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Efficiency evaluation and dynamic evolution of China's regional green economy: A method based on the Super-PEBM model and DEA window analysis

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ABSTRACT

Given the current circumstances of increasingly serious resource consumption and environmental pollution, the development of China's green economy will profoundly impact the nation's future economic prosperity and even global economic development. Based on panel data from 2008 to 2017, this paper measures the green economic efficiency (GEE) of Chinese regions and analyzes its dynamic evolution using time series, based on a novel data envelopment analysis (DEA) model. Using environmental DEA techniques, this paper introduces the Super-PEBM (EBM based on pearson correlation coefficient) model, which is developed from the Epsilon based measure (EBM) model, and combines Super-PEBM with the window analysis method. Firstly, environmental DEA technology is used to analyze GEE at the regional level in China. Secondly, based on panel data, the window analysis method is used to analyze the regional differences of China's regional GEE. Finally, the development trend of China's regional GEE in different time windows is obtained by combining the Super-PEBM model and window analysis. The empirical analysis results using panel data for regions in China from 2008 to 2017 show that: (1) the overall GEE of China is slowly increasing, and the regional differences are still significant, and (2) the improvement of GEE can help to reduce regional differences.

1. Introduction

China has made great achievements in the past four decades of economic reform and opening up, but at the cost of serious environmental damage and energy resource shortages (Wang et al., 2017). At present, China's economy is maintaining a medium-high speed of growth, and its GDP has steadily ranked second in the world. However, environmental pollution in China is serious, and so economic development and environmental pollution have received extensive attention in China (Sun et al., 2019). The *green economy* refers to the economic form developed for the purpose of harmony between the economy and environment, and it has gradually become widely recognized. It has gained momentum in both academia and policy-making arenas, leading to international programs in diverse sectors and driving national agendas all over the world (Loiseau et al., 2016; Merino-Saum et al., 2019). In order to better carry out the construction of ecological civilization in the new era and implement the development concept of harmonious coexistence between man and nature, China's economic development needs to shift to a growth mode that considers economic growth, environmental protection, and resource conservation, namely, green development, so as to realize the goal of building a beautiful China. As an emerging economic power, China's green economy development will have a far-reaching impact on its future economic prosperity and even global economic development.

According to the 13th five-year plan (2016–2020) of the Chinese government, the concept of green development should be firmly established in those five years. To achieve overall improvement in environmental quality and to pursue green development, China must adhere to the basic state policy of resource conservation and environmental protection and at the same time, follow the path of green development with an ecological civilization. The pursuit of comprehensive, coordinated, and sustainable development of the economy, society, and the environment reflects the basic requirements of green development. Pursuing such development is not only the current phase of China's economic development but also a requirement for sustainable economic and social development. Therefore, it is of great

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Abbreviation

DEA	Data envelopment analysis
GEE	Green economy efficiency
EBM	Epsilon based measure
DMU	Decision-making unit
PEBM	EBM based on pearson correlation coefficient
CRS	Constant return to scale
VRS	Variable return to scale
TE	Technical efficiency
PTE	Pure technical efficiency
SE	Scale efficiency

practical significance to evaluate the energy and environmental efficiency of Chinese regions.

Green economic efficiency (GEE) is a comprehensive indicator considering economic growth, resource conservation, and environmental protection (Lin and Tan, 2019). Specifically speaking, it includes two aspects: (1) GEE is an index to evaluate the economic efficiency of a region, i.e., the utilization efficiency of input factors in the production process. (2) GEE fully considers resource input and undesirable output, incorporating the utilization of resources and environmental costs into the production process. The obtained efficiency value is the "green" economic efficiency value after integrating resource utilization and environmental loss value on the basis of the original economic efficiency. GEE is an important means to consider the relationship between economic development, resource consumption, and environmental pollution. The improvement of GEE has become an important way to build an ecological civilization and promote economic transformation in China (Song et al., 2019).

Green development has become a new mode of world development. The traditional method of measuring economic volume and development prospects by GDP and economic growth rate is no longer the whole story under the global trend of advocating sustainable development and green development. Considering the impact of resource constraints and environmental pollution on economic efficiency, it is urgent to construct a GEE index and dynamic analysis method to evaluate the economic growth performance correctly. Such a method has important theoretical and practical significance for promoting the transformation of an economic growth mode and realizing sustainable development.

Comparing the frontier formed by the focal decision-making unit (DMU) and the optimal DMU, efficiency evaluation was first proposed by Farrell (1957). The developed frontier analysis method has become a widely used efficiency assessment method in China and internationally. The most commonly used parametric method is the stochastic frontier analysis (SFA) model (Aigner et al., 1997), which describes the production process by estimating production functions. Nonparametric methods, represented by data envelopment analysis (DEA) (Charnes et al., 1978), are used to evaluate the relative efficiency of a DMU with multiple inputs and outputs, and such methods have the advantages of avoiding subjective factors and simplifying algorithms. DEA has made remarkable progress in both theoretical development and practical application (Cook and Seiford, 2009), and is widely used in efficiency evaluation and ranking. As Sueyoshi et al. (2017) point out, it is of great significance to apply DEA to environmental evaluation to guide China's energy policy, environmental policy, and economic planning.

The types of efficiency evaluation are usually divided into radial and nonradial methods (Zhou et al., 2008a). The former (such as CCR (Charnes et al., 1978) and BCC (Banker et al., 1984)) is based on Debreu-Farrell's economic theory, while the latter (such as SBM (Tone, 2001)) is based on Pareto-Koopmans's economic theory. The radial method and nonradial methods have their own advantages and disadvantages (Sueyoshi and Goto, 2012a). The assumptions of the CCR model are too strict, which means that they can only provide radial proportional efficiency improvement and can only evaluate input or output indicators independently. However, the SBM model can adjust different inputs or outputs in nonequal proportions. Although SBM avoids the improvement of the same proportion efficiency, it is at the cost of the original proportion information of the projected value of the frontier of efficiency. Therefore, any empirical analysis should integrate the two models to get an unbiased result. Based on the Hybrid model (Cooper et al., 2007), the EBM model (Tone and Tsutsui, 2010) integrates radial and nonradial methods into one structure.

The efficiency value calculated by the traditional DEA model can only be compared statically among different cross-sections, while dynamic efficiency evaluation based on panel data can calculate more efficiency data according to the change during the time series. Window analysis, first proposed by Charnes and Cooper (1984), is an improvement on the traditional DEA method. The core idea is to treat each DMU in different periods as a different DMU, and then use the moving average method to construct different reference sets to evaluate the relative efficiency of a DMU. Compared with the Malmquist index method (Malmquist, 1953), window analysis provides a higher degree of freedom for the efficiency analysis of DMUs and improves the reliability of small sample data analysis (Avkiran, 2004).

Although the DEA environmental evaluation method is not perfect in technical heterogeneity, time lag, statistical inference, and other aspects, it has broad application prospects in the field of energy and environment (Sueyoshi et al., 2017). The main contributions of this paper are as follows: (1) Based on the EBM model (Tone and Tsutsui, 2010) and Super-efficiency model (Andersen and Petersen, 1993), this paper constructs a comprehensive framework that combines radial and nonradial efficiency evaluation. (2) Based on the parameter determination method of Tone and Tsutsui (2010) and the pearson correlation coefficient method, a nonoriented Super-PEBM (EBM based on pearson correlation coefficient) model with undesirable output is proposed for the static efficiency evaluation of GEE. (3) A dynamic analysis using the window model based on panel data is constructed on the basis of the Super-PEBM model, and the new technique is applied to the dynamic evaluation of the GEE in China from 2008 to 2017.

The structure of the paper is as follows. In Section 2, we review relevant literature on GEE and methods used in this paper. The methodology is introduced in Section 3. Section 4 describes the selection of input-output variables of GEE and the division of China's regions. Section 5 discusses the results of GEE analysis and the dynamic GEE evolution of 30 provinces in China from 2008 to 2017. Finally, conclusions and policy implications are drawn in Section 6.

2. Literature review

This section summarizes the research background, including publications on GEE and undesirable outputs. We illustrate the methods used in this paper from a literature perspective including the Super-PEBM model and window analysis. The literature research framework is shown in Fig. 1.

2.1. The literature on GEE

Many scholars have done much empirical research on the

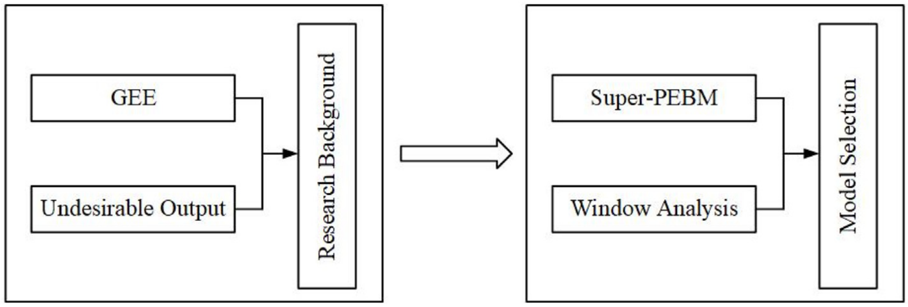

Fig. 1. The literature research framework.

efficiency of the green economy, green production efficiency, green innovation efficiency, and green technology efficiency. Yang and Hu (2010) first proposed the concept of GEE, taking the pollution output index into account in doing economic efficiency evaluation. Qian and Liu (2013) developed the definition further and considered connotations of GEE. Research efforts to date mainly focus on using different quantitative analysis models to evaluate the GEE. Lu and Lo (2007) analyzed the economic-environmental performance for regional levels in China by using cross-efficiency measure. A non-radial DEA approach was proposed by Zhou et al. (2007) to measuring environmental performance of OECD countries. While DEA radial measurement was proposed by Sueyoshi and Goto (2014) to examine the corporate sustainability of Japanese industrial sectors. In addition, Zhang et al. (2015) proposed a metafrontier slack-based efficiency measure approach to model ecological total-factor energy efficiency. Lo Storto (2016) proposed a comprehensive index to calculate the ecological efficiency of cities by combining DEA cross-efficiency model and Shannon's entropy. A Super-efficiency, advanced, slack-based model was proposed by Song and Wang (2018) to test the effectiveness and growth rate of environment-biased technological progress. He et al. (2018) presented a comprehensive environmental efficiency index at the provincial level in China in 2010 based on a slack-based measure DEA model with nonseparable undesirable output. Sun and Loh (2019) proposed a bootstrap DEA method to evaluate sustainability governance performance of 30 provinces based on ecological efficiency.

Besides, a variety of research objects or scenarios about GEE are also widely studied by scholars. Zhao et al. (2018) measured land eco-efficiency of 13 prefecture-level cities in the Beijing-Tianjin-Hebei region from an economic and ecological perspective. Similarly, the total factor energy efficiency of 27 industries in the Jing-Jin-Ji region was evaluated by Li et al. (2018) in order to realize the synergistic optimization management and sustainability development. An SBM-DEA model was applied by Hu et al. (2019) to assess the eco-efficiency of wastewater treatment plants of industrial parks. Recently, Pan et al. (2019) constructs a green productivity index based on Global Malmquist-Luenberger productivity index to evaluate the development of the green economy in China. Zhu et al. (2020) contributes to establishing a coordinated economy-environment development mode that aims at green economy catch-up from the perspective of long-term convergence of environmental total factor productivity. Super-efficiency DEA model has been employed by Shuai and Fan (2020) to measure the efficiency of China's green economy, and Tobit model is used to verify the environmental regulation influence. Song et al. (2020b) developed a directional distance function model based on the slack-based measure and endogenously determined directional vector to evaluate the regional green growth in China. Different from the above research methods, we considered the improvement of DEA evaluation model, and analyzed the dynamic evolution of efficiency.

2.2. The study of undesirable outputs

In the study of DEA, the modeling of undesirable outputs has been formalized in several ways. (1) Some researchers regard the undesirable outputs as inputs (Reinhard et al., 2000) or free disposable inputs (Hailu and Veeman, 2001). (2) Some studies treat undesirable outputs as multiplicative inverse outputs or as large-constant-added, additive inverse outputs or exponential transformation (Scheel, 2001; Seiford and Zhu, 2002; Sahoo et al., 2011; Zhou et al., 2019). (3) Other studies use two sub-technologies generating desirable output and undesirable output separately (Murty et al., 2012; Sueyoshi and Goto, 2012b). (4) Some techniques use the materials balance principle to take into account the laws of thermodynamics (Coelli et al., 2007; Rødseth, 2016; Wang et al., 2018). (5) It is common to use a DEA model based on the directional distance function (Chung et al., 1997). (6) Undesirable outputs can be treated as weakly disposable outputs (Färe et al., 1989; Färe and Grosskopf, 2004). Based on the meaning of GEE, the current paper considers the environmental DEA technology with weak disposition assumption about undesirable output, following the practices of most works in the literature (Zhou et al., 2008b).

2.3. Research on the Super-PEBM model

For the GEE model, this paper selects the Super-EBM model based on DEA environmental technology. The classical DEA model, the CCR model, was proposed based on the constant return to scale (CRS) hypothesis. The BCC model is based on the assumption of variable return to scale (VRS), thus separating the concepts of scale efficiency (SE) and technical efficiency (TE). The traditional CCR model and BCC model, both of which are radial DEA models, have the defect that only input or output indicators can be evaluated. To solve this problem, Charnes et al. (1985) proposed an additive model that can evaluate both input and output indicators, and their method can be applied using the assumptions of CRS or VRS.

To overcome the problem that the traditional DEA model uses only radial projection, Pastor et al. (1999) proposed the enhanced Russell measure (ERM) model based on the Russell measure. Aiming to overcome the problem that traditional DEA models can only distinguish inefficient DMUs and cannot distinguish between the efficient ones, Andersen and Petersen (1993) put forward the

Super-efficiency model. Considering that the additive model and ERM model often have unreasonable calculation results due to the inconsistency of variable dimensions, Tone (2001) put forward the SBM model which can solve the problem of different variable dimensions. Different from the traditional CCR or BCC models, SBM directly adds the slack vector into the objective function, so that the economic interpretation of the SBM model is to maximize the actual profit rather than just the benefit ratio.

As noted above, both radial and nonradial models have advantages and disadvantages in terms of the ratio of input or output variation. Tone and Tsutsui (2010) proposed the EBM model, which is a compromise between radial and nonradial models, integrating them into a unified framework. A review of the literature reveals that few studies use EBM model to calculate GEE. At the same time, there is little literature on combining DEA environmental technology with the research of GEE. Therefore, on the basis of EBM model, the current paper unifies the Super-efficiency model and DEA environmental technology, putting forward a Super-EBM model that incorporates undesirable output. As for the parameters in the Super-EBM model, the paper uses the pearson correlation coefficient to determine the parameters and uses those parameters to construct the specific Super-PEBM model.

2.4. Studies on window analysis

Both the traditional DEA model and the Super-EBM model can carry out static analysis on sectional data, but neither can carry out dynamic analysis on the efficiency of DMUs in different periods. Since the frontier of each DMU is different each year, the efficiency value calculated by using the Super-PEBM model is not comparable in a time series. Many studies have used the Malmquist index to analyze panel data, but Oh and Heshmati (2009) pointed out that this method does not properly reflect the characteristics of technological progress, and the efficiency growth index obtained might be biased. In addition, desirable and undesirable outputs have different technical structures, including technical heterogeneity. The dynamic analysis of GEE using the Malmquist index fails to consider spatial changes and cannot accurately explain the spatial-temporal pattern evolution of GEE; this technique fails to describe GEE's time characteristics and spatial differences. As a result, window analysis is considered a more suitable method for panel data analysis, and scholars have conducted dynamic evaluations of energy and environmental efficiency and industrial ecological efficiency based on window analysis (Halkos and Tzeremes, 2009; Zhang et al., 2011; Yang et al., 2018a,b; Zhu et al., 2019).

Using the window analysis framework, the efficiency of a DMU in one period can be compared with its efficiency in another period, and the efficiency of the other DMUs can also be compared, so as to reflect the heterogeneity between DMUs through a series of overlapping windows (Wang et al., 2013; Zhang et al., 2011). Window analysis can reflect the continuity of input and output in time, describing the dynamic evolution of the DMU. At the same time, window analysis can also compare the efficiency of DMUs under different windows in the same period and analyze the stability of the efficiency. Window analysis has two significant advantages: (1) It can multiply the number of DMUs in the reference set, which is an effective way to solve the problem of having an insufficient number of DMUs. (2) We can not only measure the efficiency of each DMU on a cross section but also measure the trend of the efficiency of all DMUs over the time series. To compare the relative efficiency of the same DMU in different periods, the current paper uses a dynamic Super-PEBM window analysis model with undesirable output to study the GEE.

3. Methodology

This section introduces the research method of this paper and constructs the model. Firstly, a Super-EBM model environmental DEA technology is constructed. Secondly, the parameters of the Super-PEBM model are determined based on pearson correlation coefficient adjustment (Cheng, 2014). Finally, the Super-PEBM model is combined with the window analysis method to explore the dynamic evolution of GEE in China.

3.1. Super-EBM model based on environmental DEA technology

The EBM model, a hybrid model including radial and SBM distance functions proposed by Tone and Tsutsui (2010), is named for the parameters ε used in the model. Each DMU can be considered as a production system that consumes multiple inputs and produces multiple outputs, so the production system can be modeled within the joint production framework of desirable and undesirable outputs. Suppose there are J decision making units, and each $DMU_j(j=1,\ldots,J)$ uses inputs $X_{pj}(p=1,\ldots,P)$ to produce desirable outputs $Y_{qj}(q=1,\ldots,Q)$ and undesirable outputs $R_{mj}(m=1,\ldots,M)$. Assuming the weak disposability (Färe et al., 1989) and "null-jointness" (Shephard and Färe, 1974) of the undesirable outputs, Färe and Grosskopf (2004) proposed an environmental DEA technology using the CRS assumption. Their environmental production possibility set (PPS) can be expressed as

$$PPS^{CRS} = \left\{ \begin{array}{l} (X,Y,R): \sum_{j=1}^{J} \lambda_j X_{pj} \le X_p, p=1,\ldots,P; \\ \sum_{j=1}^{J} Y_{qj}\lambda_j \ge Y_q, q=1,\ldots,Q; \\ \sum_{j=1}^{J} \lambda_j R_{mj} = R_m, m=1,\ldots,M; \lambda_j \ge 0, \forall j \end{array} \right\} \tag{1}$$

According to the research of Chen (2013), environmental DEA technology under the VRS assumption does not simply add the constraint $\sum_{j=1}^{J}\lambda_j = 1$ to Eq. (1). Rather, we need a convex and completely linearized model, i.e., Eq. (2), as put forward by Kuosmanen (2005).

$$PPS^{VRS} = \left\{ \begin{array}{l} (X,Y,R): \sum_{j=1}^{J} (\lambda_j+\mu_j) X_{pj} \le X_p, p=1,\ldots,P; \\ \sum_{j=1}^{J} \lambda_j Y_{qj} \ge Y_q, q=1,\ldots,Q; \\ \sum_{j=1}^{J} \lambda_j R_{mj} = R_m, m=1,\ldots,M; \\ \sum_{j=1}^{J} (\lambda_j+\mu_j) = 1, \lambda_j, \mu_j \ge 0, \forall j \end{array} \right\} \tag{2}$$

It is often assumed that *PPS* satisfies the standard axioms of the production theory (Färe and Grosskopf, 2003): (1) inactivity is always possible, i.e., $(0,0,0) \in PPS$; (2) finite amounts of inputs can produce only finite amounts of outputs; (3) *PPS* is convex; and (4) inputs and desirable outputs are often assumed to be strongly or freely disposable. After defining the environmental DEA technology, the fractional programming form of the nondirected Super-EBM model that evaluates DMU_k with undesirable output is as follows. It should be noted that Model (3) is based on VRS assumption as shown in Eq. (2).

$$\gamma = \min \frac{\theta - \varepsilon^{-}\frac{1}{\sum_{p=1}^{P} w_p^{-}}\sum_{p=1}^{P}\frac{w_p^{-}s_p^{-}}{X_{pk}}}{\phi + \varepsilon^{+}\left(\frac{1}{\sum_{q=1}^{Q} w_q^{+}}\sum_{q=1}^{Q}\frac{w_q^{+}s_q^{+}}{Y_{qk}} + \frac{1}{\sum_{m=1}^{M} w_m^{-}}\sum_{m=1}^{M}\frac{w_m^{-}s_m^{-}}{R_{mk}}\right)}$$

subject to

$$\begin{aligned}
&\sum_{j=1,k\neq j}^{J}(\lambda_j+\mu_j)X_{pj}+s_p^{-}=\theta X_{pk}\;\; p=1,\dots,P\\
&\sum_{j=1,k\neq j}^{J}\lambda_j Y_{qj}-s_q^{+}=\phi Y_{qk}\;\; q=1,\dots,Q\\
&\sum_{j=1,k\neq j}^{J}\lambda_j R_{mj}+s_m^{-}=\phi R_{mk}\;\; m=1,\dots,M\\
&\sum_{j=1}^{J}(\lambda_j+\mu_j)=1,\;\theta\le 1,\phi\ge 1\\
&\lambda_j\ge 0,\;\mu_j\ge 0,\;\; j=1,2,\dots,J(k\neq j)\\
&s_p^{-}\ge 0,\;\; s_q^{+}\ge 0,\;\; s_m^{-}\ge 0\\
&X_{pk}\neq 0,\;\; Y_{qk}\neq 0,\;\; R_{mk}\neq 0
\end{aligned} \tag{3}$$

Here, the λ_j and μ_j are referred to as intensity variables used for connecting the input and output vectors by a convex combination. Also, w_p^{-}, w_q^{+}, and w_m^{-} respectively represent the weights (relative importance) of inputs, desirable outputs, and undesirable outputs, and satisfy $\sum_{p=1}^{P} w_p^{-} = 1$, $\sum_{q=1}^{Q} w_q^{+} = 1$, and $\sum_{m=1}^{M} w_m^{-} = 1(w_p^{-}\ge 0,\; w_q^{+}\ge 0,\; w_m^{-}\ge 0,\; \forall p,q,m)$. Parameters s_p^{-},s_q^{+}, ands_m^{-}respectively represent the slack of inputs, desirable outputs, and undesirable outputs, while $\frac{w_p^{-}s_p^{-}}{X_{pk}}$, $\frac{w_q^{+}s_q^{+}}{Y_{qk}}$, and $\frac{w_m^{-}s_m^{-}}{R_{mk}}$ respectively represent the weighted average slack of inputs, desirable outputs, and undesirable outputs, where $\frac{s_p^{-}}{X_{pk}}$, $\frac{s_q^{+}}{Y_{qk}}$, and $\frac{s_m^{-}}{R_{mk}}$are unit invariant. In the model, s_p^{-}, s_q^{+}, and s_m^{-} are nonradial slacks, while $\varepsilon^{-}$and ε^{+} are key parameters representing the importance degree of the nonradial part in the calculation of efficiency value. ε^{-} indicates the relative importance of the nonradial slacks over the radial θ, and ε^{+} indicates the relative importance of the nonradial slacks over the radial ϕ. When ε is 0, Model (3) corresponds to the radial model, and when ε is 1, it corresponds to the SBM model. In this paper, constraints $\theta \le 1$, $\phi \ge 1$ are added in order to resolve logic errors that occur with the EBM model's projections (Tone and Tsutsui, 2010; Cheng, 2014). If and only if $\gamma \ge 1$, DMU_k is valid for the Super-EBM model.

3.2. Pearson correlation coefficient adjustment

Two parameters, ε and w, need to be determined before the EBM model is established. Taking input indicators a and b as examples and combining the treatment methods of Cheng (2014) and Tone and Tsutsui (2010), our method is divided into the following four steps.

Step 1 Projection values of each input are obtained through the SBM model, and denoted as P_a and P_b. The correlation between the projection values of the two indicators represents the proportional relationship between the quantities of the two inputs in the production technology, and thus the substitutability of the indicators in the production process can be concluded. A high degree of linear positive correlation indicates that the substitutability is not good, and so, radial measurement should be the main method. In this case, ε should be a small number approaching or equal to 0. If a high degree of linear negative correlation is present, then strong substitutability and nonradial measurement should be adopted, so ε should be a value approaching or equal to 1.

Step 2 Establish the correlation matrix of the projection values of the input indices. Each element of the matrix is the correlation index between the projection value of two input indices. Let S be the function of the correlation index between projection values P_a and P_b, which should conform to the rules proposed by Tone and Tsutsui (2010).

(R_1) Identical, i.e., $S(a,a) = 1$;
(R_2) Symmetric, i.e., $S(a,b) = S(b,a)$;
(R_3) Unit-invariant, i.e., $S(ta,b) = S(b,a)$ $(t>0)$;
(R_4) Numerical range, i.e., $0 \le S(a,b) \le 1$.

Step 3 Due to the known defects of the method of calculating the correlation index, the method we use is different from the method of using the discrete exponential function. In this paper, pearson correlation coefficient represents the similarity of the two indicators, which is adopted to satisfy the above properties through $S(a,b) = 0.5 + 0.5R(a,b)$ transformation. See Eq. (4) for details.

$$R(a,b) = \frac{\sum_{p=1}^{P}(a_j-\bar{a})(b_j-\bar{b})}{\sqrt{\sum_{p=1}^{P}(a_j-\bar{a})^2}\sqrt{\sum_{j=1}^{J}(b_j-\bar{b})^2}} \tag{4}$$

Step 4 The parameters of the EBM model are calculated by using the established correlation exponential matrix using Eq. (5) and Eq. (6).

$$\varepsilon = \frac{P-\max(\rho)}{P-1} \tag{5}$$

$$w_p^{-} = \frac{\nu}{\sum_{p=1}^{P}\nu} \tag{6}$$

where ρ is the eigenvector of the largest eigenroot of the associated exponential matrix, and ν is its corresponding eigenvector.

3.3. A Super-PEBM window analysis method

Suppose that the window starts at time t $(1 \le t \le T)$, and the window length is d $(1 \le d \le T-1)$ so each window has $d \times J$ DMUs. Using t_d $(1 \le d \le T-d+1)$ to represent the index of each window, the input matrix of window t_d is.

$X_{td} = (X_1^t, X_2^t, \dots, X_J^t, X_1^{t+1}, X_2^{t+1}, \dots, X_J^{t+1}, \dots, X_1^{t+d}, X_2^{t+d}, \dots, X_J^{t+d})$; and the desirable and undesirable output matrices are $Y_{td} = (Y_1^t, Y_2^t, \dots, Y_J^t, Y_1^{t+1}, Y_2^{t+1}, \dots, Y_J^{t+1}, \dots, Y_1^{t+d}, Y_2^{t+d}, \dots, Y_J^{t+d})$ and $R_{td} = (R_1^t, R_2^t, \dots, R_J^t, R_1^{t+1}, R_2^{t+1}, \dots, R_J^{t+1}, \dots, R_1^{t+d}, R_2^{t+d}, \dots, R_J^{t+d})$.

If the total length of time is T, then $T-d+1$ windows will be established for the efficiency measurement of each DMU. Each DMU obtains d efficiency values in total for the α-th window, $\alpha = 1,2,\dots,T-d+1$. Using the moving average method, d efficiency

Table 1
Window analysis of each DMU in period *T*.

	$t=1$	$t=2$	$t=3$	$t=4$	…	$t=T$-3	$t=T$-2	$t=T$-1	$t=T$
Window 1	E_{11}	E_{12}	E_{13}						
Window 2		E_{21}	E_{22}	E_{23}					
...									
Window *T-d*						$E_{T\text{-}d,1}$	$E_{T\text{-}d,2}$	$E_{T\text{-}d,3}$	
Window *T-d*+1							$E_{T\text{-}d+1,1}$	$E_{T\text{-}d+1,2}$	$E_{T\text{-}d+1,3}$

values in total from window t to window $T-d+1$ are measured successively from the first time point $t=1$ $(t=1,2,...,T)$. The average efficiency value at each time point is taken as the final efficiency value for the time series comparison of the evaluated DMU. For each DMU, a total of $(T-d+1)\times d$ efficiency values need to be determined. The process of window analysis is shown in Table 1.

Considering the undesirable output, for any evaluated DMU_k, the Super-PEBM model to calculate the GEE at time point $\beta(\beta=1,2,...,d)$ in window α $(\alpha=1,2,...,T-d+1)$ can be expressed as Model (7).

$$E_{\alpha\beta}=\min\frac{\theta^{\alpha\beta}-\varepsilon^{-}\frac{1}{\sum_{p=1}^{P}w_p^{-}}\sum_{p=1}^{P}\frac{w_p^{-}s_p^{-,\alpha\beta}}{X_{pk}}}{\phi^{\alpha\beta}+\varepsilon^{+}\left(\frac{1}{\sum_{q=1}^{Q}w_q^{+}}\sum_{q=1}^{Q}\frac{w_q^{+}s_q^{+,\alpha\beta}}{Y_{qk}}+\frac{1}{\sum_{m=1}^{M}w_m^{-}}\sum_{m=1}^{M}\frac{w_m^{-}s_m^{-,\alpha\beta}}{R_{mk}}\right)}$$

subject to

$$\begin{aligned}
&\sum_{j=1,k\neq j}^{d\times J}\left(\lambda_j^{\alpha\beta}+\mu_j^{\alpha\beta}\right)X_{pj}^{\alpha\beta}+s_p^{-,\alpha\beta}=\theta^{\alpha\beta}X_{pk}^{\alpha\beta}\ \ p=1,...,P\\
&\sum_{j=1,k\neq j}^{d\times J}\lambda_j^{\alpha\beta}Y_{qj}^{\alpha\beta}-s_q^{+,\alpha\beta}=\phi^{\alpha\beta}Y_{qk}^{\alpha\beta}\ \ q=1,...,Q\\
&\sum_{j=1,k\neq j}^{d\times J}\lambda_j^{\alpha\beta}R_{mj}^{\alpha\beta}+s_m^{-,\alpha\beta}=\phi^{\alpha\beta}R_{mk}^{\alpha\beta}\ \ m=1,...,M\\
&\sum_{j=1}^{J}\left(\lambda_j^{\alpha\beta}+\mu_j^{\alpha\beta}\right)=1,\ \theta^{\alpha\beta}\leq1,\ \phi^{\alpha\beta}\geq1\\
&\lambda_j^{\alpha\beta}\geq0,\ \mu_j^{\alpha\beta}\geq0,\ \ j=1,2,...,d\times J(k\neq j)\\
&\alpha=1,2,...,T-d+1;\ \beta=1,2,...,d\\
&s_p^{-,\alpha\beta}\geq0,\ \ s_q^{+,\alpha\beta}\geq0,\ \ s_m^{-,\alpha\beta}\geq0;\ X_{pk}^{\alpha\beta}\neq0,\ \ Y_{qk}^{\alpha\beta}\neq0,\ \ R_{mk}^{\alpha\beta}\neq0
\end{aligned}\tag{7}$$

The meanings of the variables here are basically the same as those in Model (3), except that superscript (or subscript) $\alpha\beta$ indicates that this variable is a variable at the n-th time point in the m-th window. Let$(\theta^{\alpha\beta*},\phi^{\alpha\beta*},\lambda_j^{\alpha\beta*},s_p^{-,\alpha\beta*},s_q^{+,\alpha\beta*},s_m^{-,\alpha\beta*})$be the optimal solution of Model (7). When $E_{\alpha\beta}\geq1$, and all the slack variables $s_p^{-,\alpha\beta*}=0$, $s_q^{+,\alpha\beta*}=0$, $s_m^{-,\alpha\beta*}=0$, then the evaluated DMU is efficient.

Previous papers (Avkiran, 2004; Charnes et al., 2013) tell us how to select the window width so that the best balance can be achieved in terms of reliability and stability of efficiency measures. We select the window width $d=3$ since small window widths can reduce the impact of model defects. In the example used in this paper, the sample length is 10, and 8 windows need to be established for each DMU for efficiency evaluation.

4. Variable selection and division of Chinese regions

4.1. Variable selection

On the basis of its economy, each province is regarded as a comprehensive system of resources, economy, and environment;

each is a DMU that converts input into output under certain technical conditions. GEE is a multi-factor integration process. In this paper, we take 30 provinces of China as DMUs and study the time span from 2008 to 2017. Tibet, Taiwan, Hong Kong, and Macau were excluded because of a lack of data. The selection of input variables, output variables, and data sources are described below.

As was done in previous studies (Pan et al., 2019; Shuai and Fan, 2020), energy, labor, and capital stock are selected as input indicators. (1) Energy input. Total energy consumption represents energy input, converted into units representing one million tons of standard coal. The data are collected based on the China Energy Statistical Yearbooks 2009–2018 (CNSY, 2009–2018). (2) Labor force. Employment data are used to represent labor input. Due to the difficulty in obtaining statistics about labor remuneration, labor hours, labor intensity, and other data, we select the number of laborers in each region, that is, the number of employees at the end of the year, as the labor input index. Labor force data are from the China Statistical Yearbooks from 2009 to 2018 (CSY, 2009–2018). (3) Capital investment. Based on the previous research results, we take the capital stock as the index to measure the capital input. Capital stock data from provinces are not directly available in official statistics, but macroeconomic analysis is always tied to capital stock. Therefore, referring to the study of Hu and Kao (2007), we adopt the perpetual inventory method for estimation. The estimation formula is expressed as Eq. (8) and Eq. (9).

$$P_t = U_t \times P_{t-1} \tag{8}$$

$$K_t = I_t / P_t + (1-\delta)K_{t-1} \tag{9}$$

where K_t, δ, P_t , U_t, and I_t represent the capital stock of the t-th period, depreciation rate, deflator index of the t-th period, fixed asset investment price index of the t-th period, and total fixed capital formation of the t-th period, respectively. The data for U_t and I_t came from CSMAR and $\delta = 9.6\%$. We follow the method of Zhang et al. (2004) and convert capital stock using constant price in 2008.

For the final output of GEE, we divide the output indicators into desirable outputs and undesirable outputs, namely economic output and environmental factors (Yang et al., 2018a,b). (1) Desirable output. Economic output is expressed by the regional GDP of each province, and the quarter-on-quarter GDP index of each province from 2008 to 2017 was obtained from the China economic database (CEIC). We convert the quarter-on-quarter index to the fixed-basis GDP index based on 2008 and convert the regional GDP into the constant price in 2008 based on the quarter-on-quarter index. (2) Undesirable output. As in the study of Shuai and Fan (2020), industrial wastewater, industrial SO_2, and industrial soot are used as undesirable outputs in the current paper. The data of desirable outputs and undesirable outputs are gathered from the China Statistical Yearbooks (CSY, 2009-2018) and the China Environmental Statistical Yearbooks (CESY, 2009–2018) from 2009 to 2018. Fig. 2 shows the input-output production system. In this production system, the proposed approach will increase desirable outputs (GDP) while reducing undesirable outputs (industrial wastewater, SO_2, and dust) and inputs (energy, labor force, and capital stock) in the meantime so as to increase efficiency. The descriptive statistical characteristics of input-output variables are shown in Table 2. Energy is important natural resource in the production system of provinces. Labor combines and converts capital and resource into economic outputs, while pollution emission reflects negative impacts on the environment. The selection of indicators is representative in order to avoid indicator redundancy. The pearson correlation coefficient of input (output) indicators indicates that there is no highly correlation between input (output) indicators on the whole.

4.2. Division of Chinese regions

Most of the previous studies divide Chinese regions into the eastern, central, and western areas on account of the geographical location. However, with a view to the vast geographic coverage of China, the above divided areas are too large to distinguish accurately. Also, the internal diversity of the three regions has become greater along with China's development (Zhang et al., 2018). Besides, referring to the Analysis of the Characteristic of Chinese Regional Social and Economic Development (Development Research Center of the State Council, 2002), we reject the previously common rough regional division of eastern, central, and western areas, and use a scheme with six areas. Thus, our comparison between areas is more in line with the requirements of today's economic development so our results become more realistic. To study the gaps in China's regional GEE, Chinese administrative regions are divided into six areas: the northeastern area, the northern coastal area, the southeastern coastal area, the middle reaches area of the Yellow River, the middle reaches area of the Yangtze River, and the western area, as shown in Fig. 3. The geographical distribution of the six areas is sown on this map of China obtained from http://bzdt.ch.mnr.gov.cn/.

The northeastern area includes three provinces, where economic development is advanced and the heavy industry is developed. In recent years, these provinces are facing problems such as

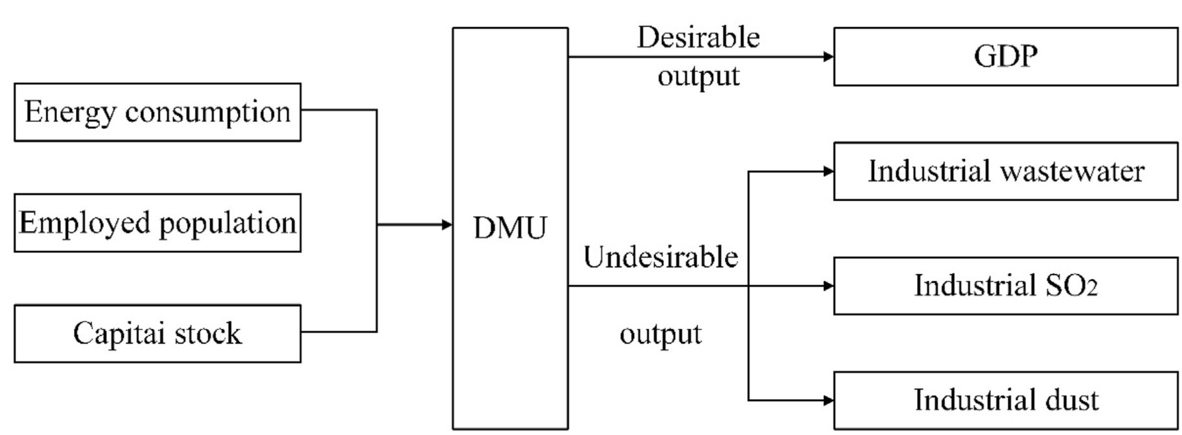

Fig. 2. Input-output production system.

Table 2
Descriptive statistical characteristics of input-output variables from 2008 to 2017.

	Variables	Units	Minimum	Maximum	Mean	Standard Deviation
Input variables	Energy consumption	Million TCE	11.35	395.82	139.41	83.96
	Employed population	Thousand people	5543.00	111690.00	44954.70	26925.68
	Capital stock	Billion RMB	297.08	22004.06	5271.44	4107.02
Output variables	GDP	Billion RMB	39.59	7647.28	1753.79	1489.04
	Industrial wastewater	Ten million tons	0.74	938.26	186.69	172.68
	Industrial SO_2	Thousand tons	14.30	1827.40	630.26	407.20
	Industrial dust	Thousand tons	8.00	1797.70	381.60	294.90

Note: TCE indicates Tonnes of Coal Equivalent.

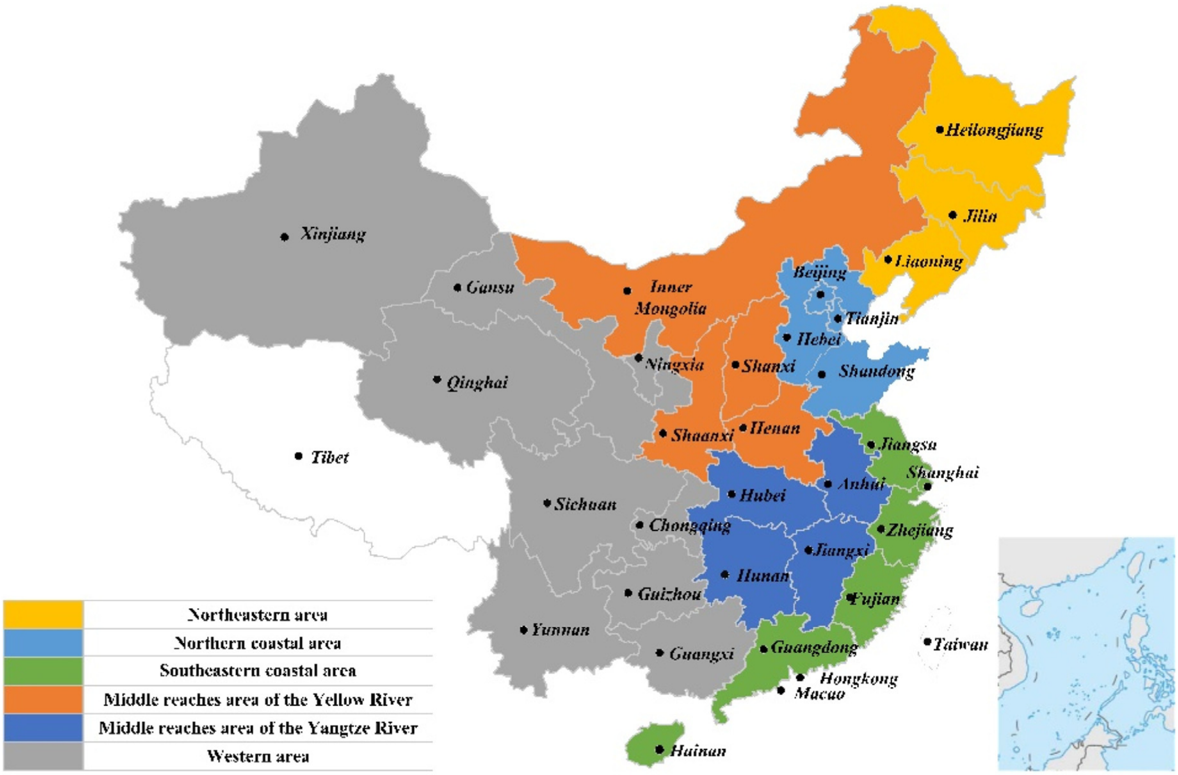

Fig. 3. Geographical distribution of six areas in China.

Table 3
The specific division of six areas in China.

Areas	Provinces, Autonomous Regions, and Municipalities
Northeastern area	Liaoning, Jilin, Heilongjiang
Northern coastal area	Beijing, Tianjin, Hebei, Shandong
Southeastern coastal area	Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan
Middle reaches area of the Yellow River	Shaanxi, Shanxi, Henan, Inner Mongolia
Middle reaches area of the Yangtze River	Hubei, Hunan, Jiangxi, Anhui
Western area	Chongqing, Guangxi, Yunnan, Guizhou, Sichuan, Gansu, Qinghai, Xinjiang, Ningxia

Note: In this study, 30 municipalities, autonomous regions, and provinces of China are clustered into six areas. Tibet, Taiwan, Hong Kong, and Macau are excluded for lack of data.

Table 4
Comparisons of average GEE from 2008 to 2017 in China based on different models.

Model	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
CCR	0.66	0.66	0.69	0.79	0.79	0.68	0.66	0.68	0.68	0.68
BCC	0.74	0.73	0.78	0.85	0.85	0.78	0.78	0.78	0.78	0.78
SBM	0.43	0.44	0.44	0.50	0.50	0.49	0.48	0.48	0.49	0.47
EBM	0.57	0.56	0.55	0.68	0.68	0.60	0.61	0.63	0.63	0.63
PEBM	0.64	0.65	0.68	0.77	0.77	0.67	0.67	0.67	0.67	0.66

Table 5
Correlation and difference comparison of efficiencies by different models.

Comparison	Pearson correlations	*t*-test (*t* value)	Mean difference
SBM versus EBM	0.872***	−17.762***	0.071
SBM versus PEBM	0.663***	−18.997***	0.106
EBM versus PEBM	0.785***	−7.527***	0.043

Note: ***Indicates that correlations are statistically significant at 1% level (2-tailed).

Table 6
Average GEE and its decompositions from 2008 to 2017 in China.

Efficiency	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
PTE	0.66	0.66	0.69	0.79	0.79	0.68	0.68	0.68	0.68	0.68
TE	0.74	0.73	0.78	0.85	0.85	0.78	0.78	0.78	0.78	0.78
SE	1.12	1.11	1.13	1.08	1.08	1.15	1.15	1.14	1.14	1.14

resource depletion and the need for industrial structure upgrading. The northern coastal area includes two municipalities and two provinces, which have advanced scientific, educational, and cultural undertakings and convenient transportation. The southeastern coastal area includes one municipality and five provinces. These areas have received a large amount of foreign investment and preferential policies due to their advantageous geographical location, and they have a high level of openness and economic development. The middle reaches area of the Yellow River includes an autonomous region and three provinces. This area is inland and rich in natural resources, especially coal and natural gas. The members of this area are all facing the need for industrial upgrading and adjustment. The middle reaches area of the Yangtze River includes four provinces, which are densely populated and have good agricultural conditions. The western area includes three autonomous regions, one municipality, and five provinces, which are rich in mineral resources, backward in production technology, and relatively low in economic development. The detailed division of the areas is shown in Table 3.

5. Empirical analysis and results

5.1. Comparisons between Super-PEBM model and other models

5.1.1. Comparisons with other models

To illustrate the relative advantages of the EBM model, Table 4 compares the evaluation results of the EBM model with those using the CCR and SBM models. The EBM model not only considers the radial ratio between the target and the actual production inputs but also considers the nonradial slacks. In this way, the combination of CCR model and SBM model can overcome each model's shortcomings to some extent, and the efficiency of the model is evaluated scientifically. Table 4 shows that the efficiency of the BCC model is higher than that of the CCR model, both of which use radial distances. The SBM model uses the longest distance to the strong effective frontier, and its efficiency is lower than that of both CCR and BCC models. The EBM model combines radial ratio and nonradial slacks, so its efficiency values are between those of the CCR model and SBM model. The efficiency value of the PEBM model is slightly higher than that of the EBM model but remains between the values for the CCR model and the SBM model. As shown in Table 5, through the paired sample t-test, the mean difference between SBM, EBM and PEBM is close to 0. According to Pearson correlations, there are significant high correlations between SBM, EBM and PEBM models. That is, the trend of the results evaluated by the three models is consistent.

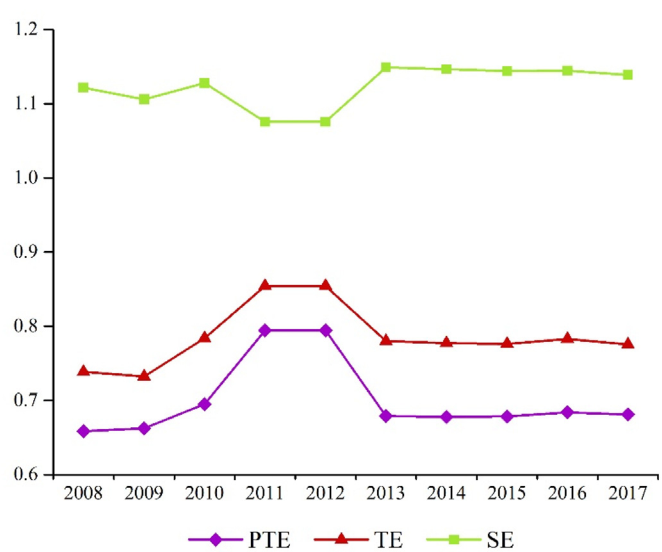

Fig. 4. GEE changes from 2008 to 2017 in China based on the traditional model.

For the traditional models (i.e., CCR model and BCC model), scale efficiency can be analyzed. Table 6 describes the efficiency and decomposition of the radial model. As analyzed above, the efficiency of the BCC model is greater than that of CCR model in each year. This is expected because the CCR model is based on the CRS hypothesis, whereas the BCC model is based on the VRS hypothesis. In decomposing the BCC model, the efficiency of the BCC model is called comprehensive technical efficiency (TE), the efficiency of CCR model is called pure technical efficiency (PTE), and the ratio is scale efficiency (SE), i.e., $TE = PTE \times SE$.

Fig. 4 gives a more intuitive explanation, reflecting the dynamic changes in Table 6. By comparison, it is found that TE and PTE determined using the Super-efficiency model are higher than when using the traditional model, and SE generally declines first and then rises. Next, we will explain the advantages of the Super-efficiency model.

5.1.2. The advantages of the super-efficiency model

Table 7 shows the efficiency values of Chinese provinces obtained by different models in 2017. Considering the regional average GEE calculated by the provincial data in 2017, the results between the different models are consistent with the conclusions given in Table 4. Through the comparison of various models, it can be concluded that the efficiency of Beijing, Tianjin, and Shanghai in 2017 in each year was equal to 1, so those DMUs cannot be fully ordered. Similarly, there are five different models in which the efficiency of more than one DMU is 1, so those DMUs cannot be fully sorted. Based on this problem, it is necessary to introduce the Super-efficiency model. Table 7 lists the results of five models without Super-efficiency, and it can be seen that the average GEE in 2017 is between 0.4 and 0.7. The following analysis in the paper will be based on the Super-efficiency model and will indicate that the efficiency calculated in Table 7 is an underestimate of the average GEE, which can be used as a comparison to reflect the advantages of the Super-efficiency model.

5.2. The change characteristics of GEE under different circumstances

5.2.1. Cases with and without undesirable outputs

Table 8 describes the GEE in China from 2008 to 2017 with the Super-PEBM model including and excluding undesirable output. Fig. 5 intuitively describes the dynamic changes of the GEE in China

Table 7
Regional GEE in China obtained by different models in 2017.

Areas	Provinces	CCR	BCC	SBM	EBM	PEBM
Northeastern area	Liaoning	0.62	0.73	0.39	0.60	0.61
	Jilin	0.69	0.69	0.39	0.60	0.65
	Heilongjiang	0.63	0.68	0.39	0.61	0.61
	Average	0.65	0.70	0.39	0.60	0.63
Northern coastal area	Beijing	1.00	1.00	1.00	1.00	1.00
	Tianjin	1.00	1.00	1.00	1.00	1.00
	Hebei	0.62	0.85	0.37	0.59	0.61
	Shandong	0.80	1.00	0.51	0.73	0.79
	Average	0.86	0.96	0.72	0.83	0.85
Southeastern coastal area	Shanghai	1.00	1.00	1.00	1.00	1.00
	Jiangsu	0.88	1.00	0.59	0.75	0.80
	Zhejiang	0.88	0.96	0.58	0.77	0.83
	Fujian	0.78	0.84	0.51	0.69	0.74
	Guangdong	0.97	1.00	0.62	0.80	0.88
	Hainan	0.60	1.00	0.34	0.52	0.57
	Average	0.85	0.97	0.61	0.75	0.80
Middle reaches area of the Yellow River	Shannxi	0.03	0.13	0.02	0.03	0.03
	Shanxi	0.48	0.52	0.27	0.45	0.47
	Henan	0.64	0.83	0.39	0.57	0.63
	Inner Mongolia	0.63	0.93	0.40	0.58	0.61
	Average	0.44	0.60	0.27	0.41	0.43
Middle reaches area of the Yangtze River	Hubei	0.66	0.75	0.40	0.61	0.66
	Hunan	0.68	0.73	0.39	0.60	0.66
	Jiangxi	0.72	0.72	0.39	0.62	0.68
	Anhui	0.71	0.74	0.39	0.62	0.69
	Average	0.69	0.73	0.39	0.61	0.67
Western area	Chongqing	0.69	0.72	0.40	0.61	0.66
	Guangxi	0.63	0.63	0.35	0.55	0.60
	Yunnan	0.50	0.50	0.28	0.45	0.48
	Guizhou	0.42	0.45	0.25	0.40	0.42
	Sichuan	0.72	0.78	0.39	0.63	0.70
	Gansu	1.00	1.00	1.00	1.00	1.00
	Qinghai	1.00	1.00	1.00	1.00	1.00
	Xinjiang	0.11	0.20	0.05	0.10	0.11
	Ningxia	0.27	0.88	0.15	0.26	0.27
	Average	0.59	0.69	0.43	0.56	0.58

Table 8
Comparison of the undesirable output in the Super-PEBM model.

Model	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Super-PEBM-C	0.87	0.87	0.82	0.84	0.84	0.93	0.92	0.91	0.90	0.90
Super-PEBM-U-C	0.64	0.65	0.68	0.77	0.77	0.67	0.67	0.67	0.67	0.66
Super-PEBM-V	0.93	0.94	0.92	0.92	0.92	0.97	0.98	0.95	0.93	0.94
Super-PEBM-U-V	0.74	0.73	0.79	0.86	0.86	0.78	0.78	0.78	0.78	0.77

Note: The symbol “C” and “V” represent CRS and VRS hypothesis, respectively. The symbol “U” means that undesirable output is considered.

from 2008 to 2017 (Table 8). The results show that the efficiency of the model containing undesirable output is lower than that of the model without undesirable output, which indicates that environmental factors cause a large degree of efficiency loss; this shows that efficiency evaluation without considering environmental factors is unrealistic. It can also be found that the efficiency under the VRS hypothesis is higher than that of the CRS hypothesis, which indicates that most scholars' research based on the CRS hypothesis is also inconsistent with reality. The current study will further explain the large regional gap of the GEE in China, showing that the VRS hypothesis is more suitable for China's reality. Under the Super-PEBM model with undesirable output, the GEE in China presents an inverted U-shaped change trend, which will be analyzed in detail later.

5.2.2. Comparison of cases with CRS and VRS hypothesis

Table 9 describes the GEE in Chinese provinces, assuming the CRS and VRS hypothesis respectively in 2017, including three types of Super-efficiency model considering undesirable output. The average efficiency of the Super-SBM, Super-EBM, and Super-PEBM models in the CRS hypothesis is 0.49,0.63 and 0.66 respectively. Under the hypothesis of VRS, the average efficiency of Super-SBM, Super-EBM and Super-PEBM models is 0.62,0.74, and 0.77, respectively. It can be seen that the GEE measure using the Super-SBM model is lower than that using the Super-EBM and Super-PEBM models. As mentioned above, the EBM model combines the advantages of radial proportion improvement and nonradial slack improvement. According to the results of Table 9, Beijing, Tianjin, Shanghai, Gansu, and Qinghai have efficient GEE under both CRS and VRS hypothesis in 2017. By comparing the GEE of the three models in terms of CRS and VRS, it can be seen that the GEE results under the VRS hypothesis results are always higher than those under the CRS hypothesis. Considering the differences between provinces and areas in China, the evaluation of GEE under VRS will be more practical, which indicates a deficiency of many previous studies.

Fig. 6 and Fig. 7 show the GEE of Chinese provinces under different models in 2017, from which it can be found that the Super-SBM results fluctuate greatly. The efficiency values of efficient DMUs will be higher, and the efficiency values of inefficient DMUs

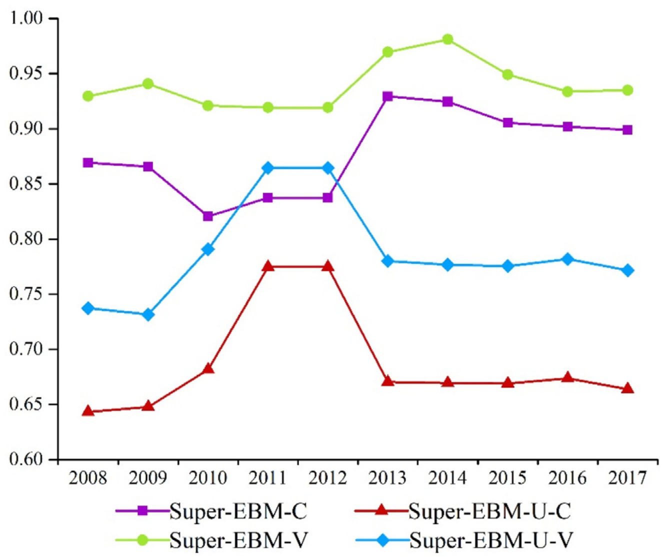

Fig. 5. Dynamic change of GEE under the Super-PEBM model.

will be lower. Under the VRS hypothesis, the error fluctuation will be larger. However, the efficiency values calculated by the Super-PEBM model are relatively stable using either hypothesis, so the GEE results in Chinese provinces are more practical when we use Super-PEBM. Fig. 8 shows the comparison of using the CRS or VRS hypothesis for the Super-PEBM model, which further indicates that it is practical to use the Super-PEBM model to calculate the GEE at the provincial level in China assuming the VRS hypothesis.

5.3. Spatial and temporal evolution of the GEE

5.3.1. The temporal evolution characteristics of the GEE

Table 10 shows the GEE of China's six areas from 2008 to 2017 based on the Super-PEBM model in the case of input-oriented VRS. According to the results, the average GEE in China from 2008 to 2017 was 0.74, which is generally above the medium level, a fluctuating growth trend occurred, and the regional differences gradually narrowed. The average GEE increased from 0.72 in 2008 to 0.75 in 2017, an increase of 4%. The northern coastal area and the middle reaches area of the Yangtze River grew faster rates of 8% and 7%, respectively, while the southeastern coastal area grew at a slower pace and remained basically stable. Fig. 9 intuitively describes the three-stage characteristics of the GEE in the six areas of China with the change of time series. From 2008 to 2011, the overall GEE increased rapidly, from 0.72 in 2008 to 0.79 in 2011, a change of 9% and an average annual growth rate of nearly 3%. From 2011 to 2015, the GEE first decreases and then increases, showing a V-shaped trend. Overall, it decreased by 6% from 0.79 in 2011 to 0.74 in 2015. From 2015 to 2017, the GEE grew steadily from 0.74 in 2015 to 0.75 in 2017, with a change rate of 1% and an average annual growth rate of 0.5%. Therefore, the temporal evolution of GEE in China shows obvious stage characteristics, which is very similar to the period division from the 11th five-year plan (2006–2010) to the 13th five-year plan (2016–2020) in China.

5.3.2. Spatial differentiation characteristics of the GEE

It can be intuitively found from Fig. 9 that the GEE values in the southeastern coastal area and northern coastal area are much higher than the national average. The GEE in the southeastern coastal area and the middle reaches area of the Yangtze River remained stable with the change of time series. However, the GEE

Table 9
The efficiency values of the three models under CRS and VRS hypotheses in 2017.

Provinces	CRS			VRS		
	Super-SBM	Super-EBM	Super-PEBM	Super-SBM	Super-EBM	Super-PEBM
Beijing	1.12	1.05	1.04	1.27	1.11	1.03
Tianjin	1.03	1.01	1.01	1.03	1.01	1.00
Hebei	0.37	0.59	0.61	0.42	0.72	0.83
Shanxi	0.27	0.45	0.47	0.28	0.47	0.51
Inner Mongolia	0.40	0.58	0.61	0.44	0.72	0.89
Liaoning	0.39	0.60	0.61	0.39	0.63	0.72
Jilin	0.39	0.60	0.65	0.43	0.60	0.68
Heilongjiang	0.39	0.61	0.61	0.40	0.62	0.67
Shanghai	1.08	1.03	1.02	1.08	1.04	1.01
Jiangsu	0.59	0.75	0.80	1.04	1.02	1.00
Zhejiang	0.58	0.77	0.83	0.83	0.92	0.95
Anhui	0.39	0.62	0.69	0.40	0.63	0.73
Fujian	0.51	0.69	0.74	0.55	0.75	0.82
Jiangxi	0.39	0.62	0.68	0.41	0.63	0.71
Shandong	0.51	0.73	0.79	1.03	1.01	1.00
Henan	0.39	0.57	0.63	0.51	0.75	0.83
Hubei	0.40	0.61	0.66	0.44	0.68	0.75
Hunan	0.39	0.60	0.66	0.42	0.64	0.73
Guangdong	0.62	0.80	0.88	1.08	1.03	1.01
Guangxi	0.35	0.55	0.60	0.36	0.56	0.62
Hainan	0.34	0.52	0.57	1.15	1.44	1.11
Chongqing	0.40	0.61	0.66	0.43	0.65	0.70
Sichuan	0.39	0.63	0.70	0.44	0.67	0.78
Guizhou	0.25	0.40	0.42	0.27	0.43	0.45
Yunnan	0.28	0.45	0.48	0.30	0.46	0.49
Shaanxi	0.02	0.03	0.03	0.08	0.10	0.12
Gansu	1.08	1.03	1.00	1.08	1.04	1.01
Qinghai	1.08	1.03	1.00	1.53	1.19	1.03
Ningxia	0.15	0.26	0.27	0.46	0.64	0.81
Xinjiang	0.05	0.10	0.11	0.14	0.18	0.20
Average	**0.49**	**0.63**	**0.66**	**0.62**	**0.74**	**0.77**

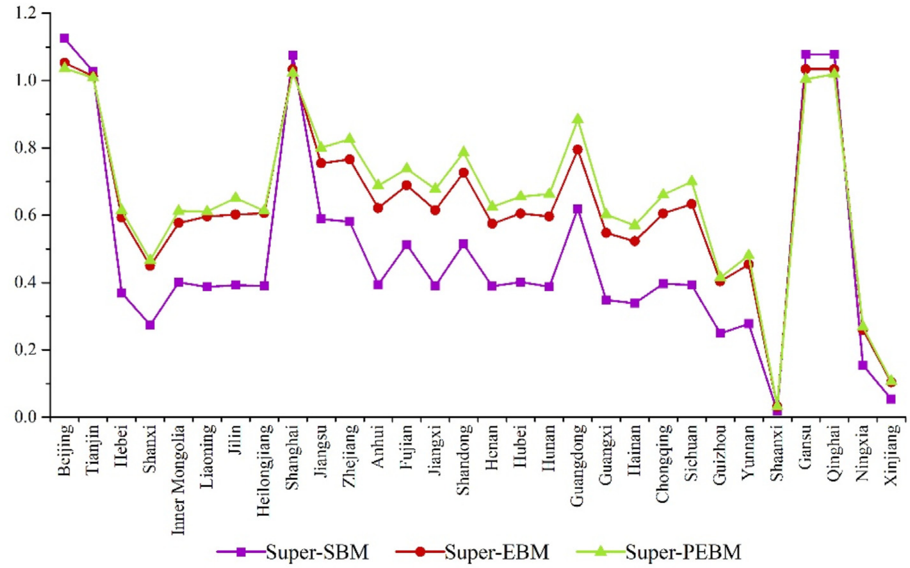

Fig. 6. The GEE of three models under the CRS hypothesis in 2017.

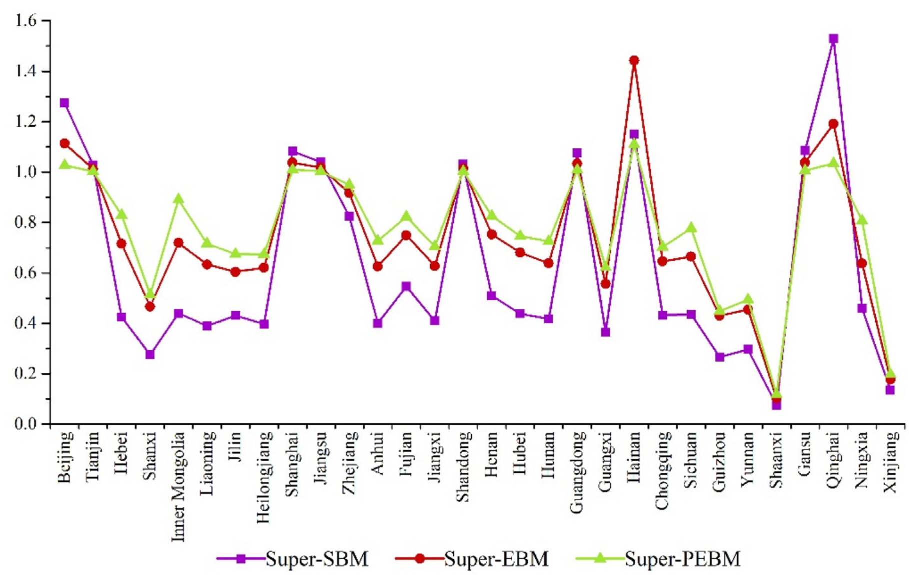

Fig. 7. The GEE of three models under the VRS hypothesis in 2017.

in the western area and the middle reaches area of the Yellow River varied greatly with the time series, but eventually tended to be stable and show a slow growth trend. As can be seen from Fig. 10, the spatial distribution of GEE considering different efficiency levels in 2008–2017 changes significantly. The high-efficiency area (GEE efficiency average above 0.90 in 2008–2017) is distributed in a relatively scattered way, with an inverted triangular spatial pattern in Qinghai - Gansu - Beijing - Tianjin - Shanghai - Guangdong provinces. The distribution in the areas with relatively high-efficiency (GEE efficiency average between 0.70 and 0.90 in 2008–2017) is concentrated, which shows a zonal spatial pattern in Shandong-Jiangsu-Zhejiang-Fujian-Hainan provinces. The medium-efficiency area (GEE efficiency average between 0.60 and 0.70 in 2008–2017) is concentrated in central China, showing a blocky spatial pattern. Except for Xinjiang, the distribution of low-efficiency areas (GEE efficiency average below 0.60 in 2008–2017) is relatively concentrated, showing a T-shaped spatial pattern of Ningxia-Shaanxi-Shanxi-Chongqing-Guizhou provinces. Fig. 11 shows the provincial differences in GEE between the western area and the middle reaches area of the Yellow River. The western area includes high-efficiency, medium-efficiency, and low-efficiency provinces, and the middle reaches area of the Yellow River includes medium-efficiency and low-efficiency provinces. It is obvious that the GEE varies greatly within the area.

The above analysis shows that although the GEE varies greatly among different areas in China, the improvement of the GEE promotes the reduction of regional differences to some extent. In the 12th five-year plan (2011–2015), the government paid much attention to industrial restructuring, energy conservation, and emission reduction of pollutants, as well as coordinated regional development. Therefore, after such comprehensive work on economic growth, energy consumption, and environmental pollution,

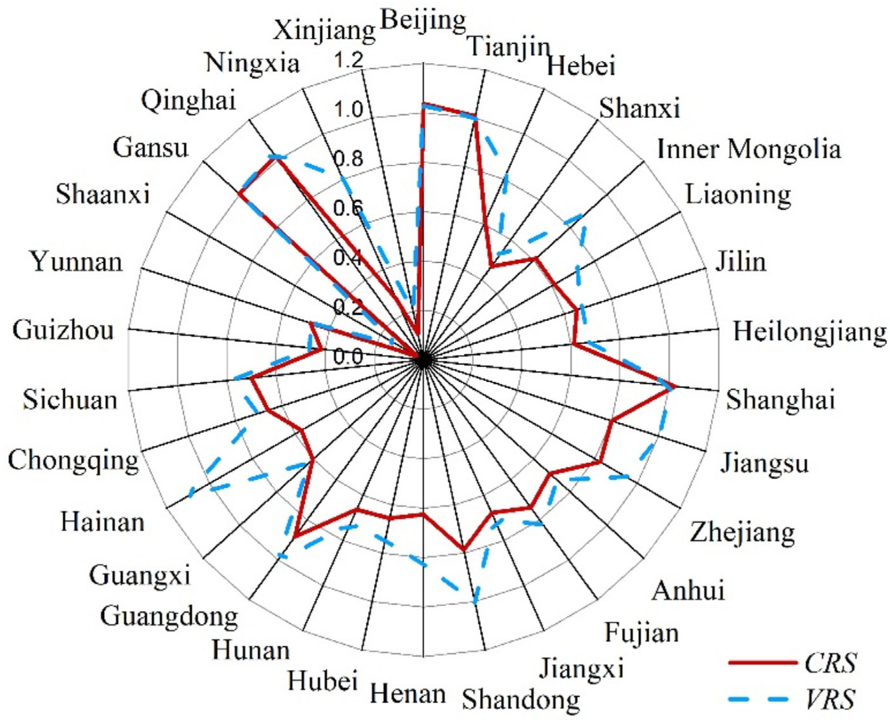

Fig. 8. Comparison of three models under both CRS and VRS hypothesis in 2017.

Table 10
The GEE in six areas of China from 2008 to 2017.

Areas	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Northeastern area	0.63	0.64	0.65	0.66	0.65	0.66	0.64	0.63	0.65	0.65
Northern coastal area	0.86	0.88	0.89	0.94	0.92	0.92	0.92	0.92	0.92	0.93
Southeastern coastal area	0.97	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.97	0.96
Middle reaches area of the Yellow River	0.52	0.50	0.69	0.73	0.53	0.53	0.52	0.52	0.53	0.54
Middle reaches area of the Yangtze River	0.69	0.69	0.68	0.68	0.69	0.70	0.70	0.70	0.70	0.70
Western area	0.66	0.66	0.68	0.74	0.68	0.69	0.70	0.70	0.70	0.70
Average	0.72	0.72	0.76	0.79	0.74	0.74	0.74	0.74	0.75	0.75

the GEE values in Chinese provinces have gradually increased, and the phenomenon of "polarization" between areas has been alleviated.

5.4. Dynamic window analysis of the GEE

In order to better show the changes of GEE in different regions over different time periods, we select panel data from 2008 to 2017 for window analysis. The window length is three years, so the data is divided into eight windows (2008–2010, 2009–2011, 2010–2012, 2011–2013, 2012–2014, 2013–2015, 2014–2016, 2015–2017). The GEE values of each group in China for three consecutive years are shown in Table 11 and Fig. 12. Table 11 shows that the average GEE at China's provincial level from 2008 to 2010. Qinghai has a green economy efficient in every period of three consecutive years, and the average GEE of Beijing, Shanghai, Guangdong, and Gansu is above 0.9. However, the GEE of Hainan and Shaanxi stayed at 0.7 and 0.1 respectively and showed a downward trend. The average GEEs of Shaanxi, Guizhou, Ningxia, and Xinjiang were all below 0.5. On the whole, the average GEE shows a slow upward trend for 30 provinces in China. Except for Jilin, Hainan, and Shaanxi, the GEE of the other provinces changes little, showing strong stability. As shown in Fig. 12, the average GEE of the four windows from 2009 to 2011, 2011 to 2013, 2013 to 2015, and 2015 to 2017 is 0.65, 0.66, 0.65, and 0.65, respectively, which

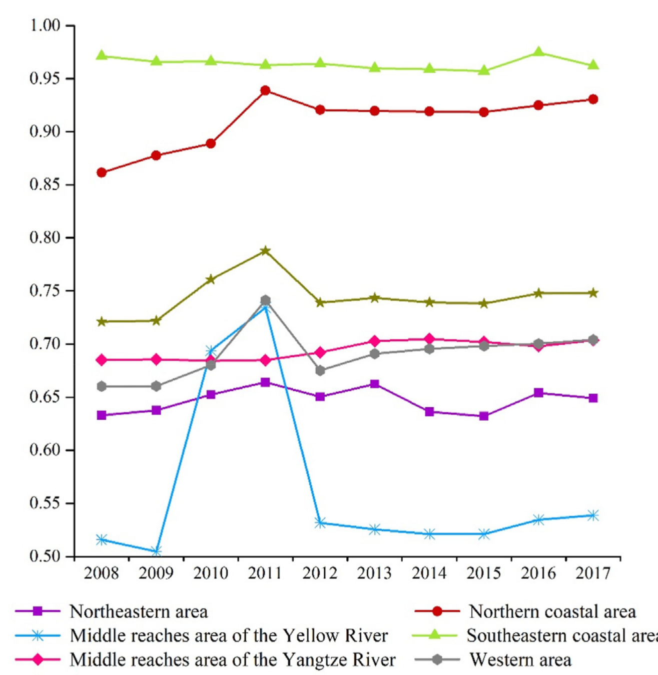

Fig. 9. GEE in six areas of China with time series change.

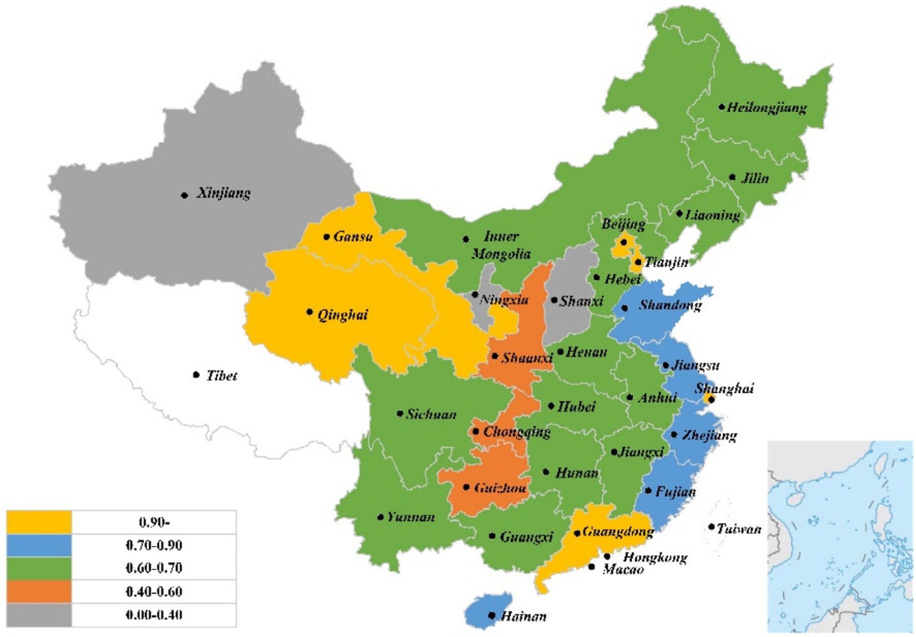

Fig. 10. The spatial distribution of the average GEE from 2008 to 2017 in China.

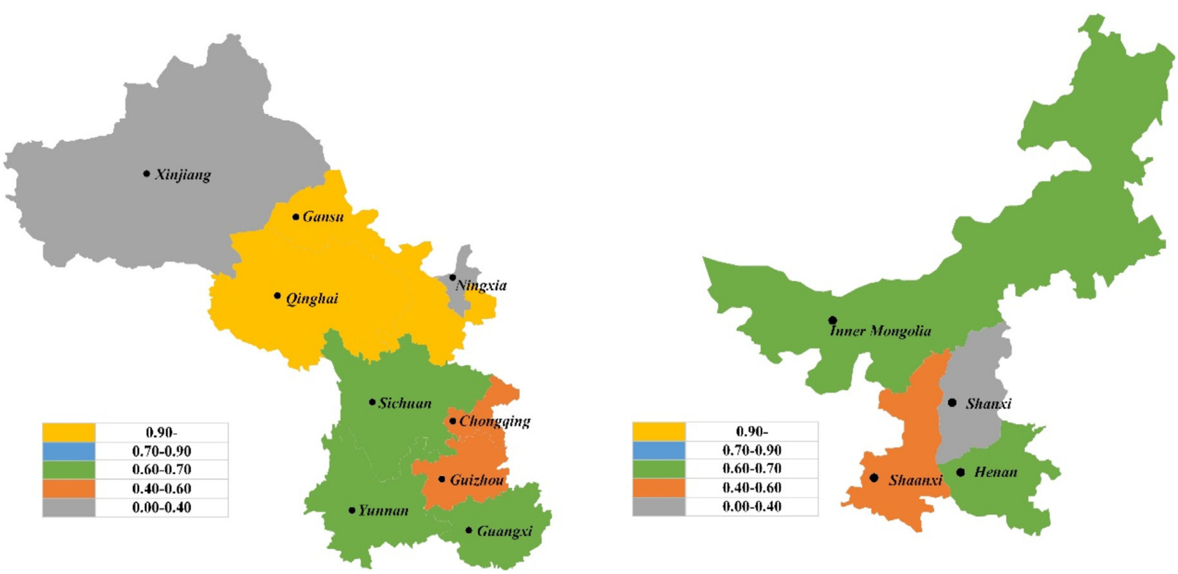

Fig. 11. Spatial difference of the GEE within two areas.

indicates that the overall GEE in the four window periods changes little and remains stable. It should be noted that just four windows are shown, and those windows can cover all study periods. However, GEE varies greatly among provinces, with obvious gap between Shaanxi and Qinghai, which shows the Matthew effect of the strong getting stronger and the weak getting weaker.

Next, the GEE in different areas of China is further analyzed. The descriptive statistics of GEE in the six areas of China for three-year periods are shown in Table 12 and Fig. 13. Table 12 describes the average, standard deviation, and coefficient of variation of the GEE in the six areas. In terms of the average value, the GEE of the southeastern coastal area is 0.84 for the three-year periods, which is the highest, while that of the middle reaches area of the Yellow River is 0.42, which is the lowest. In terms of standard deviation, the standard deviation of the western area is 0.28, which indicates that there is a large gap in the GEE of each province within the western area. The standard deviation of the northeastern area and the middle reaches area of the Yangtze River is 0.03, which indicates that the GEE of each province within that group is relatively stable. Fig. 13 shows more intuitively that the variation coefficient of the GEE in the northeastern area and the middle reaches area of the Yangtze River is about 0.05, indicating that the GEE of the provinces in these two areas is relatively concentrated for three-year periods. However, the coefficient of variation of the GEE in the middle reaches area of the Yellow River and the western area is 0.49, indicating that the GEE values of the provinces in these two areas are relatively scattered. Fig. 14 shows the GEE of six areas in China. It is obvious that six areas in China have a large difference in the GEE. The average GEE in the four windows from 2009 to 2011, 2011 to 2013, 2013 to 2015, and 2015 to 2017 remains basically

Table 11
Window analysis of the GEE in Chinese provinces for periods of three consecutive years.

Provinces	Average window GEE for three consecutive years							
	2008–2010	2009–2011	2010–2012	2011–2013	2012–2014	2013–2015	2014–2016	2015–2017
Beijing	0.99	1.01	1.01	1.00	1.00	0.99	0.98	1.00
Tianjin	0.85	0.92	0.96	0.99	0.99	0.97	0.91	0.94
Hebei	0.54	0.52	0.51	0.52	0.54	0.56	0.54	0.57
Shanxi	0.39	0.38	0.39	0.40	0.39	0.40	0.42	0.44
Inner Mongolia	0.55	0.58	0.55	0.52	0.55	0.55	0.56	0.57
Liaoning	0.52	0.56	0.56	0.58	0.59	0.59	0.57	0.59
Jilin	0.54	0.54	0.54	0.59	0.63	0.64	0.66	0.63
Heilongjiang	0.58	0.58	0.59	0.61	0.62	0.62	0.58	0.59
Shanghai	0.95	0.98	0.99	0.97	0.99	0.99	0.95	0.99
Jiangsu	0.79	0.78	0.78	0.80	0.81	0.81	0.79	0.81
Zhejiang	0.83	0.82	0.82	0.84	0.85	0.84	0.81	0.83
Anhui	0.66	0.66	0.67	0.68	0.69	0.69	0.65	0.67
Fujian	0.78	0.77	0.76	0.78	0.78	0.77	0.73	0.74
Jiangxi	0.69	0.69	0.69	0.67	0.68	0.67	0.64	0.66
Shandong	0.74	0.71	0.70	0.75	0.76	0.74	0.72	0.75
Henan	0.60	0.60	0.60	0.61	0.62	0.61	0.61	0.61
Hubei	0.66	0.64	0.62	0.66	0.67	0.66	0.63	0.64
Hunan	0.58	0.59	0.60	0.65	0.66	0.65	0.62	0.64
Guangdong	0.99	0.98	1.00	1.00	0.99	0.98	0.92	0.91
Guangxi	0.65	0.63	0.62	0.60	0.60	0.59	0.58	0.59
Hainan	0.82	0.78	0.74	0.69	0.67	0.63	0.59	0.59
Chongqing	0.49	0.50	0.52	0.57	0.61	0.62	0.61	0.64
Sichuan	0.58	0.60	0.61	0.71	0.72	0.71	0.64	0.67
Guizhou	0.49	0.44	0.43	0.42	0.41	0.41	0.41	0.41
Yunnan	0.53	0.71	0.70	0.68	0.50	0.49	0.47	0.48
Shanxi	0.16	0.18	0.18	0.17	0.03	0.03	0.03	0.03
Gansu	0.97	0.93	0.90	1.00	1.00	0.99	1.00	1.00
Qinghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ningxia	0.27	0.28	0.28	0.26	0.26	0.26	0.26	0.26
Xinjiang	0.10	0.10	0.11	0.11	0.09	0.10	0.10	0.10

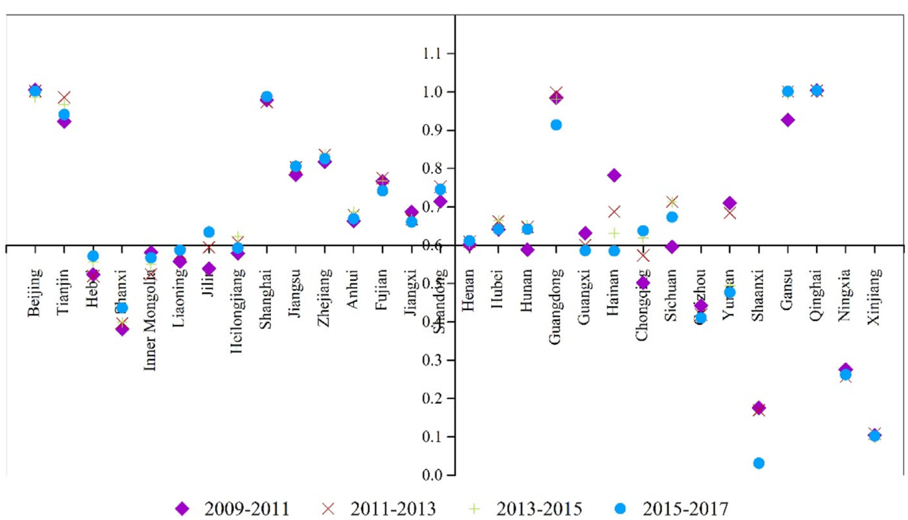

Fig. 12. Window analysis of the GEE in Chinese provinces for periods of three consecutive years.

stable at around 0.65. In general, it shows an inverted U-shaped trend of first rising and then falling.

5.5. Inefficiency analysis of the GEE

Table 13 describes the inefficiency analysis of the inefficient DMUs for the time window from 2015 to 2017. Based on the analysis, it can be seen that the average GEE from 2015 to 2017 is high in Beijing (1.00), Tianjin (0.94), Shanghai (0.99), Guangdong (0.91), Gansu (1.00), and Qinghai (1.00). However, there are also low average GEE values in Shanxi (0.44), Guizhou (0.41), Shaanxi (0.03), Ningxia (0.26), and Xinjiang (0.10). Table 13 calculates the efficiency value of inefficient DMUs in each year of the window period from 2015 to 2017, as well as the inefficiencies from input and output angles. At the same time, for each input-output variable, the corresponding ratio improvement, slack improvement, and target value are given, providing the benchmark for the improvement of the ineffective DMUs.

Taking Shanxi province as an example, its annual GEE values for the time window from 2015 to 2017 are 0.42, 0.43, and 0.46, respectively, indicating that the annual GEE in this window period is increasing. From the perspective of input-output inefficiency,

Table 12
Descriptive statistics of the GEE in six areas of China for three-year periods.

Areas	Average	Standard Deviation	Variation Coefficient
Northeastern area	0.59	0.03	0.06
Northern coastal area	0.80	0.19	0.23
Southeastern coastal area	0.84	0.11	0.13
Middle reaches area of the Yellow River	0.42	0.20	0.49
Middle reaches area of the Yangtze River	0.65	0.03	0.04
Western area	0.58	0.28	0.49

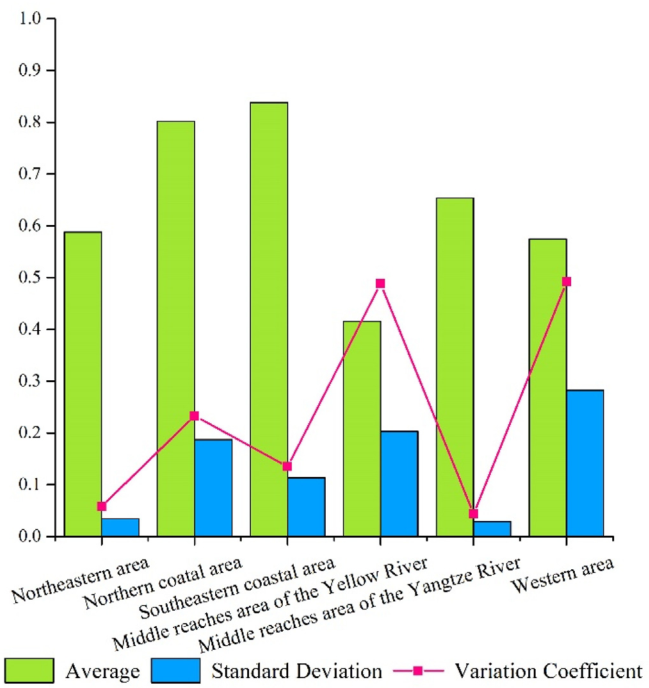

Fig. 13. Statistical chart of the GEE's change in six areas of China for three-year periods.

each year's output inefficiency is greater than that of input inefficiency, and it can be concluded that the reasons for its inefficiency stem more from the output side. In terms of the improvement of input and output, the Super-PEBM model combines proportional improvement and slack improvement. Taking the energy input of Shanxi province in 2017 as an example, the proportion improvement should reduce 72.55 million tons of standard coal, and the slack improvement should reduce 26.50 million tons of standard coal, with the target value of 96.82 million tons of standard coal. Therefore, energy input should be reduced by 37% from the current level to achieve the efficiency of "green" economy.

6. Conclusion and policy implication

6.1. Conclusion

This paper, building on environmental DEA technology, introduces a technique using the Super-PEBM model and window analysis to systematically analyze the sequential evolution characteristics, spatial differentiation characteristics, and dynamic evolution of GEE in Chinese provinces from 2008 to 2017. The main conclusions are as follows.

First, for the evaluation of GEE in the provinces, the GEE calculated considering environmental DEA technology is lower than that without considering the undesirable output. The combination of environmental DEA technology and the Super-PEBM model can more effectively calculate the GEE of China. Our results show that considering the differences between provinces and areas in China, the evaluation of GEE using VRS hypothesis with environment DEA technology will be more practical. Second, in terms of time series evolution, the average GEE from 2008 to 2017 in China was 0.74, showing a fluctuating growth trend and gradually narrowing regional differences. In terms of spatial differentiation, the GEE of the southeastern coastal area and the northern coastal area is much higher than the national average, and the GEE of the southeastern coastal area and the middle reaches area of the Yangtze River remains stable with the change of time series. Although the GEE varies greatly among different regions in China, the improvement

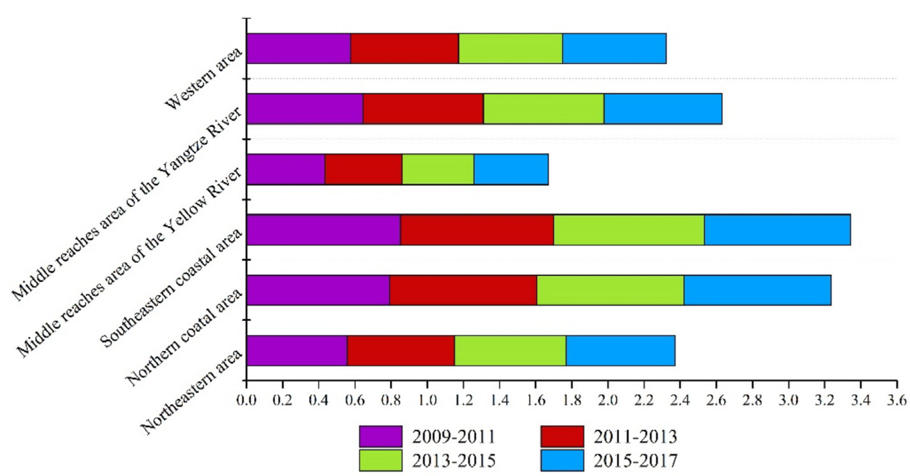

Fig. 14. The GEE of six areas in China for three-year periods.

Table 13
Inefficiency analysis of the low-efficiency DMUs of the time window from 2015 to 2017.

DMU	Time	Score	Input Inefficiency	Output Inefficiency	Proportionate Movement (Energy Consumption)	Slack Movement (Energy Consumption)	Projection (Energy Consumption)	Proportionate Movement (Employed Population)	Slack Movement (Employed Population)	Projection (Employed Population)	Proportionate Movement (Capital Stock)	Slack Movement (Capital Stock)	Projection (Capital Stock)
Shanxi	2015	0.42	0.39	0.45	-75.37	-25.38	93.09	-14246.29	0	22394.91	-1900.20	0	2987.08
	2016	0.43	0.39	0.41	-75.89	-20.38	97.74	-14403.41	0	22416.59	-2055.69	0	3199.35
	2017	0.46	0.37	0.38	-72.55	-26.50	96.82	-13711.32	0	23308.68	-2118.32	0	3601.05
Guizhou	2015	0.40	0.42	0.45	-41.76	-3.33	54.39	-14816.64	-1346.34	19132.02	-1212.94	0	1676.43
	2016	0.42	0.40	0.42	-40.98	-4.67	56.62	-14243.61	-2552.61	18753.78	-1351.43	0	2021.54
	2017	0.41	0.41	0.43	-43.07	-1.17	61.15	-14630.33	-1845.84	19323.83	-1693.42	0	2450.33
Shaanxi	2015	0.03	0.94	0.95	-110.07	0	7.09	-35636.01	0	2293.99	-5836.33	0	375.70
	2016	0.03	0.94	0.94	-113.74	0	7.46	-35781.87	0	2348.13	-6445.57	0	422.98
	2017	0.03	0.94	0.94	-117.05	0	7.69	-35985.26	0	2364.74	-7462.28	0	490.38
Ningxia	2015	0.27	0.57	0.60	-31.04	-4.66	18.36	-3835.39	0	2843.41	-811.19	0	601.38
	2016	0.26	0.58	0.60	-32.56	-3.99	19.37	-3930.13	0	2819.87	-959.28	0	688.28
	2017	0.26	0.58	0.60	-33.04	-4.10	19.60	-3970.98	0	2849.02	-1141.71	0	819.13
Xinjiang	2015	0.10	0.81	0.82	-126.84	-6.90	22.77	-19123.53	0	4473.77	-3130.83	0	732.43
	2016	0.10	0.81	0.81	-131.94	-7.57	23.51	-19408.21	0	4571.79	-3524.24	0	830.17
	2017	0.10	0.82	0.82	-137.81	-4.94	25.60	-20015.13	0	4434.87	-4211.02	0	933.06

of GEE can promote the reduction of regional differences. Thirdly, the window analysis based on panel data shows that, on the whole, the GEE presents a slow upward trend. In the window period, the overall GEE of China changes little and remains stable, but the GEE varies greatly among different provinces. Furthermore, the average GEE remained stable at around 0.65, showing an inverted U-shaped trend of first rising and then falling.

6.2. Policy implication

These conclusions have important policy implications. There is no ready-made model or experience to follow and learn from, so we need to explore a path of green economy development with Chinese characteristics. First, it is important to ensure green development through innovation in ideas and institutions. We should further develop strategic emerging industries, accelerate green innovation, and make breakthroughs in core and key technologies (Zuo et al., 2019). Second, it is necessary to establish differentiated regional development strategy and high-quality urbanization development strategy to lead green development. We should encourage green regional development strategies based on the development potential of each region, and give full play to the capabilities and potential of each area. Thirdly, try to build a green industrial system, seek the green industrial production process under the guidance of green innovation strategy, and achieve a win-win situation of economic and environmental efficiency. Finally, establish a regional environmental protection compensation mechanism, and reasonably allocate regional environmental protection costs (Shuai and Fan, 2020). We should also actively transform the economic development mode, develop circular economy, low-carbon economy, sustainable economy and green economy, and change the traditional economic growth mode characterized by high consumption and high pollution.

6.3. Limitation and further research

Due to the limited research capacity, the following deficiencies exist in this paper: (1) When measuring the efficiency of the green economy, the calculation results are different due to the different input-output system and different setting of undesirable outputs. In the real production system, weak and managerial disposability assumption may be fit more and worth in-depth study. (2) Different divisions of regions in China may lead to different empirical results. The division of regions in China needs to be more cautious. (3) Environmental regulations and ecological efficiency are the driving force and objective function of China's economic growth, respectively (Song et al., 2020a). The environmental regulation influence on efficiency of China's regional green economy extent and direction is not discussed, which is a limitation and the further research direction. In the future, we will conduct in-depth research and analysis on green development in multiple periods and at different scales, and further, reveal the spatial-temporal variation rules of GEE in Chinese regions. In addition, it is necessary to combine macro and micro research, carrying out the research from the whole to the part at multiple levels and angles, and systematically consider the multidisciplinary interaction of green development. It is of far-reaching significance to bring different factors into the research framework and deeply analyze the interaction coupling stress among various factors, so as to explore the interaction between GEE and various factors.

Declaration of competing interest

The authors declare no conflict of interest.

CRediT authorship contribution statement

Dongdong Wu: Conceptualization, Writing - original draft. **Yuhong Wang:** Methodology, Supervision, Validation, Writing - review & editing. **Wuyong Qian:** Data curation, Software.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.121630.

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