ECOLOGY ENVIRONMENT RESEARCH ABOUT CARBON EMISSION EFFICIENCY IN CHINA BASED ON A NOVEL SUPER EPSILON-BASED MEASURES (SEBM) MODEL

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Abstract. With China's rapid economic development, the carbon emission has become a serious issue and the evaluation of carbon emission efficiency has drawn the attention of academia. Although the Data Envelopment Analysis (DEA) method is widely used in determining carbon emission efficiency, there are many limitations in the traditional DEA mathematical models including the original elements information loss due to the change of the proportion of the elements, too narrow efficiency boundaries, and the existence of undesirable outputs. As a result, a novel super epsilon-based measures (SEBM) carbon emission efficiency evaluation model is expected to overcome the limitations in the traditional carbon emission efficiency determination models, based on which the carbon emission efficiency of China is analyzed from time and spatial dimensions respectively. Finally, contrastive empirical analysis results of SEBM model and other classical DEA models indicate that the former has remarkable superiority over the other models. Based on the experimental results, it is found that China's carbon emission efficiency is inversely proportional to the level of economic development, and carbon emission efficiency values in China have generally increased, which highlights the significance of energy-saving emission reduction policies.
Keywords: *data envelopment analysis (DEA), carbon emission efficiency, super epsilon-based measures (SEBM) model, empirical analysis (EA), model efficiency evaluation*

Introduction

The competition between traditional energy and new energy has been intensifying. Traditional energy does not have the clean and pollution-free features of hydropower, solar energy, wind energy and other new energies (Wang et al., 2016). By contrast, traditional energies such as oil, coal and natural gas still occupy the principal position in global energy (Xu et al., 2014). A major concern of traditional energy sources is that carbon emissions are considered. Since energy conservation and emission reduction regulations were proposed in 2006, carbon emission reduction and carbon emission efficiency improvement are used as metrics by all sectors of society (Roar Adland et al., 2017). The emergence of electric vehicles is caused by industrial circles (Yun et al., 2017). Research on carbon emission efficiency is also on the rise (Henson et al., 2015). China, as the world's largest developing

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country, has continuously and rapidly expanded its economy since the late 1980s, maintaining an annual growth rate of more than 9% for over three decades (Wang et al., 2015). China's extensive economic growth is condemned to have high-energy consumption, high carbon emissions and other issues (Wang et al., 2013). Taking carbon emission efficiency as the entry point, this study takes the information from all of the regions in China as data support, conducts innovation research expansion on the most popular carbon emission efficiency model from the academic literature, and comparatively analyses on the carbon emission efficiency model in 29 provinces and cities in China (Liu et al., 2014).

Our study aims to design an SEBM model to evaluate carbon emission efficiency, which can solve the problems which other models cannot solve. There are two streams of relevant literature surrounding this research: the focus issues of carbon emission efficiency in the academic literature and the data envelopment analysis (DEA)-based carbon emission efficiency evaluation models.

Early researchers primarily used the ratio of total carbon emissions together with a select factor as the evaluation index of carbon efficiency, namely, single element carbon efficiency. For example, the carbon emissions efficiency, known as carbon productivity, was defined as the ratio of GDP and the carbon emissions during a select period (Kaya and Yokobori, 1993). Later, carbon index (carbon emissions perunit energy consumption), energy intensity (energy consumption per unit of GDP) and carbon emissions intensity index (CO_2 emissions per unit of GDP) were used as the evaluation index to measure carbon efficiency (Mielnik and Goldemberg, 1999; Ang, 1999; Sun, 2005). In addition, new evaluation indices such as industrialization cumulative per capita emissions, and carbon emissions by per capita per unit GDP were found to better reflect scientific, fair and reasonable principles, so they became more reasonable indices for the measurement of carbon efficiency evaluation (Zhang et al., 2008). Single factor index evaluation carbon efficiency is easy to understand and operate, but there are different opinions about its usefulness, because of the diversity of the measurement index (Zhou et al., 2010). Therefore, many researchers have relied on total factor efficiency to determine carbon emissions. For instance, the carbon emissions efficiency should be integrated into the three contexts of energy consumption, economic development and carbon emissions; so that the evaluation results are comprehensive and rational (Ramanathan, 2002). And slack variables were used to measure the comprehensive performance of carbon emissions of 30 OECD countries during the period of 1998-2002 (Zhou et al., 2006). Furthermore, bidirectional causality between economic growth and energy use and between energy use and carbon emissions (Wang et al., 2016).

In recent years, domestic and foreign researchers have generally used DEA to examine the efficiency of carbon emissions within the framework of the total factor. Ramanathan (2005, 2006) integrated the four indices of CO_2 emissions using DEA, and obtained the CO_2 emissions efficiency of 17 countries in the Middle East and North Africa. Marklund and Samakovlis (2007) estimated the cost of carbon emissions reduction of the European countries by building a distance-direction function based on the DEA. Zhou et al. (2010) measured the carbon emissions efficiency of 18 countries with the highest global CO_2 emissions using MCPI, and constructed a correlation analysis of the influencing factors of carbon emissions efficiency. Wang and Zhou (2012) used the DEA method to measure the carbon emission efficiency of each province in China from 2001 to 2007 and concluded that China's carbon emission efficiency varied. Zhou and Nie used the slack-based measure

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(SBM) to quantify the inter-provincial industrial carbon emission efficiency of 30 provinces in China and analyse the similarities and differences (Grinsven et al., 2016).

From the perspective of a carbon emission efficiency model, the academic community relies on DEA to analyze carbon emission efficiency (Niu et al., 2016). The model development process first adopted the CCR-DEA model and then the BCC-DEA model, which examines carbon emission efficiency in constant returns to scale (CRS) and variable returns to scale (VRS) (Cranmer, 2016). After the DEA model developed the SBM and other models to consider the non-expected output, researchers have mostly used the SBM-DEA model or other relevant models supported by it. For example, carbon emission efficiency is calculated using the SBM model; the stochastic frontier analysis or redundancy analysis is used to revise the efficiency value, and the three-stage DEA model of SBM efficiency, Tobit regression or Malmquist index is used to analyze the carbon emission efficiency (Kim, 2016). Alternatively, the SBM from an operational research perspective and statistical regression are combined to examine carbon emission efficiency (Baleentis et al., 2016), but research on the applicability of the model is not comprehensive. Some scholars have proposed the super-efficiency-DEA (SE-DEA) to enlarge the efficiency boundary of carbon emission and effectively eliminate the limitation of the efficiency value boundary of the original DEA model (Szczepańska and Wiśniewska, 2012). Some scholars have partially supplemented the DEA model from the radial direction and non-radial direction angles of the directional distance function. In 2016, a series of significant progress in theory was made: Tone summarised the shortcomings of CRS and SBM models and proposed the epsilon-based measure model (EBM), which solves the problem of the proportional change in factors and the original ratio information of loss efficiency frontier (Andrie and Ursu, 2016). However, the efficiency boundary remained restricted, and the model was still insufficient. In consideration of the advantages and disadvantages of the CCR-BCC-SBM-EBM-SE model, this study proposes the SEBM model (Bretschger and Valente, 2016), which can effectively expand the efficiency of the boundary and solve the factor changes in the same proportion, the original ratio information of factors in the leading edge of loss efficiency and other issues (Shao and Wang, 2016). The current study also provides further theoretical and data support for other scholars in studying carbon emission efficiency.

The article structure is presented as follows: in Section 2, the classical mathematical models in data envelopment analysis (DEA) are presented, including the Charnes, Cooper and Rhodes (CCR) model, the Banker, Charnes and Cooper (BCC) model, the super-efficiency-data envelopment analysis (SE-DEA) model and the epsilon-based measure (EBM) model. Then, a novel super epsilon-based measures (SEBM) model is proposed further in Section 3. Section 4 discusses and analyses the differences in carbon emission efficiency in 29 regions in China from 2004 to 2014, where the characteristics of classical DEA models of CCR, EBM, SE models and the proposed SEBM model are comparatively analyzed from the time and spatial dimension. Section 5 concludes the paper.

Materials and methods: theoretical model establishment

The DEA method is widely used in determining carbon emission efficiency (Xian and Huang, 2016). This section discusses the CCR-DEA, BCC-DEA, SE-DEA, EBM-DEA and SEBM-DEA models from a theoretical perspective. From the variable perspective, the DEA model has an input-oriented angle and an output-oriented angle but no guidance angle (Dzonzi-Undi and Li, 2016; Obeng et al., 2016; Vaidya and

Campbell, 2016). This study only provides the theoretical formula of the three angle models of the SEBM model.

Suppose we have a set of independent homogeneous decision-making units denoted by $DMU_j (j = 1, 2, ..n)$. Each observation $DMU_j (j = 1, 2, ..n)$ uses m inputs $x_{ij} (i = 1, 2, ..m)$ to produce s outputs $y_{rj} (r = 1, 2...s)$. DMU_o represents one of the n DMUs under evaluation, and x_{io} and y_{ro} are the ith input and r[th] output for DMU_o, respectively.

CCR model

The technical efficiency of the Oth DMU can be calculated by the input-oriented CCR (Charanes et al., 1978) model (*Eq.1*):

$$
\begin{aligned}
Min \quad & \theta_o \\
subject\ to \quad & \sum_{j=1}^{n} x_{ij}\lambda_j \le \theta_o\, x_{io}, i = 1, 2, \ldots, m, \\
& \sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro}, r = 1, 2, \ldots, s, \\
& \lambda_j \ge 0,\ j = 1, 2, \ldots, n.
\end{aligned}
\tag{Eq.1}
$$

where v_i and u_r are the weights assigned to input i $(i = 1, 2, ..m)$ and output r $(r = 1, 2, ..s)$, respectively, and λ is the weight multiplier of each DMU. In the above formula, the optimal solution θ_o^* represents the efficiency value $\theta_o^* \in (0,1]$.

BCC model

The BCC model assumes that the production process belongs to a fixed-scale gain. That is, when the input amount increases in geometric proportion, the output also increases in geometric proportion (Sarkar, 2013). However, the actual production process may also belong to the state of increasing returns to scale or decreasing returns to scale. To analyze the changes in returns to scale of the DMUs, Banker et al. (1984) proposed the BCC model (*Eq. 2*):

$$
\begin{aligned}
Min \quad & \theta_o \\
subject\ to \quad & \sum_{j=1}^{n} x_{ij}\lambda_j \le \theta_o\, x_{io}, i = 1, 2, \ldots, m, \\
& \sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro}, r = 1, 2, \ldots, s, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \ge 0,\ j = 1, 2, \ldots, n.
\end{aligned}
\tag{Eq.2}
$$

Compared with the CCR model, the constraint $\sum_{i=1}^{n} \lambda j = 1$ is added to the BCC model, so that the production scale of the projection point is at the same level as the scale of production being evaluated.

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SE-DEA model

If the effective DMUs are too affected by the effect of data on the CCR model, no comparison exists. Andersen and Petersen (1993) removed the assessed DMUs from the efficient boundary and took the remaining DMUs as basis to form a new efficiency boundary and calculate the distance from the removed DMU to the new efficient boundary. Thus, all of the DMUs achieved complete sequencing, that is, the super-efficiency model. The SE-DEA model (*Eq. 3*) based on the CCR model is expressed as follows:

$$Min \quad \theta_o$$

$$subject\ to \quad \sum_{\substack{j=1 \\ j \neq o}}^{n} x_{ij}\lambda_j \leq \theta_o\, x_{io}, i = 1, 2, \ldots, m,$$

$$\sum_{\substack{j=1 \\ j \neq o}}^{n} y_{rj}\lambda_j \geq y_{ro}, r = 1, 2, \ldots, s, \tag{Eq.3}$$

$$\sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0,\ j \neq o.$$

Banker and Chang (2006) demonstrated that the super-efficiency model is highly susceptible to outliers, and thus, the model could detect the existence of outliers in the dataset. In a number of datasets of effective DMUs, SE-DEA effectively was shown to amplify the efficiency boundary, and many practical problems were analyzed effectively because of the limitation of the previous efficiency boundary. The SE-DEA reveals the potential for these practical applications.

EBM model

In 2010, Tone argued that the same rate reduction of input factor in traditional DEA (CCR) models violates physical truth and that the SBM model has the original ratio information of factors aside from loss efficiency. He proposed the EBM model which overcame the above shortcomings. The model's theoretical formulas are expressed as follows (*Eq. 4*):

$$\gamma* = Min\ \theta_o - \varepsilon^- \sum_{i=1}^{m} \frac{w_i^-\, s_i^-}{x_o}$$

$$subject\ to\ \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta_o x_{io},\ i = 1, \ldots, m,$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{ro},\ r = 1, \ldots, s,$$

$$\lambda_j, s_i^- \geq 0,\ \forall i, j, r. \tag{Eq.4}$$

This formulation indicates that $\gamma*$ is obtained as the optimal internally dividing value between the radial θ_o and the non-radial term $\varepsilon \sum_{i=1}^{m} \frac{w_i^-\, s_i^-}{x_o}$, where s_i^- is the amount

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of slack in the ith input, and w_i^- is the ith input weight and satisfies $\sum\limits_{i=1}^{m} w_i^- = 1 (w_i^- \geq 0, \forall i)$.

ε^- is a key parameter in the range of [0,1], and it indicates the importance of the non-radial part in the calculation of the efficiency value. If $\varepsilon^- = 0$, the EBM model will be simplified as the input-oriented CCR model. If $\theta_o = \varepsilon^- = 1$, the EBM model will be transformed into the SBM model. Before calculating the EBM efficiency scores, we should first estimate the value of the core parameters ε^- and w_i^-. We determine ε^- and w_i^- using Pearson's correlation coefficient (Tavana et al., 2013; Tone and Tsutsui, 2010).

Results: the proposed SEBM model

The theoretical analysis and research on the CCR, BCC, SEDEA and EBM models are presented. To overcome these three problems, first, the input efficiency should have the same reduction rate. Second, if too many effective units exist, the actual problems will not be effectively analyzed. Third, the original ratio information of the factor of the leading edge of loss efficiency should be obtained. In this study, the SEBM model is presented, and the theoretical formula of the SEBM model is given in three aspects:

Input-orientation (*Eq. 5*):

$$\gamma* = Min \; \theta_o - \varepsilon^- \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_o}$$

$$subject \; to \; \sum_{\substack{j=1 \\ j\neq o}}^{n} x_{ij}\lambda_j + s_i^- = \theta_o x_{io}, \; i = 1,\dots,m,$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} y_{rj}\lambda_j \geq y_{ro}, \; r = 1,\dots,s, \qquad (Eq.5)$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j = 1,$$

$$\lambda_j, s_i^- \geq 0, \; \forall i, j, r.$$

Output-orientation (*Eq. 6*):

$$\gamma* = Min \; \frac{1}{\varphi_o - \varepsilon^+ \sum\limits_{i=1}^{s} \frac{w_i^+ s_i^+}{x_o}}$$

$$subject \; to \; \sum_{\substack{j=1 \\ j\neq o}}^{n} x_{ij}\lambda_j \geq x_{io}, \; i = 1,\dots,q,$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} y_{rj}\lambda_j - s_r^+ = \varphi_o y_{ro}, \; r = 1,\dots,s, \qquad (Eq.6)$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j = 1,$$

$$\lambda_j, s_r^+ \geq 0, \; \forall i, j, r.$$

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In the above model, the reciprocal of γ^* is obtained as the optimal internally dividing value between the radial φ_o and the non-radial term $\varepsilon^+ \sum\limits_{i=1}^{m} \frac{w_i^- s_i^-}{x_O}$, where s_i^+ is the amount of slack in the ith output, and w_i^+ is the ith output weight and satisfies $\sum\limits_{i=1}^{m} w_i^+ = 1 (w_i^+ \geq 0, \forall i)$. ε^+ is a key parameter in the range of [0,1]. This indicates the importance of the non-radial part in the calculation of the efficiency value.

Non-orientation (*Eq. 7*):

$$\gamma* = Min \ \frac{\theta_o - \varepsilon^- \sum\limits_{i=1}^{n} \frac{w_i^- s_i^-}{x_o}}{\varphi_o - \varepsilon^+ \sum\limits_{i=1}^{s} \frac{w_i^+ s_i^+}{x_o}}$$

$$subject \ to \ \sum\limits_{\substack{j=1 \\ j \neq o}}^{n} x_{ij}\lambda_j + s_i^- = \theta_o x_{io}, \ i = 1, \ldots, m,$$

$$\sum\limits_{\substack{j=1 \\ j \neq o}}^{n} y_{rj}\lambda_j - s_r^+ = \varphi_o y_{ro}, \ r = 1, \ldots, s,$$

$$\sum\limits_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j = 1,$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \ \forall i, j, r.$$

(Eq.7)

The SEBM model effectively solves several problems of the DEA model. Regarding applicability, the expansion of an efficient boundary can be applied in more datasets. SEBM can be applied in an actual situation to remove the ratio change restrictions of the input elements. System errors can be avoided without loss of the original data information.

Discussion: empirical analysis

Data description

In this study, Chinese human capital stock and total energy consumption in 2017 are taken as input factors. Output indicators include GDP and carbon emissions, which are desirable outputs in the CCR/BCC/SE model and are undesirable outputs in the EBM and SEBM models. The input and output data are obtained from the 'China Statistical Yearbook' and 'China Energy Statistical Yearbook'. The basic descriptive statistics of the 29 regions in China are shown in *Table 1*.

Spatial dimension analysis

In this section, we first calculate the optimal value of each DMU using CCR, BCC, SE-DEA, EBM and SEBM models under CRS and VRS. The results are shown in *Tables 2* and *3,* respectively. We then analyze the differences in carbon emission efficiency in 29 regions of China from the spatial dimension. According to the spatial distribution, the efficiency value in the west is the highest, followed by the middle, and the lowest in the east. This finding suggests that the technology and management level

in the west is relatively high. To reflect clearly the regional variability of the four models results, we illustrate them in *Figures 1* and *2*.

Table 1. *Descriptive statistics*

Statistics	Minimum (M)	Maximum (X)	Average value (E)	Standard error	Standard deviation
GDP (billion yuan)	113.52	16413.66	3196.5712	162.21195	2897.19812
Labor force (ten thousand people)	94.10	4500.05	1002.3773	41.45137	740.34507
Capital stock (ten thousand yuan)	178.68	48416.44	7317.7862	421.18654	7522.63220
Total energy consumption (million tons of standard coal)	742.48	38899.25	11990.4673	437.90044	7821.15186
Carbon emission (ton)	343.47	34923.51	9373.4433	381.42376	6812.44625

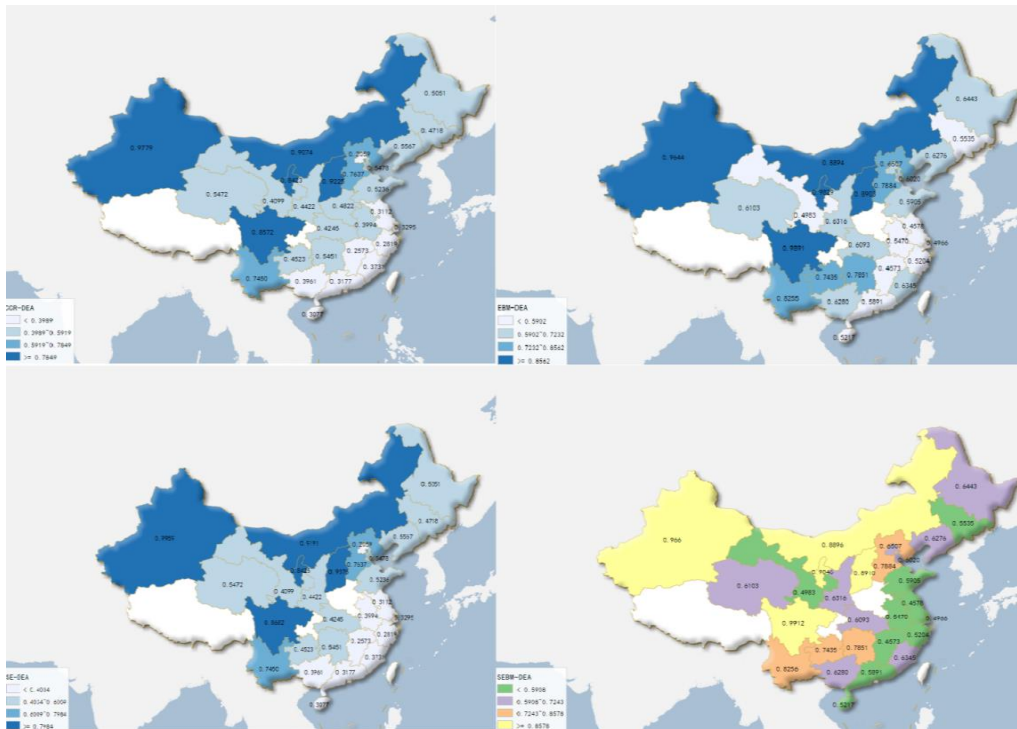***Table 2.*** *Carbon emission efficiency in China's provinces: constant returns to scale*

	Regions	CCR-DEA	Ranking	EBM-DEA	Ranking	SE-DEA	Ranking	SEBM-DEA	Ranking
Central regions	Henan	0.482	14	0.577	21	0.482	14	0.577	21
	Hubei	0.425	18	0.609	17	0.425	18	0.609	17
	Hunan	0.545	11	0.785	8	0.545	11	0.785	8
	Jiangxi	0.257	28	0.457	29	0.257	28	0.457	29
	Anhui	0.399	20	0.547	23	0.399	20	0.547	23
	Shanxi	0.923	2	0.890	4	0.938	2	0.891	4
	Jilin	0.472	15	0.554	22	0.472	15	0.554	22
	Heilong jiang	0.505	13	0.644	11	0.505	13	0.644	11
Eastern regions	Beijing	0.206	29	0.651	10	0.206	29	0.651	10
	Tianjin	0.548	9	0.602	18	0.548	9	0.602	18
	Hebei	0.764	6	0.788	7	0.764	6	0.788	7
	Liaoning	0.557	8	0.628	15	0.557	8	0.628	15
	Shanghai	0.329	23	0.497	27	0.329	23	0.497	27
	Jiangsu	0.311	25	0.458	28	0.311	25	0.458	28
	Zhejiang	0.282	27	0.520	25	0.282	27	0.520	25
	Fujian	0.373	22	0.634	12	0.373	22	0.634	12
	Shandong	0.524	12	0.590	19	0.524	12	0.590	19
	Guangdong	0.318	24	0.589	20	0.318	24	0.589	20
	Hainan	0.308	26	0.522	24	0.308	26	0.522	24

	Region	BCC-DEA	Ranking	EBM-DEA	Ranking	SE-DEA	Ranking	SEBM-DEA	Ranking
Western regions	Inner Mongolia	0.907	3	0.889	5	0.919	3	0.890	5
	Guangxi	0.396	21	0.628	14	0.396	21	0.628	14
	Sichuan	0.857	4	0.989	1	0.868	4	0.991	1
	Guizhou	0.452	16	0.744	9	0.452	16	0.744	9
	Yunnan	0.745	7	0.826	6	0.745	7	0.826	6
	Shaanxi	0.442	17	0.632	13	0.442	17	0.632	13
	Gansu	0.410	19	0.498	26	0.410	19	0.498	26
	Qinghai	0.547	10	0.610	16	0.547	10	0.610	16
	Ningxia	0.842	5	0.983	2	0.842	5	0.985	2
	Xinjiang	0.978	1	0.964	3	0.996	1	0.966	3

Table 3. *Carbon emission efficiency in China's provinces: variable returns to scale*

	Region	BCC-DEA	Ranking	EBM-DEA	Ranking	SE-DEA	Ranking	SEBM-DEA	Ranking
Central regions	Henan	0.655	11	0.834	12	0.655	11	0.834	12
	Hubei	0.480	21	0.785	14	0.480	21	0.785	14
	Hunan	0.675	10	0.956	8	0.675	10	0.957	8
	Jiangxi	0.278	28	0.512	29	0.278	28	0.512	29
	Anhui	0.406	25	0.640	25	0.406	25	0.640	25
	Shanxi	0.986	1	0.985	4	1.018	3	0.987	5
	Jilin	0.481	20	0.660	23	0.481	20	0.660	23
	Heilong jiang	0.515	18	0.767	16	0.515	18	0.767	16
Eastern regions	Beijing	0.234	29	0.686	21	0.234	29	0.686	21
	Tianjin	0.553	16	0.665	22	0.553	16	0.665	22
	Hebei	0.969	4	0.987	3	0.981	5	0.989	4
	Liaoning	0.740	9	0.820	13	0.740	9	0.820	13
	Shanghai	0.341	27	0.611	27	0.341	27	0.611	27
	Jiangsu	0.489	19	0.764	17	0.489	19	0.764	17
	Zhejiang	0.419	23	0.690	20	0.419	23	0.690	20
	Fujian	0.381	26	0.723	19	0.381	26	0.723	19
	Shandong	0.973	3	0.957	7	0.991	4	0.958	7
	Guangdong	0.571	12	0.912	11	0.571	13	0.914	11
	Hainan	0.565	14	0.619	26	0.591	12	0.624	26
	Region	**BCC-DEA**	**Ranking**	**EBM-DEA**	**Ranking**	**SE-DEA**	**Ranking**	**SEBM-DEA**	**Ranking**
Western regions	Inner Mongolia	0.953	6	0.928	9	0.968	6	0.929	9
	Guangxi	0.410	24	0.734	18	0.410	24	0.734	18
	Sichuan	0.955	5	0.995	1	1.023	2	1.003	2
	Guizhou	0.569	13	0.963	6	0.569	14	0.964	6
	Yunnan	0.762	8	0.916	10	0.764	8	0.918	10
	Shaanxi	0.517	17	0.781	15	0.517	17	0.781	15
	Gansu	0.425	22	0.599	28	0.425	22	0.599	28
	Qinghai	0.558	15	0.659	24	0.558	15	0.659	24
	Ningxia	0.929	7	0.992	2	0.960	7	1.003	1
	Xinjiang	0.984	2	0.983	5	1.030	1	0.989	3

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Figure 1. Spatial dimension analysis of carbon emissions efficiency in China from 2004 to 2014: constant returns to scale
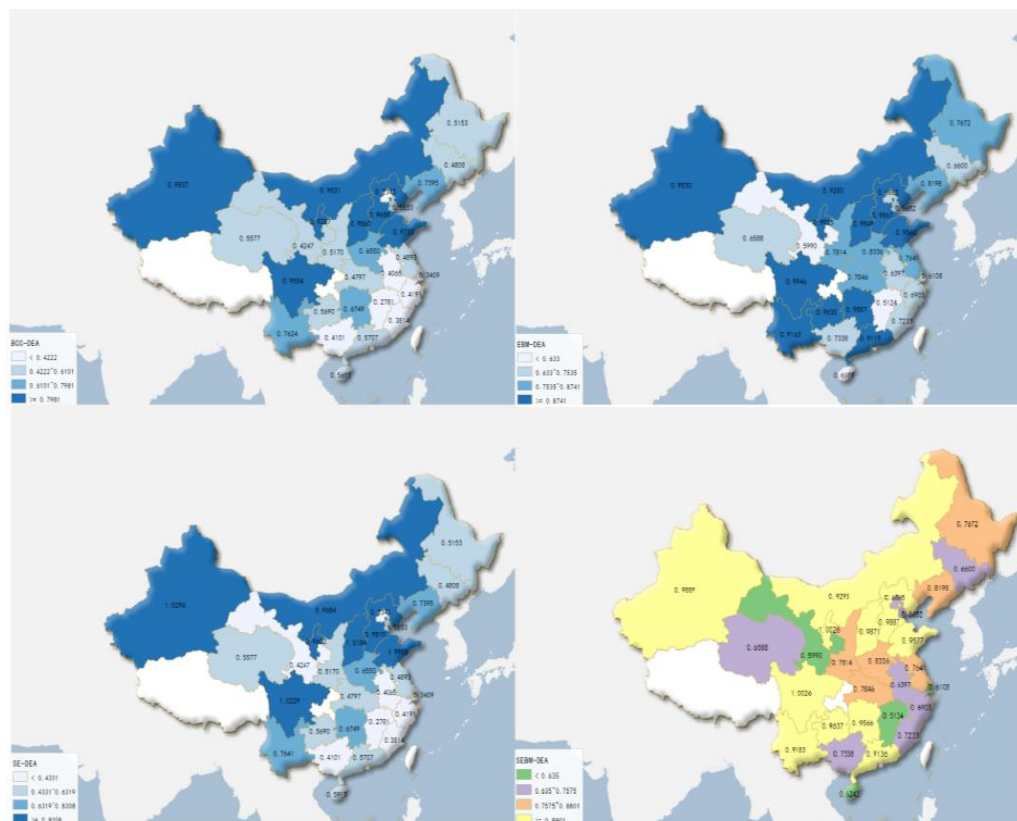
Figure 2. Spatial dimension analysis of carbon emissions efficiency in China from 2004 to 2014: variable return scale

CCR-DEA/BCC-DEA efficiency evaluation

CCR is the most basic DEA model under the CRS angle. Technical efficiency is the production efficiency of the DMU under an optimal scale. However, the DMU is mostly provided with VRS, and thus the BCC model is more suitable in real situations.

As shown in *Tables 2* and *3* and *Figures 1* and *2,* specific to the CCR model, the efficiency values in all provinces are below 1, and the DEA is not valid in all. The carbon emission efficiencies in Xinjiang, Shanxi and Inner Mongolia are above 0.9, which is relatively high. The efficiency values in Jiangxi, Beijing and Zhejiang are below 0.3, which is relatively low. This finding indicates a huge difference in carbon emission efficiency among the different provinces and that the total carbon emission efficiency in China is relatively low. The carbon emission efficiency value in the western region is high, and the efficiency values in six of the ten provinces in the western region are greater than 0.5. The carbon emission efficiency values in the eastern region are the lowest, and the efficiency values in seven of the eleven provinces are less than 0.4. The carbon emission efficiency values in the middle are ranked between those in the west and those in the east. The efficiency values in most of these provinces range from 0.4-0.55.

Specific to the BCC model, the efficiency values in all provinces are below 1. The pure technical efficiency is not valid, but the whole efficiency values are higher than those of the CCR model. The efficiency values in seven provinces are above 0.9, and Shanxi, Xinjiang and Shandong are the top three in efficiency value. The efficiency values in Jiangxi, Beijing and Shanghai are the lowest at below 0.4. In summary, the efficiency values obtained from the BCC model with VRS are applicable in actual situations.

EBM-DEA efficiency evaluation

As the assumed condition of the radial CCR model is too strict, the identified efficiency values usually differ from the actual economy conditions. Therefore, the EBM model combined with radial and non-radial characteristics can effectively solve the problems existing in the CCR model measurement.

From the CRS angle, the comparison of efficiency values of the CCR model and the EBM model shows that the EBM efficiency value is higher than the CCR efficiency value. As shown in *Tables 2* and *3* and *Figures 1* and *2,* Sichuan, Ningxia and Xinjiang are the top three in efficiency values obtained from the EBM model with the efficiency values above 0.9. Jiangxi, Jiangsu and Shanghai are at the bottom three. The ranks decrease compared with the CCR efficiency value. But the efficiency values, which are all above 0.45, increase. This result shows that the EBM model can effectively solve conditions with extreme measurement values in the CCR model with the measurement result closer to the actual economy conditions.

From the VRS angle, BCC efficiency value and EBM efficiency value indicate that the EBM efficiency value is relatively high. Sichuan, Ningxia and Hebei are the top three in efficiency values gained from the EBM model. They all increased compared with BCC efficiency value ranking. Jiangxi, Gansu and Shanghai are the bottom three. Although Shanghai, Jiangxi and Gansu are ranked in a lower position than the BCC efficiency value ranking, all efficiency values approximately increase.

SE-DEA efficiency evaluation

When the traditional DEA model measures and compares the efficiency value, there is a defect that multiple decision-making units of leading surface cannot be further compared and evaluated. However, the SE-DEA model can measure the valid DMUs of the DEA by transmitting the DMUs to the leading surface.

In the CRS angle, with respect to the basic CCR model, the average SE-DEA efficiency value in Shanxi, Inner Mongolia, Xinjiang and Sichuan in 2004–2014 decreases because the DEA in these four provinces is valid for some of the identified years. Therefore, the SE-DEA measures those years in which the leading line for production is reached. For example, as shown in *Tables 2* and *3* and *Figures 1* and *2,* the DEA of Shanxi is valid in 2004, 2005 and 2007. The CCR efficiency value is 1, and the SE-DEA efficiency values are 1.101, 1.024, 1.034 and 1.006, respectively. Therefore, the average SE-DEA efficiency value is completely improved.

In the VRS angle, the SE-DEA efficiency values in Xinjiang, Sichuan and Shanxi are relatively high at 1.030, 1.023 and 1.018, respectively. After the BCC-DEA in these regions becomes valid, further analysis is conducted using the SE-DEA, which evaluates the carbon emission efficiency in various provinces accurately.

SEBM-DEA efficiency evaluation

The SEBM model integrates the advantages of the SE-DEA model and the EBM model and further compares and analyzes the DMUs.

As shown in *Tables 2* and *3* and *Figures 1* and *2,* in the CRS angle, the average SEBM efficiency values in Shanxi, Inner Mongolia, Sichuan and Xinjiang in 2004–2014 increase compared with the EBM efficiency values because the DEA in the five provinces in 2004–2014 is valid in some years. Therefore, the SEBM further analyses the years in which the leading line for production is reached. For example, the DEA of Shanxi in 2004, 2005, 2006 and 2007 is valid, and the EBM efficiency value is 1. The SEBM further measures these four years, and the SEBM efficiency values are 1.003, 1.003, 1.001 and 1.001, respectively. Therefore, the average SEBM efficiency value is improved overall. Compared with the SE-DEA and SEBM efficiency values in the four years, the SEBM efficiency value is lower than the SE-DEA efficiency value, and the differences in the four years are lessened. The SEBM model is not only able to further evaluate valid DMUs but also reduce the problem on extreme values, lessen the differences among efficiency values, and ensure that the measurement results meet the actual economic conditions.

In the VRS angle, the SEBM efficiency values in 12 provinces increases compared with the EBM efficiency value. The SEBM-DEA efficiency value in Sichuan and Ningxia is 1, but the SEBM efficiency value in Sichuan decreases compared with SE-DEA efficiency value. The SEBM efficiency value in Ningxia increases compared with the SE-DEA efficiency value in Sichuan. This result shows that the SEBM efficiency value lessens the differences in the efficiency values in various regions.

Analysis on time dimension

To analyze the results on a large scale, we divide the 29 regions into three categories: eastern, central and western. We utilize the CCR, BCC, SE-EBM and SEBM models to analyze the differences in carbon emission efficiency in the three areas and the whole country from 2004 to 2014. The results are reported in *Tables 4* and *5*. The time trends

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of the calculated results in these three areas and the whole country from 2004 to 2014 are reported in *Figures 3* and *4*.

Table 4. *Carbon emission efficiency in China's areas: constant returns to scale*

Year	CCR-DEA model				EBM-DEA model			
	Central regions	Eastern regions	West regions	The whole country	Central regions	Eastern regions	West regions	The whole country
2006	0.541	0.423	0.692	0.548	0.687	0.609	0.816	0.702
2007	0.551	0.432	0.685	0.552	0.683	0.595	0.814	0.695
2008	0.539	0.436	0.687	0.551	0.666	0.597	0.816	0.692
2009	0.523	0.421	0.671	0.535	0.645	0.584	0.786	0.670
2010	0.512	0.444	0.678	0.544	0.625	0.594	0.777	0.666
2011	0.497	0.426	0.678	0.532	0.609	0.583	0.772	0.655
2012	0.475	0.411	0.656	0.513	0.595	0.581	0.754	0.645
2013	0.410	0.363	0.579	0.450	0.527	0.557	0.692	0.595
2014	0.393	0.345	0.571	0.436	0.537	0.550	0.679	0.591
Year	SE-DEA model				SEBM-DEA model			
	Central regions	Eastern regions	West regions	The whole country	Central regions	Eastern regions	West regions	The whole country
2004	0.544	0.405	0.664	0.533	0.701	0.610	0.817	0.706
2005	0.540	0.414	0.689	0.544	0.689	0.619	0.820	0.708
2006	0.545	0.423	0.700	0.552	0.687	0.609	0.817	0.702
2007	0.552	0.432	0.685	0.552	0.683	0.595	0.814	0.695
2008	0.539	0.436	0.693	0.553	0.666	0.597	0.816	0.692
2009	0.523	0.421	0.671	0.535	0.645	0.584	0.786	0.670
2010	0.512	0.444	0.679	0.544	0.625	0.594	0.777	0.666
2011	0.497	0.426	0.689	0.536	0.609	0.583	0.772	0.655
2012	0.475	0.411	0.656	0.513	0.595	0.581	0.755	0.645
2013	0.410	0.363	0.582	0.451	0.527	0.557	0.692	0.595
2014	0.393	0.345	0.572	0.436	0.537	0.550	0.680	0.591

Table 5. *Carbon emission efficiency in China's areas: variable return scale*

Year	BCC-DEA model				EBM-DEA model			
	Central regions	Eastern regions	West regions	The whole country	Central regions	Eastern regions	West regions	The whole country
2004	0.551	0.547	0.714	0.605	0.779	0.752	0.853	0.794
2005	0.565	0.573	0.716	0.620	0.776	0.760	0.867	0.801
2006	0.575	0.588	0.725	0.632	0.783	0.765	0.869	0.806
2007	0.587	0.595	0.726	0.638	0.787	0.766	0.877	0.810
2008	0.578	0.586	0.728	0.633	0.789	0.772	0.880	0.814
2009	0.569	0.575	0.713	0.621	0.780	0.766	0.862	0.803
2010	0.579	0.587	0.717	0.630	0.777	0.780	0.863	0.808
2011	0.587	0.577	0.723	0.630	0.777	0.783	0.874	0.813
2012	0.575	0.565	0.717	0.620	0.783	0.790	0.866	0.814
2013	0.497	0.524	0.643	0.558	0.699	0.750	0.808	0.756
2014	0.493	0.519	0.647	0.556	0.709	0.751	0.786	0.752

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Year	SE-DEA model				SEBM-DEA model			
	Central regions	Eastern regions	West regions	The whole country	Central regions	Eastern regions	West regions	The whole country
2004	0.564	0.572	0.817	0.654	0.780	0.754	0.870	0.801
2005	0.568	0.573	0.730	0.626	0.776	0.764	0.869	0.803
2006	0.582	0.588	0.735	0.637	0.784	0.765	0.870	0.806
2007	0.597	0.602	0.727	0.644	0.788	0.767	0.877	0.811
2008	0.578	0.587	0.736	0.636	0.789	0.772	0.882	0.814
2009	0.569	0.575	0.713	0.621	0.780	0.766	0.862	0.803
2010	0.579	0.591	0.723	0.633	0.777	0.781	0.864	0.809
2011	0.590	0.583	0.742	0.639	0.778	0.783	0.877	0.814
2012	0.578	0.574	0.723	0.627	0.783	0.791	0.867	0.815
2013	0.497	0.525	0.646	0.559	0.699	0.750	0.809	0.756
2014	0.498	0.522	0.653	0.560	0.709	0.752	0.789	0.753

Figure 3. *Time dimension analysis of carbon emissions efficiency in China from 2004 to 2014: constant returns to scale*

CCR-DEA/BCC-DEA efficiency evaluation

As shown in *Tables 4* and *5* and *Figures 3* and *4,* In the CRS angle, the nationwide carbon emission efficiency value is low at 0.4–0.56. The trends increased, decreased, and then reached a peak of 0.552 in 2007. These trends tend to decrease in an increscent range in 2013. The carbon emission efficiency values are high in the west at above 0.57 and reached its peak in 2006 at 0.692. Then, the values tend to fluctuate and decrease. In the middle area, the efficiency values are 0.4–0.56 and reach its peak at 0.551 in

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2007. These values decrease continuously and reach 0.393 in 2014. The efficiency values in the east are the lowest at 0.35–0.45. These values tend to increase and then decrease, reaching a peak at 0.444 in 2010, finally decreasing continuously.

In the VRS angle, the nationwide efficiency value is 0.55–0.64, which is lower than the CCR efficiency value, but still tends to fluctuate and decrease. The value reached its peak at 0.638 in 2007, decreases continuously, and then decreases in an increscent range in 2013. The efficiency value in the west is high at 0.6–0.73. It tended to fluctuate and decrease, and then increase steadily from 2004 to 2008. It started to decrease in 2009 and decreased in an increscent range in 2013. The east follows with an efficiency value of 0.5–0.6, which fluctuated to decrease and then reached its peak at 0.587 in 2007. The efficiency value in the middle area is relatively low but is not much different from that in the east. The value reached its peak at 0.587 in 2011 and decreased in an increscent range in 2013.

Figure 4. *Time dimension analysis of carbon emissions efficiency in China from 2004 to 2014: variable return scale*

EBM-DEA efficiency evaluation

In the CRS angle, EBM-DEA efficiency values in the east, middle, west and nationwide increase compared with the CCR-DEA efficiency value and tend to decrease steadily. The efficiency value is the highest in the west, followed by the middle, and the lowest in the east. This finding clearly shows that the difference in efficiency values in the east, middle and west gradually decreases and that EBM-DEA can decrease the difference in efficiency values in various regions and years.

The EBM-DEA efficiency value with the VRS angle is higher than the EBM-DEA efficiency value with the CRS angle. In the VRS angle, the difference in EBM-DEA

efficiency values in the east, middle, west and nationwide gradually decreases, and the efficiency values from 2004 to 2012 tended to increase steadily. As shown in *Tables 4* and *5* and *Figures 3* and *4,* the efficiency value is highest in the west (0.77–0.88), followed by the middle (0.7–0.79), and the lowest (0.75–0.79) in the east. In sum, under the VRS angle, the carbon emission efficiency values in the east, middle, west and even nationwide are relatively balanced from 2004 to 2014.

SE-DEA efficiency evaluation

In the CRS angle, the SE-DEA efficiency value in the middle, west and nationwide increases compared with CCR-DEA efficiency value because the partial CCR-DEA efficiency value of some provinces in some years is 1 and the DEA is valid. The SE-DEA model further analyses valid DMUs. As shown in *Tables 4* and *5* and *Figures 3* and *4,* for example, the SE-DEA efficiency value in the middle area in 2004, 2005, 2006 and 2007 was higher than the CCR-DEA efficiency value. The reason for this finding is that the DEA of Shanxi in the middle in 2004, 2005, 2006 and 2007 is valid, and the SE-DEA efficiency values are 1.101, 1.024, 1.034 and 1.006, respectively. Therefore, the average SE-DEA efficiency value in the middle from 2004 to 2007 was higher than the CCR-DEA efficiency value. The carbon emission efficiency value in the middle, east, west and nationwide tends to fluctuate and then decrease. The efficiency value in the west fluctuates greatly, and the carbon emission efficiency value nationwide barely fluctuates.

In the VRS angle, the SE-DEA efficiency values in the east, middle, west and nationwide increase compared with that of the BCC-DEA model. The peak efficiency value in the west appeared in 2004, thus indicating that the SE-DEA further evaluates the DMUs reaching the leading line for production.

SEBM-DEA efficiency evaluation

In the CRS angle, the SEBM-DEA efficiency values in the middle, east, and west and nationwide increase compared with the EBM-DEA efficiency values and tend to decrease year by year. The efficiency value in the west is the highest. Compared with that in the SE-DEA model, the difference in efficiency values in the west, middle and east decrease, and the difference in different regions and years decreases, as well.

In the VRS angle, the efficiency values in the middle, east, west and even nationwide decrease progressively and increase to different extents compared with EBM-DEA efficiency values. With respect to the SE-DEA model, the difference in different regions and years gradually decreases. This finding shows that the SEBM-DEA model integrates the characteristics of EBM-DEA and SE-DEA to evaluate the efficiency value of DMUs more completely than the other models.

Conclusion

First, this study thoroughly analyses the development of a theoretical model for carbon emission efficiency and finds that traditional DEA models, namely, CCR-DEA, BCC-DEA, SE-DEA and EBM-DEA, have some inadequacies. For the CCR/BCC model, the application restriction of efficient boundary is not considered. The problem of factor proportion change synchronization (non-realistic) also exists. The SBM/EBM model is unsuitable for a data cube with more valid cells. The SE-DEA model is

unsuitable for a condition in which the factors of leading surface are not changeable in the same proportion. Therefore, this study proposes the SEBM model, which can effectively solve the above-mentioned problems and contribute to carbon emission efficiency theory using data analysis in China.

Second, we analyze and calculate the carbon emission efficiency in 29 regions of China in 2004–2014 using five models: CCR-DEA, BCC-DEA, SE-DEA, EBM-DEA and SEBM-DEA. The analysis result in spatial dimension shows that China has the highest carbon emission efficiency in the west, average in the middle, and the lowest in the east. Under the CRS angle (in five models), Hebei and Liaoning rank high in the east, Shanxi ranks high in the middle and Xinjiang and Ningxia rank high in the west. Under the VRS angle (in five models), Hebei and Shandong have the highest efficiency in the east, Shanxi has the highest in the middle and Sichuan and Xinjiang are the highest in the west. The analysis result in the time dimension shows that in the CRS and VRS angles, the west has the highest efficiency, followed by the middle, and the east has the lowest. Conversely, in the CRS angle, the east and the west have a huge difference in efficiency. Since 2006, China's carbon emission efficiency values have generally increased, thus indicating that the policy of energy saving and emission reduction is effective in China.

Finally, based on the efficiency values in various regions in China, the environment has been damaged to an extreme degree, carbon emission is too high, carbon emission efficiency is the lowest in the country, and the energy utilization rate is low in the east. These results likely stem from the extensive development of the economy in recent years. Although the economy in the east is developing rapidly, the industrial sector will be further transformed to reduce carbon emission. In the middle regions, development is fast, but with the unreasonable output-input matching, the economic aggregate cannot be guaranteed to expand rapidly, and the carbon emission efficiency cannot be guaranteed to be low. Clearly, the middle regions follow behind the east in terms of economic development. The extensive economy of the west cannot continue while it is developing on a large scale. Moreover, the west should realize that its geographic position is not good and that it should pay more attention to the development of new energy and high value-added economy to develop its economy.

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