improving EEE; therefore, maintaining the current environment is essential. Besides, other ways need to be cultivated.

(1) To improve EEE, it is essential to accelerate low carbon and transform a green developed model, such as shifting

from fossil fuels to solar energy, wind energy, and hydro-power, and limiting the high energy consumption and pollution industries. Additionally, narrowing efficiency gaps is needed, and all provinces should share obligations and cooperate. Developed areas can exchange carbon emissions and pollution rights through investments and technologies from less advanced regions. Meanwhile, the less developed provinces must learn from the eastern coastal provinces to promote energy conservation and environmental protection technology. Moreover, the central government should provide policies for balanced and sustainable development.

(2) Instead of increasing various resource inputs, improving the ability to manage and operate established resources, reasonably arranging the combination of elements, and improving technology and equipment in energy use will promote SE and PEEE improvement. In particular, the provinces in the low-low group need to provide their own executable goals, such as controlling total energy consumption and formulating specific and easily attainable pollutant reduction targets, to maintain



efficiency performance. Their governments should not lower environmental regulation standards, even if they encounter emergencies.

- (3) The abovementioned strategies played a limited role in promoting EEE and their decompositions. To form a targeted and practical strategy, policymakers should consider regional differences such as restricted resource endowment, development phase gaps, and geographical characteristics. Future strategies need to be improved over time and anchored in the long run. Moreover, the impact of unknown events must be considered to avoid uncertainties and instability, and emergency measures must be drafted in advance.

**Author contribution** Yufeng Chen: funding acquisition, supervision, conceptualization, methodology, writing—review and editing. Kelong Liu: conceptualization, data curation, methodology, software, visualization, formal analysis, validation, writing—original draft, writing—review and editing. Liangfu Ni: data curation, methodology, software, visualization, validation, writing—review and editing.

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**Data availability** The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

**Code availability** DEA-SOLVER Pro5.0.

## Declarations

**Conflict of interest** The authors declare no competing interests.

## References

- An Q, Wu Q, Li J et al (2019) Environmental efficiency evaluation for Xiangjiang River basin cities based on an improved SBM model and Global Malmquist index. *Energy Econ* 81:95–103. <https://doi.org/10.1016/j.eneco.2019.03.022>
- Banker RD, Charnes A, Cooper WW et al (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manage Sci* 30:1078–1092. <https://doi.org/10.1287/MNSC.30.9.1078>
- Bertoldi P, Mosconi R (2020) Do energy efficiency policies save energy? A new approach based on energy policy indicators (in the EU Member States). *Energy Policy* 139:111320. <https://doi.org/10.1016/j.enpol.2020.111320>
- Bian Y, Liang N, Xu H (2015) Efficiency evaluation of Chinese regional industrial systems with undesirable factors using a two-stage slacks-based measure approach. *J Clean Prod* 87:348–356. <https://doi.org/10.1016/j.jclepro.2014.10.055>
- BP (2020) Statistical Review of World Energy 2020. In: BP. <https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2020-full-report.pdf>. Accessed 31 Mar 2022
- Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. *Eur J Oper Res* 2:429–444
- Chen Y, Ma Y (2021) Does green investment improve energy firm performance? *Energy Policy* 153:1–10. <https://doi.org/10.1016/J.ENPOL.2021.112252>
- Chen N, Xu L, Chen Z (2017) Environmental efficiency analysis of the Yangtze River Economic Zone using super efficiency data envelopment analysis (SEDEA) and tobit models. *Energy* 134:659–671. <https://doi.org/10.1016/j.energy.2017.06.076>
- Chen F, Zhao T, Wang J (2019) The evaluation of energy–environmental efficiency of China’s industrial sector: based on Super-SBM model. *Clean Technol Environ Policy* 21:1397–1414. <https://doi.org/10.1007/s10098-019-01713-0>
- Chen Y, Zhu Z, Yu XI (2020) How urbanization affects energy–environment efficiency: evidence from China. *Singapore Econ Rev* 65:1401–1422. <https://doi.org/10.1142/S0217590820500447>
- Chen Y, Miao J, Zhu Z (2021) Measuring green total factor productivity of China’s agricultural sector: a three-stage SBM-DEA model with non-point source pollution and CO2 emissions. *J Clean Prod* 318:128543. <https://doi.org/10.1016/J.JCLEPRO.2021.128543>
- Cui Y, Huang G, Yin Z (2015) Estimating regional coal resource efficiency in China using three-stage DEA and bootstrap DEA models. *Int J Min Sci Technol* 25:861–864. <https://doi.org/10.1016/j.ijmst.2015.07.024>
- ENS (2019) Coal equivalent-ENS. In: *Eur Nucl Soc*. <https://www.euronuclear.org/glossary/coal-equivalent/>. Accessed 22 Jul 2022
- Farrell MJ (1957) The measurement of productive efficiency. *J R Stat Soc Ser A* 120:253–281. <https://doi.org/10.2307/2343100>
- Feng M, Li X (2020) Evaluating the efficiency of industrial environmental regulation in China: a three-stage data envelopment analysis approach. *J Clean Prod* 242:118535. <https://doi.org/10.1016/j.jclepro.2019.118535>
- Feng C, Wang M, Zhang Y, Liu GC (2018) Decomposition of energy efficiency and energy-saving potential in China: a three-hierarchy meta-frontier approach. *J Clean Prod* 176:1054–1064. <https://doi.org/10.1016/j.jclepro.2017.11.231>
- Fried HO, Lovell CAK, Schmidt SS, Yaisawarng S (2002) Accounting for environmental effects and statistical noise in Data Envelopment Analysis. *J Product Anal* 17:157–174. <https://doi.org/10.1023/A:1013548723393>
- Hu JL, Wang SC (2006) Total-factor energy efficiency of regions in China. *Energy Policy* 34:3206–3217. <https://doi.org/10.1016/j.enpol.2005.06.015>
- Huang H, Wang T (2017) The total-factor energy efficiency of regions in China: based on three-stage SBM model. *Sustain* 9:1–20. <https://doi.org/10.3390/SU9091664>
- IBRD-IDA (2019) World Bank Open Data. In: *World Bank Gr*. <https://data.worldbank.org/cn/country/china?view=chart>. Accessed 6 Apr 2021
- IEA (2019) CO2 emissions statistics Data services-IEA. <https://www.iea.org/subscribe-to-data-services/co2-emissions-statistics>. Accessed 5 Apr 2021
- Jondrow J, Knox Lovell CA, Materov IS, Schmidt P (1982) On the estimation of technical inefficiency in the stochastic frontier production function model. *J Econom* 19:233–238. [https://doi.org/10.1016/0304-4076\(82\)90004-5](https://doi.org/10.1016/0304-4076(82)90004-5)
- Kumbhakar SC, Lovell CAK (2000) Stochastic frontier analysis. *Stoch Front Anal* 136–142

- Li LB, Hu JL (2012) Ecological total-factor energy efficiency of regions in China. *Energy Policy* 46:216–224. <https://doi.org/10.1016/j.enpol.2012.03.053>
- Li Z, Solaymani S (2021) Effectiveness of energy efficiency improvements in the context of energy subsidy policies. *Clean Technol Environ Policy* 23:937–963. <https://doi.org/10.1007/s10098-020-02005-8>
- Liu Z, Zhang H, Zhang YJ, Zhu TT (2020) How does industrial policy affect the eco-efficiency of industrial sector? Evidence from China. *Appl Energy* 272:115206. <https://doi.org/10.1016/J.APENERGY.2020.115206>
- Olesen OB, Petersen NC (2016) Stochastic data envelopment analysis - a review. *Eur J Oper Res* 251:2–21
- Patt A, van Vliet O, Lilliestam J, Pfenninger S (2019) Will policies to promote energy efficiency help or hinder achieving a 1.5 °C climate target? *Energy Effic* 12:551–565. <https://doi.org/10.1007/s12053-018-9715-8>
- Qin Q, Li X, Li L et al (2017) Air emissions perspective on energy efficiency: an empirical analysis of China's coastal areas. *Appl Energy* 185:604–614. <https://doi.org/10.1016/j.apenergy.2016.10.127>
- Qin M, Sun M, Li J (2021) Impact of environmental regulation policy on ecological efficiency in four major urban agglomerations in eastern China. *Ecol Indic* 130:108002. <https://doi.org/10.1016/J.ECOLIND.2021.108002>
- Ren W, Xue B, Yang J (2020) Lu C (2020) Effects of the Northeast China revitalization strategy on regional economic growth and social development. *Chinese Geogr Sci* 305(30):791–809. <https://doi.org/10.1007/S11769-020-1149-5>
- Simar L, Wilson PW (1998) Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Manage Sci* 44:49–61. <https://doi.org/10.1287/mnsc.44.1.49>
- Song M, Song Y, An Q, Yu H (2013) Review of environmental efficiency and its influencing factors in China: 1998–2009. *Renew Sustain Energy Rev* 20:8–14. <https://doi.org/10.1016/j.rser.2012.11.075>
- Tone K (2001) Slacks-based measure of efficiency in data envelopment analysis. *Eur J Oper Res* 130:498–509. [https://doi.org/10.1016/S0377-2217\(99\)00407-5](https://doi.org/10.1016/S0377-2217(99)00407-5)
- Wang Z, Feng C (2015) A performance evaluation of the energy, environmental, and economic efficiency and productivity in China: an application of global data envelopment analysis. *Appl Energy* 147:617–626. <https://doi.org/10.1016/j.apenergy.2015.01.108>
- Wang J, Zhao T (2017) Regional energy-environmental performance and investment strategy for China's non-ferrous metals industry: a non-radial DEA based analysis. *J Clean Prod* 163:187–201. <https://doi.org/10.1016/J.JCLEPRO.2016.02.020>
- Wang K, Lu B, Wei YM (2013) China's regional energy and environmental efficiency: a Range-Adjusted Measure based analysis. *Appl Energy* 112:1403–1415. <https://doi.org/10.1016/j.apenergy.2013.04.021>
- Wang Q, Su B, Zhou P, Chiu CR (2016) Measuring total-factor CO<sub>2</sub> emission performance and technology gaps using a non-radial directional distance function: a modified approach. *Energy Econ* 56:475–482. <https://doi.org/10.1016/j.eneco.2016.04.005>
- Wang Y, Li Y, Zhu Z, Dong J (2021) Evaluation of green growth efficiency of oil and gas resource-based cities in China. *Clean Technol Environ Policy* 1–11. <https://doi.org/10.1007/s10098-021-02060-9>
- Wiese C, Larsen A, Pade LL (2018) Interaction effects of energy efficiency policies: a review. *Energy Effic* 11:2137–2156
- Wu H, Hao Y, Ren S (2020) How do environmental regulation and environmental decentralization affect green total factor energy efficiency: evidence from China. *Energy Econ* 91:104880. <https://doi.org/10.1016/J.ENERCO.2020.104880>
- Xie BC, Duan N, Wang YS et al (2017) Environmental efficiency and abatement cost of China's industrial sectors based on a three-stage data envelopment analysis. *J Clean Prod* 153:626–636. <https://doi.org/10.1016/j.jclepro.2016.12.100>
- Zhang N, Wei X (2015) Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. *Appl Energy* 146:409–420. <https://doi.org/10.1016/j.apenergy.2015.01.072>
- Zhang N, Kong F, Yu Y (2015) Measuring ecological total-factor energy efficiency incorporating regional heterogeneities in China. *Ecol Indic* 51:165–172. <https://doi.org/10.1016/j.ecolind.2014.07.041>
- Zhang C, Chen N, Zhou B (2017a) Eastern development strategy and total factor productivity improvement—based on propensity score matching—an empirical analysis of double difference method. In: *Contemp Financ*. <https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2017a&filename=DDCJ2017a11001&uniplatform=NZKPT&v=TAGVucR6SMJ2tueCdGeoRfFmECLIsV9urXFoBEx57ORayIn8SK EevzzCONvS3Osv>. Accessed 20 Aug 2022
- Zhang J, Liu Y, Chang Y, Zhang L (2017b) Industrial eco-efficiency in China: a provincial quantification using three-stage data envelopment analysis. *J Clean Prod* 143:238–249. <https://doi.org/10.1016/j.jclepro.2016.12.123>
- Zhang J, Li H, Xia B, Skitmore M (2018) Impact of environment regulation on the efficiency of regional construction industry: a 3-stage Data Envelopment Analysis (DEA). *J Clean Prod* 200:770–780. <https://doi.org/10.1016/J.JCLEPRO.2018.07.189>
- Zhang Y, Li X, Jiang F et al (2020) Industrial policy, energy and environment efficiency: evidence from Chinese firm-level data. *J Environ Manage* 260:110123. <https://doi.org/10.1016/j.jenvman.2020.110123>
- Zhao H, Guo S, Zhao H (2019) Provincial energy efficiency of China quantified by three-stage data envelopment analysis. *Energy* 166:96–107. <https://doi.org/10.1016/j.energy.2018.10.063>
- Zhong Z, Peng B, Elahi E (2020) Spatial and temporal pattern evolution and influencing factors of energy–environmental efficiency: a case study of Yangtze River urban agglomeration in China. *Energy Environ* 32:242–261. <https://doi.org/10.1177/0958305X20923114>
- Zhou Y, Liu Z, Liu S et al (2020) Analysis of industrial eco-efficiency and its influencing factors in China. *Clean Technol Environ Policy* 22:2023–2038. <https://doi.org/10.1007/s10098-020-01943-7>
- Zhuo C, Deng F (2020) How does China's Western Development Strategy affect regional green economic efficiency? *Sci Total Environ* 707:135939. <https://doi.org/10.1016/j.scitotenv.2019.135939>

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