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Measuring China's regional energy and carbon emission efficiency with DEA models: A survey

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HIGHLIGHTS

- China's regional efficiency studies using data envelopment analysis are reviewed.
- The main features of 46 studies published in 2006–2015 are summarized.
- Six models are compared from the perspective of methodology and empirical results.
- Empirical study of China's 30 regional efficiency assessment in 1995–2012 is presented.

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ABSTRACT

The use of data envelopment analysis (DEA) in China's regional energy efficiency and carbon emission efficiency (EE&CE) assessment has received increasing attention in recent years. This paper conducted a comprehensive survey of empirical studies published in 2006–2015 on China's regional EE&CE assessment using DEA-type models. The main features used in previous studies were identified, and then the methodological framework for deriving the EE&CE indicators as well as six widely used DEA models were introduced. These DEA models were compared and applied to measure China's regional EE&CE in 30 provinces/regions between 1995 and 2012. The empirical study indicates that China's regional EE&CE remained stable in the 9th Five Year Plan (1996–2000), then decreased in the 10th Five Year Plan (2000–2005), and increased a bit in the 11th Five Year Plan (2006–2010). The east region of China had the highest EE&CE while the central area had the lowest. By way of conclusion, some useful points relating to model selection are summarized from both methodological and empirical aspects.

Contents

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1. Introduction

Global awareness of energy security and climate change has created much interest in measuring energy utilization and carbon emissions, which are usually measured in the form of efficiency index. Various approaches have been developed for constructing such efficiency index. Among these, data envelopment analysis (DEA) has attracted much attention due to its advantages and ease of use.[1] For example, it can measure the relative efficiency of a set of decision-making units (DMUs) that apply multiple inputs to produce multiple outputs, and treat a DMU as a whole unit, without considering its internal structure [4]. Following the seminal work of Charnes et al. [5], DEA has been widely investigated and many important methodological developments have been reported in the literature [6].

In the past two decades, the DEA method has gained great popularity in energy and environment efficiency measurements at the country and regional levels [7–13]. As the largest energy consumer and CO_2 emitter in the world, China's regional energy and CO_2 emission efficiency assessments become hot topics in recent years. Many DEA studies on China's regional efficiency have been reported in the literature, such as Hu and Wang [14], Wang et al. [15–17], and Zhang et al. [18]. They focus on different time periods, regions, sectors, input and output items, and use different DEA models which lead to difficulties in comparing their empirical results.

Although the literature survey by Zhou et al. [11] discusses many issues relating to DEA for energy and environment analysis, there is no comprehensive review of the use of DEA models to measure regional efficiency considering different factors (such as time periods, regions and model characters). Therefore, this paper conducts a systematic review of the empirical studies carried out to date on China's regional energy and carbon emission efficiency (EE&CE) assessments using DEA models.

The main contributions of this study are as follows: (i) summarization of the features of previous studies which are useful for researchers to understand the past developments and future directions in this field, (ii) provision of a helpful reference for DEA model selection from the perspective of methodology and empirical results, (iii) generation of comparable results for different DEA models using the same data sets, and (iv) investigation of the variations in China's energy and carbon emission efficiency over time and space during three of China's Five Year Plan periods (1996–2010).

In the sections that follow, the main features of previous DEA studies published in the last decade (2006–2015) focusing on China's regional EE&CE are firstly presented. Section 3 gives a detailed description of the DEA models used in previous studies and discusses their similarities and differences. The empirical study examining China's regional efficiency in period 1995–2012 with different DEA models is shown in Section 4. Section 5 concludes this study.

2. Review of the DEA literature

The Web of Science database (up to the end of 2015) is used to collect the journal publications on China's regional EE&CE assessment with DEA models. In total, 46 relevant studies are published in 18 different journals, which are shown in Table 1. The top two articles are in *Energy Policy* and *Applied Energy*. It is not surprising that around 80% of the studies are published in energy-/environment-related journals as most of them are DEA empirical studies on EE&CE, separate from theoretical work.

Fig. 1 shows the number of publications over time. From 2012, the number of publications increases rapidly. By dividing the time frame into two equal timespans, i.e., 2006–2010 and 2011–2015, the publications in the second timespan account for over 90% of total studies. The first DEA paper on China's regional EE assessment was published in 2006, while the first study on China's regional CE

Table 1
Summary of the papers published on China's regional EE&EC assessment by journal.

Journal	No. of papers	Percentage
Energy Policy	12	26
Applied Energy	10	22
Energy Economics	3	7
Energy	3	7
Mathematical and Computer Modelling	3	7
Ecological Indicators	2	4
Sustainability	2	4
Computers & Industrial Engineering	1	2
Economic Modelling	1	2
Energies	1	2
Energy Efficiency	1	2
European Journal of Agronomy	1	2
Expert Systems with Applications	1	2
Journal of Cleaner Production	1	2
Journal of Renewable and Sustainable Energy	1	2
Polish Journal of Environmental Studies	1	2
The Social Science Journal	1	2
Transportation Research Part D	1	2

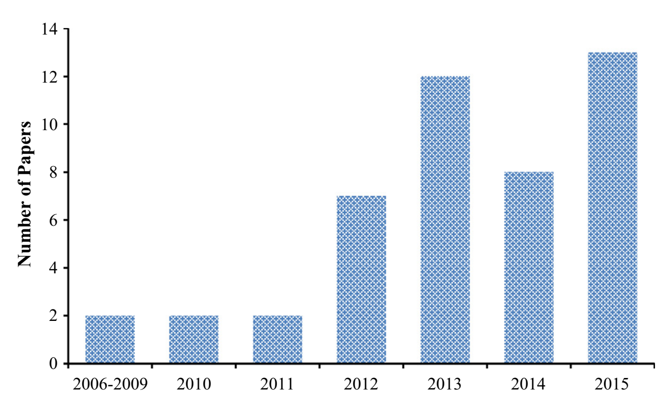


Fig. 1. Number of papers published over time.

[1] The other approach is the decomposition analysis. Two commonly used techniques are index decomposition analysis (IDA) and structural decomposition analysis (SDA). The review of these two techniques can be found in Su and Ang [1]. Both techniques are applied to analyze the driving forces to the historical energy/emission changes, or called temporal decomposition analysis. Recently, such temporal decomposition analysis framework has been extended to spatial decomposition analysis, see Ang et al. [2] on IDA and Su and Ang [3] on SDA. Similar as DEA, spatial-IDA/SDA can also be applied to analyze the relative efficiency performance and provide the performance ranking among various countries/regions.

appeared around 2011. The EE and CE publication trends were similar to those for the total papers, as shown in Fig. 2. The number of studies focusing on EE is much larger than that focusing on CE.

To gain a better understanding of these regional DEA studies on China reported in the literature, Table 3 lists all of them according to their key features, including application attribute, variable scheme and model aspect, which are discussed in the following subsections.

2.1. Application attribute

In Table 3, the application attribute category includes region, sector and period. For the region attribute, there are 31 administrative provinces/regions in Mainland China, but most of the studies focused on 28–30 provinces/regions. Tibet, Hainan and Ningxia are often excluded in the study due to missing data. Since Chongqing did not become an independent administrative region until 1997, some studies combined Chongqing with Sichuan Province to maintain data consistency. From the sector attribute, two-thirds of the studies estimated China's regional EE&CE at the macro level, while the remaining estimated them at the sectoral level, e.g. industrial or transport sector. Regarding to the timespan, Fig. 3 presents the occurrence frequency of different years reported in the previous studies, spanning from 1992 to 2012. In these 21 years, the 2000–2010 period was the most popular, especially the 2005–2009 period (or 11th Five Year Plan) was examined in more than 30 studies.

2.2. Variable scheme

Selections of input and output variables reflect how the DEA model is close to real situations, and affects the values of relative efficiency for DMUs. Since DEA has a strong linkage with production theory, the raw materials and resources used during production processes are usually treated as inputs, and the products as outputs. Generally speaking, DEA minimizes inputs and maximizes outputs. However, if undesirable outputs (e.g. various forms of pollution) are included, DEA has to maximize the desirable outputs and at the same time minimize the undesirable outputs. Fig. 4 shows the input and output variables used in the literature. In terms of input variables, labor force, capital stock and total energy consumption are the three major variables used in previous studies. Particularly, labor force was used in over 90% of the studies. Regarding output variables, GDP and CO_2 are the most selected variables among the desirable outputs and undesirable outputs, respectively. Value added (VA) was also a popular indicator used in the studies at the sectoral level, such as Wei et al. [19], Shi et al. [20], Wu et al. [21], Pan et al. [22], Bi et al. [23], and Zhang and Wei [24]. As for undesirable outputs, SO_2 ranks behind only CO_2 as the second most used variable.

In addition to variables selection, the disposability property of inputs and outputs also plays an important role in the variable scheme. In traditional DEA without undesirable outputs, the inputs and outputs are assumed to be strongly disposable [11,25]. This means that a firm can produce any level of the outputs which are less than present value by using the same inputs. But when examining the undesirable outputs, the traditional assumption does not work. Generally, there are two categories of methods used to incorporate undesirable outputs into DEA models. One is premised on data translation, i.e. the undesirable outputs are treated as inputs or desirable outputs in terms of their property; the other assumes that the undesirable outputs are weakly disposable. The weak disposability assumption proposed by Färe et al. [26] implies that the proportional reduction in desirable and undesirable outputs is possible, but it is not feasible to solely reduce undesirable outputs. The only way to remove all the undesirable outputs is to terminate the production process.

The 7th to 9th columns in Table 3 show the disposability property of inputs and outputs in related studies. It is not surprising that all of the inputs and desirable outputs are assumed to be strongly disposable according to the rules of "the less the better" for inputs and "the more the better" for desirable outputs. As to undesirable outputs, more than 35% of the studies do not take them into consideration, because they focus on the energy and economic efficiency rather than the environmental issues, such as Hu and Wang [14], Wei et al. [19], Chang and Hu [27], and Song et al. [28]. Apart from these, nearly 70% of the remaining studies adopt weak disposability assumption on undesirable outputs, such as Choi et al. [29], Wang et al. [30–32], Wu et al. [21], Bian et al. [33], Yang and Wang [34], and Zhou et al. [35]. There are also some studies following the rule based on data translation, for example, Shi et al. [20] and Wang et al. [30–32] who take undesirable outputs as inputs due to their property of "the less the better" like inputs. Others, like Li and Hu [36], Rao et al. [37], Chang et al. [38], Zhang and Choi [39], Wang and Wei [40] and Zhang et al. [2], treat undesirable outputs as common outputs in order to obtain some good mathematical characters, such as positive shadow prices from a dual model.

2.3. Model aspect

The model aspect is further characterized by the DEA model type and the returns to scale property of reference technology. Based on the review, six types of DEA models have been used in China's regional EE&CE measurement, namely the Radial model, Modified-Radial Model (M-Radial), Russell Measure Model (RMM), Tone's Slack Based Model (SBMT), Range Adjusted Model (RAM) and Directional Distance Function Model (DDF). Table 2 shows the DEA models and their sources. These models can be classified in terms of proportional adjustment or not. The Radial model adjusts inputs and outputs proportionally. The other models mentioned above are all Non-Radial models. Among them, the SBMT

Table 2
DEA models on China's EE&CE assessment.

Model	For short	Source
Radial Model	R	Charnes et al. [5], Banker et al. [45]
Modified Radial Model	M-R	Färe and Lovell [46], Hu and Wang [14]
Russell Measure Model	RMM	Russell [47]
Tone's Slack Based Measure	SBMT	Tone [48]
Range Adjusted Model	RAM	Cooper et al. [49]
Directional Distance Function	DDF	Chung et al. [50]

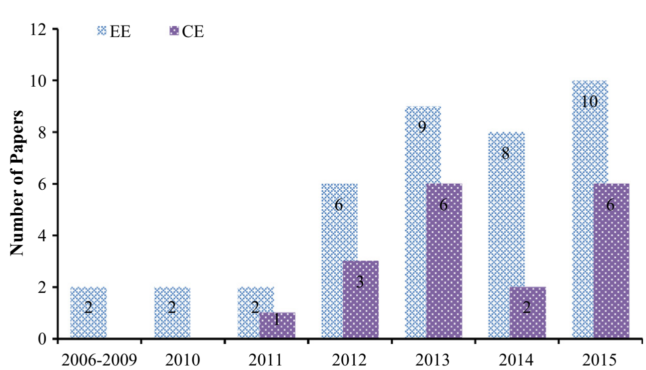


Fig. 2. Number of papers on EE and CE published over time.

Table 3
Studies of DEA in China's EE&CE with their specific features, 2006–2015.

	Publication	EE/CE	Application attribute			Variable scheme			Model aspect	
			# of Region	Sector	Period	Input	Desirable output	Undesirable output	Type	RTS
1	Hu and Wang [14]	EE	29regs	All sectors	1995–2002	L,K,E,A(SD)	GDP(SD)	–	M-R	C
2	Wei et al. [19]	EE	25regs	Iron and steel sectors	1994–2003	OGE, Coal, Coke(SD)	Pig iron, Crude steel, Finished steel(SD)	–	R, Ma	C
3	Chang and Hu [27]	EE	29regs	All sectors	2000–2004	L,K,E,A(SD)	GDP(SD)	–	DDF,Le	C
4	Shi et al. [20]	EE	28regs	Industrial sectors	2000–2006	L,E,IFA(SD)	VA(SD)	WG(SD)	R	C,V, NI
5	Guo et al. [59]	EE,CE	29regs	All sectors	2005–2007	L,K,E(SD)	GDP(SD)	CO_2(WD)	R	C
6	Lin et al. [67]	EE	30regs	All sectors	2006–2010	E,SO_2,Soot,Dust,COD, Ammonia Nitrogen (SD)	GDP(SD)	–	R,Ma	C
7	Choi et al. [29]	EE,CE	30regs	All sectors	2001–2010	L,K,E(SD)	GDP(SD)	CO_2(WD)	SBMT	C
8	Li and Hu [36]	EE	30regs	All sectors	2005–2009	L,K,E(SD)	GDP(SD)	SO_2,CO_2(SD)	SBMT	C
9	Rao et al. [37]	EE	30regs	All sectors	2000–2009	L,K,E(SD)	GDP(SD)	COD,SO_2(SD)	SBMT	C
10	Wang et al. [30]	CE	28regs	All sectors	2001–2007	L,K,E(SD)	GDP(SD)	CO_2(WD)	DDF	C
11	Wang et al. [30]	EE	30regs	Industrial sectors	2005–2009	L,E,FCF(SD)	Gross industrial output(SD)	–	R	C,V
12	Wang et al. [30]	EE,CE	30regs	All sectors	2000–2009	L,K, Coal, Oil, Natural Gas(SD)	GDP(SD)	SO_2,CO_2(WD)	M-R	V
13	Wu et al. [21]	EE	28regs	Industrial sectors	1997–2008	L,K,E(SD)	VA(SD)	CO_2(WD)	R,Ma	C
14	Bian et al. [33]	EE,CE	29regs	All sectors	2009	L,K, coal, oil, natural gas and non-fossil energy(SD)	GDP(SD)	CO_2(WD)	RMM	C
15	Chang et al. [38]	CE	30regs	Transport sectors	2009	L,K,E(SD)	VA(SD)	CO_2(SD)	SBMT	C
16	Pan et al. [22]	EE	28regs	Industrial sectors	2000–2006	L,E,FCF(SD)	VA(SD)	WG(unknown)	R	C
17	Song et al. [28]	EE	Overall	All sectors	1992–2010	L,E, FCF(SD)	GDP(SD)	–	SBMT	C
18	Wang et al. [17]	EE,CE	30regs	All sectors	2006–2010	L,K,E(SD)	GDP(SD)	CO_2(SD)	RAM	V
19	Wang et al. [17]	EE	29regs	All sectors	2000–2010	L,K,E(SD)	GDP(SD)	–	DDF	C
20	Wang et al. [17]	EE	28regs	All sectors	2005–2010	L,K,E(SD)	GDP(SD)	CO_2(WD)	DDF, Ma	C
21	Wang et al. [17]	EE,CE	30regs	All sectors	1997–2010	L,K,E(SD)	GDP(SD)	CO_2(SD)	DDF	C
22	Yang and Wang [34]	CE	29regs	All sectors	2000–2007	L,K,E(SD)	GDP(SD)	CO_2(SD,WD)	DDF	V
23	Zhou et al. [60]	EE	30regs	All sectors	1998–2009	L,K,E(SD)	GDP(SD)	–	M-R	C
24	Zhang and Choi [39]	EE	30regs	All sectors	2001–2010	L,K,E(SD)	GDP(SD)	SO_2,COD,CO_2(SD)	SBMT	C,V
25	Zhou et al. [35]	CE	30regs	Transport sectors	2003–2009	L, Coal, Gasoline, Kerosene, Diesel, Oil, Electricity, Other energy(SD)	PKM,TKM(SD)	CO_2(WD)	R	C,V, NI
26	Bi et al. [23]	EE	29regs	Thermal power industry	2007–2009	L, Installed thermal generating capacity, Coal, Gas(SD)	Power Generated (SD)	SO_2,NOx,Soot(WD)	SBMT	C
27	Cui and Li [68]	EE	30regs	Transport sectors	2003–2012	L,K,E(SD)	PKM,TKM(SD)	–	R	C
28	Wang and Wei [40]	EE,CE	30regs	Industrial sectors	2006–2010	L,E,FCF(SD)	VA(SD)	SO_2,CO_2(SD,WD)	DDF	V
29	Wang et al. [61]	EE	30regs	All sectors	2001–2010	L,K,E(SD)	GDP(SD)	WG,WW,SW(WD)	R, Ma	C
30	Wu et al. [69]	EE	30regs	Industry sectors	2006–2009	L,K,E,IFA(SD)	GDP(SD)	–	R,Ma	NI
31	Xue et al. [62]	EE	26regs	Construction industry	2004–2009	Coal, Electricity(SD)	VA(SD)	–	R	C
32	Zhou et al. [63]	CE	30regs	All sectors	1995–2011	L,K,E(SD)	GDP(SD)	CO_2(WD)	R	C
33	Zhou et al. [63]	EE	30regs	Transport sectors	2003–2009	L, Coal, Gasoline, Kerosene, Diesel, Oil, Electricity, Other energy(SD)	PKM,TKM(SD)	CO_2(WD)	RMM	C,V, NI

Table 3 (*continued*)

Publication	EE/CE	Application attribute			Variable scheme			Model aspect	
		# of Region	Sector	Period	Input	Desirable output	Undesirable output	Type	RTS
34 Duan et al. [64]	EE,CE	30regs	Thermal power industry	2005–2012	L,K, fossil fuel, auxiliary electricity(SD)	Electricity(SD)	CO_2(WD)	DDF, Ma	C
35 Guo et al. [70]	EE	29regs	All sectors	2001–2011	L,E,IFA(SD)	GDP(SD)	CO_2,WG,WW,SW (SD)	R	C,V
36 Li and Lin [41]	EE	30regs	All sectors	1997–2011	L,K,E(SD)	GDP(SD)	CO_2(WD)	DDF, Ma	C
37 Lin and Fei [71]	CE	30regs	Agricultural sector	2003–2010	L,K,E(SD)	GDP(SD)	CO_2(WD)	R	C
38 Pan et al. [65]	EE	30regs	All sectors	1999–2010	L,K,E(SD)	GDP(SD)	–	M-R	C
39 Song et al. [72]	EE,CE	30regs	Transport sectors	2003–2012	L,K,E(SD)	GDP(SD)	CO_2(SD)	SBM	C
40 Shen et al. [73]	EE	30regs	All sectors	2000–2012	L,K,E(SD)	GDP(SD)	WG,WW,SW(SD)	R	C,V
41 Wang and Feng [66]	EE	30regs	All sectors	2002–2011	L,K,E(SD)	GDP(SD)	SO_2,COD,CO_2(WD)	DDF, Ma	C
42 Wang et al. [61]	EE	29regs	All sectors	2001–2010	L,K,E(SD)	GDP(SD)	–	DDF	C
43 Wu et al. [43]	EE,CE	30regs	All sectors	2006–2010	L,K,E, Funds(SD)	GDP,SO_2 Removed, WW Removed, PCEC (SD)	SO_2,WW(WD)	RMM	V
44 Yao et al. [74]	EE,CE	29regs	All sectors	2011	L,K,E(SD)	GDP(SD)	CO_2(WD)	DDF	C
45 Zhang and Wei [24]	CE	30regs	Transport sectors	2000–2012	L,K, fossil fuel(SD)	Gross product(SD)	CO_2(WD)	DDF,Le	C
46 ZhAng et al. [2]	EE	30regs	All sectors	2001–2010	L,K,E(SD)	GDP(SD)	SO_2,COD,CO_2(SD)	SBMT	C,V

Note: R: Radial; M-R: Modified Radial; RMM: Russell Measure Model; RAM: Range adjusted model; SBMT: Tone's Slack based model; DDF: Directional distance function; Ma: Malquist index; Le: Leuenberger index. L: Labor force; K: Capital Stock; E: Total Energy Consumption; A: sown area of farm crops; OGE: Fuel oil, natural gas, electricity; IFA: Investment in fixed assets; FCF: Fixed capital formation; VA: Value added; PKM: Passenger kilometers; TKM: Tonne kilometers; COD: Chemical Oxygen Demand; WG: Waste gas; WW: Waste Water; SW: Solid waste. SD: Strong disposability; WD: Week disposability. C: Constant returns to scale; V: Variable returns to scale; NI: Non-increasing returns to scale.

and RAM models are slack-based measurement methods because they construct efficiency indicators directly from the slacks in inputs/outputs. Details about the properties and formulations of these models are discussed in the next section.

Fig. 5 shows the number of studies that use these six types of models in different years. It can be seen that over time, more types of models are developed and employed. Before 2011, Radial and M-Radial models were mostly used. However, from 2012 to 2015, various models were adopted. Secondly, the Radial model has been the most widely used model, but Non-Radial models, especially the SBMT and DDF models, have become increasingly popular in recent years due to their relatively strong discriminating power and capability to expand desirable outputs and reduce undesirable outputs simultaneously. In order to estimate the dynamic change of EE&CE over time, some studies calculated the Malmquist index or Leunberger index based on above models, such as Wei et al.

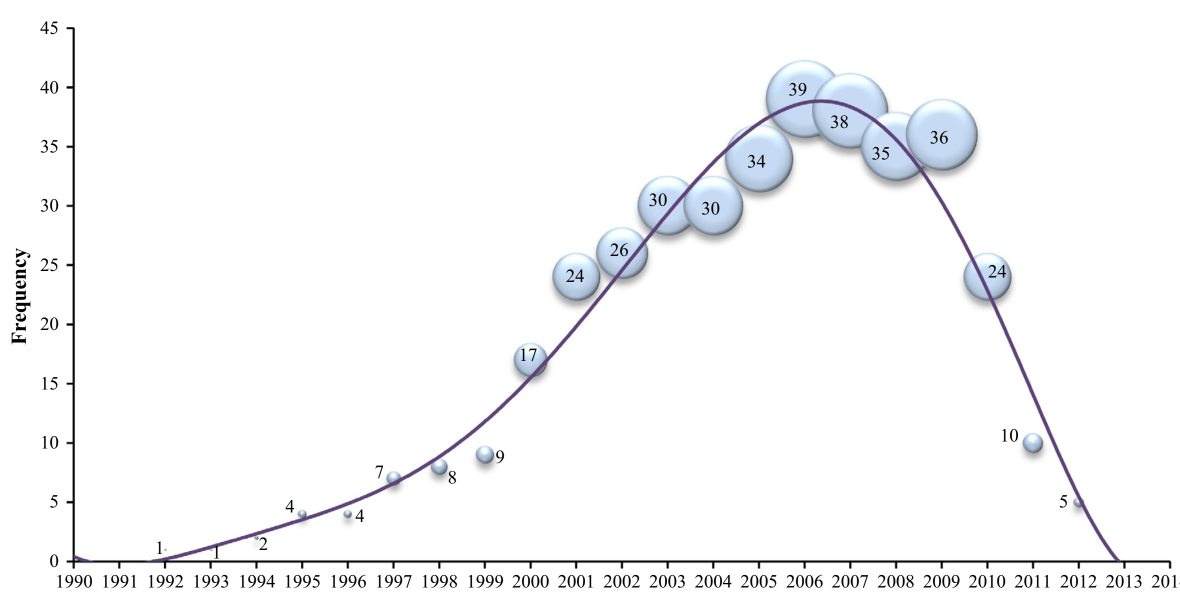


Fig. 3. Frequency of different years analyzed in previous studies.

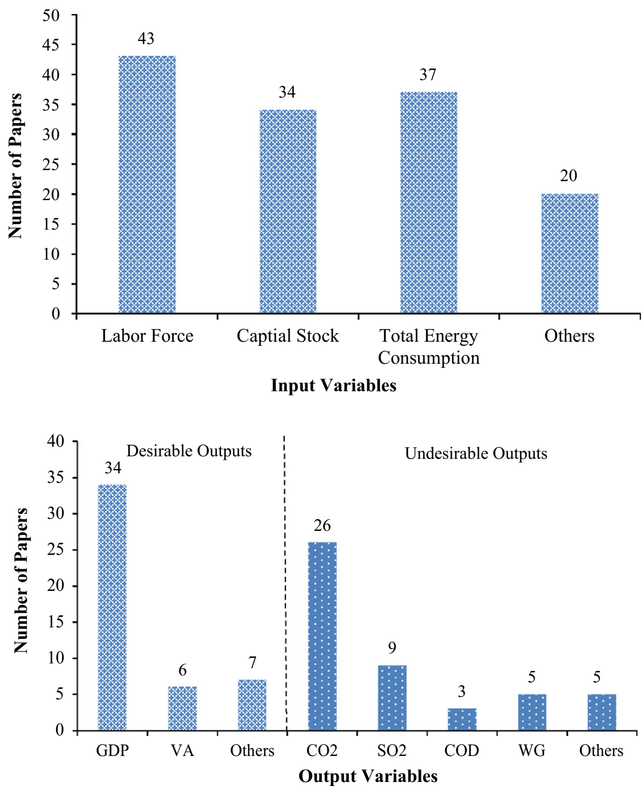


Fig. 4. Input and output variables used in previous studies.

[19], Chang and Hu [27], Wu et al. [21], Wang et al. [15–17], and Li and Lin [41].

Returns to scale (RTS) is an economic concept referring to the variation of outputs when the inputs change proportionally with other conditions remaining stable. In DEA, RTS reflects the reference technology and determines the shape of the production frontier. Generally speaking, there are four types of RTS categories, namely constant RTS (CRS), non-increasing RTS (NIRS), non-decreasing RTS (NDRS) and variant RTS (VRS). Fig. 6 illustrates the differences among these four types of RTS categories. RTS is considered to be constant if a proportional increase in all the inputs results in an equal proportional increase in the output. Otherwise, if it leads to a more than or less than proportional increase in the output, then RTS is considered increasing or decreasing [42]. Among them, CRS is the most widely used RTS category in previous studies. Table 3 reveals that nearly 70% of the studies assumed the CRS reference technology. Only five studies adopted VRS reference technology, i.e. Wang et al. [30–32], Wang et al. [15–17], Yang and Wang [34], Wang and Wei [40], and Wu et al. [43]. About 20% of the studies used CRS, VRS and NIRS reference technologies together. In this case, the scale efficiency and the RTS properties of different DMUs can be studied.

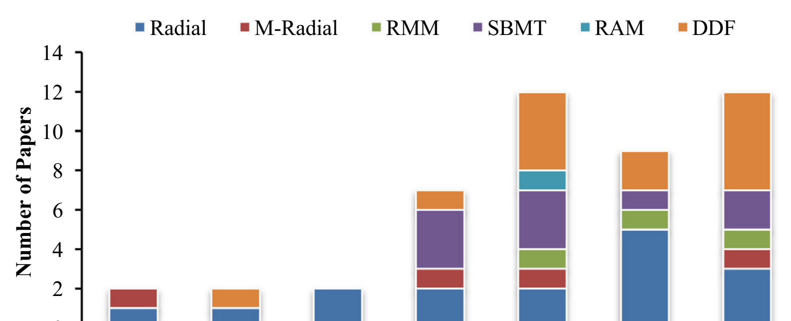
In addition to above two aspects, some recent studies further considered technology heterogeneities across DMUs (regions) and time series. Since technology heterogeneity can be reflected by the production frontier, several methods, such as group-frontier, meta-frontier and global-frontier, have been proposed. Group frontier and meta-frontier methods focus on the technology heterogeneities across DMUs (regions). The group frontier method divides the regions into several groups having similar levels of technology. The efficiency of DMUs (regions) are calculated within each group. Then meta-frontier covers all DMUs and envelops all group frontiers. Examples of such studies include Wang et al. [15–17] and Li and Lin [41]. By contrast, the global-frontier method pays attention to the technology heterogeneities in different periods. Suppose there are T periods (reference production sets at time t, and $t+1, \ldots, T$), the global-frontier envelopes all of these sets by establishing a single reference. In this way the dynamic change of energy efficiency over time can be presented.

3. DEA models for regional efficiency assessment

3.1. Reference technology and basic model

This section mathematically explains the DEA models mentioned in Section 2.3. Consider a given production process with K decision making units (DMUs) which transform non-energy inputs ($\boldsymbol{x}$) and energy inputs ($\boldsymbol{e}$) to produce desirable outputs ($\boldsymbol{y}$). Microeconomic theory defines the production technology T as follows:

$$T = \{(\boldsymbol{x}, \boldsymbol{e}, \boldsymbol{y}) : (\boldsymbol{x}, \boldsymbol{e}) \text{ can produce } \boldsymbol{y}\},$$



	2006-2009	2010	2011	2012	2013	2014	2015
DDF	0	1	0	1	4	2	5
RAM	0	0	0	0	1	0	0
SBMT	0	0	0	3	3	1	2
RMM	0	0	0	0	1	1	1
M-Radial	1	0	0	1	1	0	1
Radial	1	1	2	2	2	5	3

Fig. 5. Distribution of six model types used in different years.

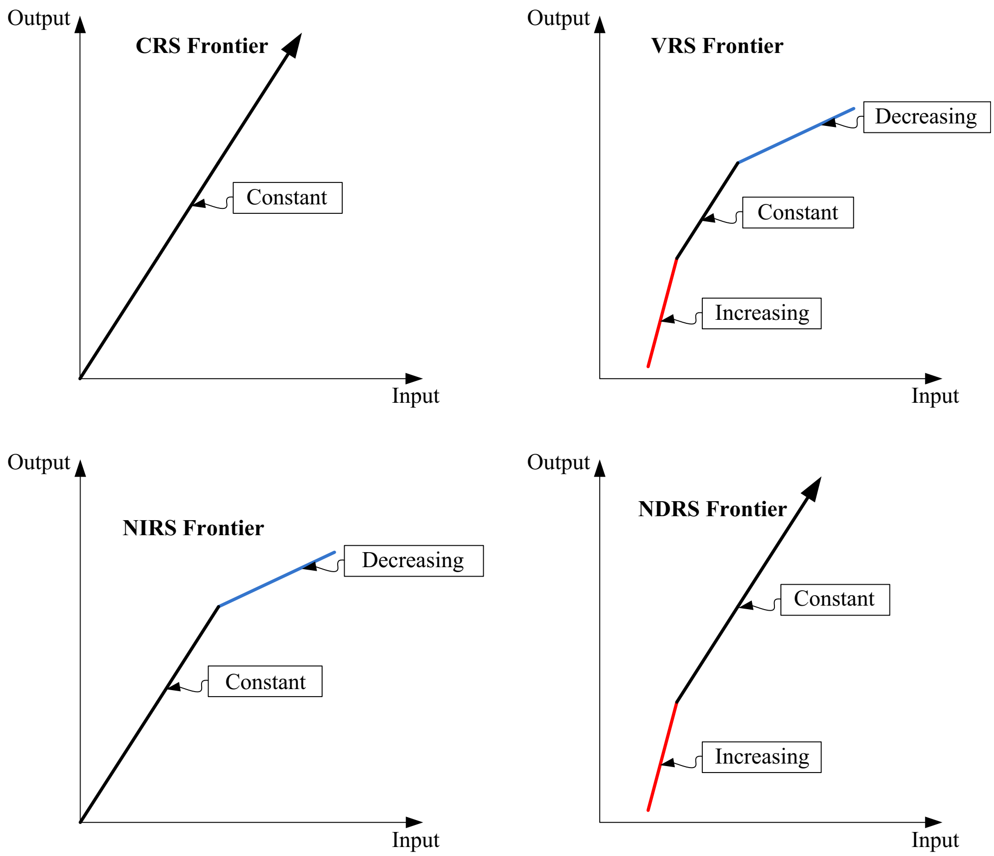


Fig. 6. The production frontier shapes of different types of RTS.

where T is also known as reference technology which is a closed and bounded set. In reference technology T, the inputs and outputs are all assumed to be strongly disposable, i.e. if $(\boldsymbol{x}, \boldsymbol{e}, \boldsymbol{y}) \in T$ and $(\boldsymbol{x}', \boldsymbol{e}') \geqslant (\boldsymbol{x}, \boldsymbol{e})$ (or $\boldsymbol{y}' \leqslant \boldsymbol{y}$), then $(\boldsymbol{x}', \boldsymbol{e}', \boldsymbol{y}) \in T$ (or $(\boldsymbol{x}, \boldsymbol{e}, \boldsymbol{y}') \in T$). A non-parametric framework is usually used to characterize the reference technology to put the concept into practice. Suppose there are N non-energy inputs, M energy inputs and I desirable outputs, then $\boldsymbol{x}_k = (x_{1k}, x_{2k}, \ldots, x_{Nk})$, $\boldsymbol{e}_k = (e_{1k}, e_{2k}, \ldots, e_{Mk})$, $\boldsymbol{y}_k = (y_{1k}, y_{2k}, \ldots, y_{Ik})$. Thus, the reference technology T can be formulated as:

$$T = \{(\boldsymbol{x}, \boldsymbol{e}, \boldsymbol{y}) : \sum_{k=1}^{K} \lambda_k x_{nk} \leqslant x_n \quad (n = 1, \ldots, N)$$
$$\sum_{k=1}^{K} \lambda_k e_{mk} \leqslant e_m \quad (m = 1, \ldots, M)$$
$$\sum_{k=1}^{K} \lambda_k y_{ik} \geqslant y_i \quad (i = 1, \ldots, I)$$
$$\lambda_k \geqslant 0 \quad (k = 1, \ldots, K)\}. \tag{1}$$

The reference technology in formula (1) exhibits constant returns to scale (or CRS). It will become variant return to scale (or VRS) by adding the constraint condition $\sum_{k=1}^{K} \lambda_k = 1$, where $(\lambda_1, \lambda_2, \ldots \lambda_k)$ denotes the intensity levels at which the production activities are conducted by the K DMUs. The combination of CRS and VRS can provide information about both technical efficiency and scale efficiency. If the properties of RTS are of interest, non-increasing returns to scale (or NIRS) and non-decreasing returns to scale (or NDRS), which can be present by appending the constraint $\sum_{k=1}^{K} \lambda_k \leqslant 1$ and $\sum_{k=1}^{K} \lambda_k \geqslant 1$ respectively, are helpful.

With the rising awareness of environmental issues, many experiments have incorporated environment pollution as undesirable outputs in the production process into the reference technology T. The most popular way to involve desirable and undesirable outputs jointly is to impose two assumptions as follows [26]:

(i) Weak disposability on undesirable outputs, i.e. if $(\boldsymbol{x}, \boldsymbol{e}, \boldsymbol{y}, \boldsymbol{b}) \in T'$ and $0 \leqslant \theta \leqslant 1$, then $(\boldsymbol{x}, \boldsymbol{e}, \theta\boldsymbol{y}, \theta\boldsymbol{b}) \in T'$. This means that the proportional reduction in desirable and undesirable outputs is possible, whereas it may not be feasible to solely reduce undesirable outputs.

(ii) Desirable and undesirable outputs are null-joint, i.e. if $(\boldsymbol{x}, \boldsymbol{e}, \boldsymbol{y}, \boldsymbol{b}) \in T'$ and $\boldsymbol{b} = 0$, then $\boldsymbol{y} = 0$. This implies that undesirable outputs must be produced in order to produce desirable outputs. The only way to remove all of the undesirable outputs is to cease the production process.

Here $\boldsymbol{b} = (b_1, b_2, \ldots, b_J)$ represents the vector of undesirable outputs and T' represents the reference technology incorporating undesirable outputs. According to above assumptions, T' can be characterized as:

$$T' = \{(\boldsymbol{x}, \boldsymbol{e}, \boldsymbol{y}, \boldsymbol{b}) : \sum_{k=1}^{K} \lambda_k x_{nk} \leqslant x_n \quad (n = 1, \ldots, N)$$
$$\sum_{k=1}^{K} \lambda_k e_{mk} \leqslant e_m \quad (m = 1, \ldots, M)$$
$$\sum_{k=1}^{K} \lambda_k y_{ik} \geqslant y_i \quad (i = 1, \ldots, I)$$
$$\sum_{k=1}^{K} \lambda_k b_{jk} = b_j \quad (j = 1, \ldots, J)$$
$$\lambda_k \geqslant 0 \quad (k = 1, \ldots, K)\}. \tag{2}$$

It is found that the reference technology T' also exhibits CRS. The other types of RTS pertaining to reference technology can be integrated with undesirable outputs in some ways, see Färe et al. [44] and Zhou et al. [25]. Based on the reference technology, with and without undesirable outputs, several of the previous studies were devoted to development of models for measuring energy and carbon emission performance.

3.2. Alternative models for efficiency measure

This section discusses the DEA-type models for China's regional EE&CE measurement in the literature, as shown in Table 4. As mentioned in Section 2.3, there are six alternative DEA models (i.e. Radial, M-Radial, RMM, SBMT, RAM and DDF). We classify them into EE and CE measurements, which have the same mathematical form for the same model type besides the orientation (input orientation for EE and output orientation for CE).

The Radial model, which adjusts the inputs and outputs proportionally, is probably the most widely used model in this field. The most famous Radial models are the CCR model [5] and BCC model [45]. Their major difference is the RTS type of reference technology sets. The Radial model is based on the environmental DEA technology. EE and CE can be examined by employing input-oriented and undesirable output-oriented models, respectively.

The M-Radial model attempts to measure efficiency by constructing an index which utilizes radial indicators and slacks together. It is considered to be a modified form of Radial model with input and output slacks. The EE calculated from the M-Radial model is also called total factor energy efficiency [14]. There is no M-Radial Model for CE in Table 4 because it is based on the environmental DEA technology where undesirable outputs are weekly disposable and the slacks for undesirable outputs are equal to 0.

The RMM model [46,47] is a category of Non-Radial model which allows non-proportionally adjustment of the inputs or outputs. The RMM model incorporates a user-specified weight vector ϖ_m which represents the desirability degree of decision-makers for adjusting the inputs or outputs. It has stronger discrimination

Table 4
Alternative nonparametric models for China's regional EE&CE measures.

	Energy efficiency	Carbon emission efficiency
Radial Model (Radial)	$Min\ \beta$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} \leqslant x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} \leqslant \beta e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} \geqslant y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} = b_{j0} \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0 \quad (k=1,\ldots,K)$ $EE=\beta^*$	$Min\ \beta$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} \leqslant x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} \leqslant e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} \geqslant y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} = \beta b_{j0} \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0 \quad (k=1,\ldots,K)$ $CE=\beta^*$
Modified Radial Model (M-Radial)	$Min\ [\beta - \varepsilon(e^T s_n^- + e^T s_m^- + e^T s_i^+)]$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} + s_n^- = \beta x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} + s_m^- = \beta e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} - s_i^+ = y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} = b_{j0} \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0;\ s_n^-, s_m^-, s_i^+ \geqslant 0 \quad (k=1,\ldots,K)$ $EE=\sum_{m=1}^{M}\varpi_m \frac{\beta^* e_{m0} - s_m^{-*}}{e_{m0}}$	
Russell Measure Model (RMM)	$Min\ \sum_{m=1}^{M}\varpi_m\beta_m$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} \leqslant x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} \leqslant \beta_m e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} \geqslant y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} = b_{j0} \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0 \quad (k=1,\ldots,K)$ $EE=\sum_{m=1}^{M}\varpi_m\beta_m^*$	$Min\ \sum_{j=1}^{J}\varpi_j\beta_j$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} \leqslant x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} \leqslant e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} \geqslant y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} = \beta_j b_{j0} \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0 \quad (k=1,\ldots,K)$ $CE=\sum_{j=1}^{J}\varpi_j\beta_j^*$
Tone's Slack Based Measure (SBMT)	$Min\ \frac{1-\frac{1}{N+M}\left(\sum_{n=1}^{N}s_n^-/x_{n0}+\sum_{m=1}^{M}s_m^-/x_{m0}\right)}{1+\frac{1}{I+J}\left(\sum_{i=1}^{I}s_i^+/y_{i0}+\sum_{j=1}^{J}s_j^+/b_{j0}\right)}$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} + s_n^- = x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} + s_m^- = e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} - s_i^+ = y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} + s_j^- = b_{j0} \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0; s_n^-, s_m^+, s_i^+, s_j^- \geqslant 0 \quad (k=1,2,\ldots,K)$ $EE=\sum_{m=1}^{M}\varpi_m \frac{e_{m0}-s_m^{-*}}{e_{m0}}$	$Min\ \frac{1-\frac{1}{N+M}\left(\sum_{n=1}^{N}s_n^-/x_{n0}+\sum_{m=1}^{M}s_m^-/x_{m0}\right)}{1+\frac{1}{I+J}\left(\sum_{i=1}^{I}s_i^+/y_{i0}+\sum_{j=1}^{J}s_j^+/b_{j0}\right)}$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} + s_n^- = x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} + s_m^- = e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} - s_i^+ = y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} + s_j^- = b_{j0} \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0; s_n^-, s_m^+, s_i^+, s_j^- \geqslant 0 \quad (k=1,2,\ldots,K)$ $CE=\sum_{j=1}^{J}\varpi_j \frac{b_{j0}-s_j^{-*}}{b_{j0}}$
Range Adjusted Model (RAM)	$Max\ \sum_{n=1}^{N}R_n s_n^- + \sum_{m=1}^{M}R_m s_m^- + \sum_{i=1}^{I}R_i s_i^- + \sum_{j=1}^{J}R_j s_j^-$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} + s_n^- = x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} + s_m^- = e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} - s_i^+ = y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} + s_j^- = b_{j0} \quad (j=1,\ldots,J)$ $\lambda_j \geqslant 0; s_n^-, s_m^-, s_i^+, s_j^- \geqslant 0 \quad (k=1,\ldots,K)$ $EE=1-\sum_{m=1}^{M}R_m s_m^-$	$Max\ \sum_{n=1}^{N}R_n s_n^- + \sum_{m=1}^{M}R_m s_m^- + \sum_{i=1}^{I}R_i s_i^- + \sum_{j=1}^{J}R_j s_j^-$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} + s_n^- = x_{n0} \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} + s_m^- = e_{m0} \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} - s_i^+ = y_{i0} \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} + s_j^- = b_{j0} \quad (j=1,\ldots,J)$ $\lambda_j \geqslant 0; s_n^-, s_m^-, s_i^+, s_j^- \geqslant 0 \quad (k=1,\ldots,K)$ $CE=1-\sum_{j=1}^{J}R_j s_j^-$
Directional Distance Function (DDF)	$\vec{D}(x,e,y,b;g) = Max\ \omega_x\beta_x + \omega_e\beta_e + \omega_y\beta_y + \omega_b\beta_b$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} \leqslant x_{n0} - \beta_x g_x \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} \leqslant e_{m0} - \beta_e g_e \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} \geqslant y_{i0} + \beta_y g_y \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} = b_{j0} - \beta_b g_b \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0 \quad (k=1,\ldots,K)$ $EE=\frac{\sum_{i=1}^{I}y_{i0}\Big/\sum_{m=1}^{M}e_{m0}}{\sum_{i=1}^{I}(y_{i0}+\beta_y^* g_y)\Big/\sum_{m=1}^{M}(e_{m0}-\beta_e^* g_e)}$	$\vec{D}(x,e,y,b;g) = \max\ \omega_x\beta_x + \omega_e\beta_e + \omega_y\beta_y + \omega_b\beta_b$ s.t. $\sum_{k=1}^{K}\lambda_k x_{nk} \leqslant x_{n0} - \beta_x g_x \quad (n=1,\ldots,N)$ $\sum_{k=1}^{K}\lambda_k e_{mk} \leqslant e_{m0} - \beta_e g_e \quad (m=1,\ldots,M)$ $\sum_{k=1}^{K}\lambda_k y_{ik} \geqslant y_{i0} + \beta_y g_y \quad (i=1,\ldots,I)$ $\sum_{k=1}^{K}\lambda_k b_{jk} = b_{j0} - \beta_b g_b \quad (j=1,\ldots,J)$ $\lambda_k \geqslant 0 \quad (k=1,\ldots,K)$ $CE=\frac{\sum_{j=1}^{J}(b_{j0}-\beta_b^* g_b)\Big/\sum_{i=1}^{I}(y_{i0}+\beta_y^* g_y)}{\sum_{j=1}^{J}b_{j0}\Big/\sum_{i=1}^{I}y_{i0}}$

Table 5
Summary of model characteristics.

Model	Radial	M-Radial	RMM	SBMT	RAM	DDF
Input-/Output-Oriented	I/O Oriented	I/O Oriented	I/O Oriented	Non	Non	Non
Returns to Scale (RTS)	C(V)RS	C(V)RS	C(V)RS	C(V)RS	C(V)RS	C(V)RS
Optimal Value	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
Proportional Adjustment	Yes	No	No	No	No	No
Slacks	No	Yes	No	Yes	Yes	No

power than the Radial model. The Radial model is a special case of the RMM model when there is only one input or output.

The SBMT [48] model and RAM model [49] both belong to slack-based measurement, i.e., they construct the efficiency index with slacks of inputs and outputs. As shown in Table 4, since the SBMT model considers all inefficiencies for the inputs and outputs, its discrimination power is much higher. The RAM model can be considered as a kind of additive model which allows the input variables to equal zero.

The DDF model [50] can satisfy the common desire of the public and policy-makers to reduce inputs/undesirable outputs and increase desirable outputs simultaneously. It allows adjusting the desirable outputs and inputs/undesirable outputs at different rates on the basis of different vector directions for input-output variables. It also provides a common framework for deriving the required models by changing the direction vectors. A weight vector was recently appended to the traditional DDF model. It has the same meaning with the user-specified weight vector in the RMM model. It is noted that the models in Table 4 are all based on the assumption that constant returns to scale prevail at the efficient frontiers.

Table 5 lists some characteristics of the above models. It is found that they have some properties in common. For example, they can choose any type of RTS as required by incorporating an additional constraint on $\sum_{k=1}^{K}\lambda_k$ in appropriate ways, and the optimal values of the models are between 0 and 1.

There are also many different features among these models. First of all, whether they are input-/output-oriented (I/O oriented) is one of the considerations to be taken into account. I/O oriented implies the directions along which we project the inefficient DMUs onto the production frontiers. Input-oriented models minimize input levels under at least the present outputs, while output-oriented ones maximize output levels under, at most, the present inputs. Radial, M-Radial and RMM models can be either input-oriented or output-oriented, according to the aim of the studies. In other words, input-/output-oriented models should be assumed before applying these three types of models. On the other hand, there is a third choice for the direction adopted by SBMT, RAM and DDF models, i.e. dealing with the input excesses and output shortfalls simultaneously by utilizing slacks and directional vectors.

Secondly, there are other differences in the existence of proportional adjustment and slacks. They are important in terms of adjusting the inputs and outputs. Among these models, the Radial model adjusts the inputs and outputs proportionally to the efficient targets without considering slacks, while other models, collectively called Non-Radial models, deal with inputs and outputs in a non-proportional way. For instance, M-Radial, SBMT and RAM models use slacks for all input and output terms to eliminate the inefficiencies of DMUs. The RMM model allows inputs (outputs) to increase (decrease) by different proportions through setting adjustment coefficients based on different inputs (outputs). The DDF model decreases inputs and increases outputs simultaneously at different rates by setting different directional vectors.

As Cooper et al. [51] mentioned, "it is wise to try different models when we cannot identify the characteristics of the production frontiers by preliminary surveys". In some cases, the results from one particular model may not reflect realities. Therefore, in the next sections, we try different models to analyze China's regional EE&CE assessment, and compare their results to draw some conclusions on both model selection and empirical analysis.

4. Empirical study of China's regional efficiency assessment

4.1. Data source

China's regional EE&CE assessments from 1995 to 2012 are examined with six DEA models mentioned above in this section. 30 provinces/regions in Mainland China (all except Tibet) are chosen as the application attributes. Since Chongqing was not a politically independent region until 1997, its final energy consumption and CO_2 emissions in 1995 and 1996 were calculated from the *Chongqing Statistical Yearbooks* and then deducted from the respective estimates for Sichuan Province. As for the timeframe, the observation period is 1995–2012, which covers China's 9th Five Year Plan (1996–2000), 10th Five Year Plan (2001–2005) and 11th Five Year Plan (2006–2010). It is helpful to provide policy recommendations based on these empirical results.

Regarding variable scheme, we selected the commonly used inputs and outputs used in the previous literature (see Section 2.2). The details are given below:

(i) ***Inputs:*** Input variables include labor force, capital stock and total energy consumption. Total number of employed persons by the end of a year is used to represent the labor force. The data were collected from the *China Statistical Yearbooks*.[2] Capital stock data are not reported in the Chinese statistical system. Following Hu and Kao [52] and Chien and Hu [53], the capital stock data were estimated using the perpetual inventory method:

$$K_t = (1-\delta)K_{t-1} + I_t/P_t \tag{3}$$

where K_t and K_{t-1} are the real values of capital stock in the current year and previous year, respectively; I_t is the nominal value of gross fixed capital formation in the current year; P_t is the price index of investment; and δ is the depreciation rate of the capital stock. According to Zhang et al. [54], the value of δ was set as 9.6%, and the initial value for K in the basic year (i.e. year 1978 in this study) was assigned I_{1978} divided by 10%. The basic data came from the *China Compendium of Statistics* and *Data of Gross Domestic Product of China 1952–1995* published by the National Bureau of Statistics of China.

The total energy consumption data were obtained from "final energy consumption" published in the regional energy balance tables from the *China Energy Statistical Yearbooks*, 1996–2013.

[2] The data for 2006 was not provided in the *China Statistical Yearbooks*, the missing data were estimated by using a linear interpolating method, which is the usual practice.

(ii) ***Desirable Outputs:*** GDP was chosen as the single desirable output. The real GDP data before 2008 were collected from the *China Compendium of Statistics*, while the 2008–2012 data were obtained from the National Bureau of Statistics of China.

(iii) ***Undesirable Outputs:*** The CO_2 emissions related to energy consumption was chosen as the undesirable output. As official data on provincial CO_2 emissions is unavailable, the carbon emissions from fuel combustion were estimated following the guidelines of IPCC (2006).

Table 6 summarizes the descriptive statistics of the inputs and outputs variables for 30 provinces/regions of China over the 1995–2012 period. The final datasets constructed and used in this paper are given in Tables A.1–A.5 in the Appendix A.

4.2. Empirical results

China's regional EE and CE values at the provincial level from 1995 to 2012 were calculated using the six DEA models discussed in Section 3. In order to detect efficiency trends of DMUs over time, the DEA window analysis introduced by Charnes and Cooper [55] was adopted. Since their seminal work, DEA window analysis has been widely used in efficiency assessment, for example Halkos and Tzeremes [56], Zhang et al. [13] and Sueyoshi et al. [57]. Essentially it generalizes the notion of moving averages to examine efficiency trends of DMUs. DEA window analysis establishes efficiency measures by treating each DMU of different periods as a separate unit. In our analysis, we follow the suggestion by Färe et al. [58] to use a three-year window method, i.e. constructing the DEA technology in period t using the observations in period t, t − 1 and t − 2.

Since only one energy input/undesirable output is considered in this study, the RMM model becomes the Radial model (see Table 4). Due to limited space, only China's regional EE&CE values based on different models in 2012 are shown in Fig. 7(a)–(b). There are three preliminary findings: (1) there are striking differences in the range of data distribution among these models, indicating that each model has its own discrimination power, strong or weak; (2) the efficiency values vary depending on the model selection. For energy efficiency, EE values calculated by the Radial, M-Radial, RMM and RAM models are obviously larger than those computed

Table 6
Summary statistics of I/O variables in 30 regions of China, 1995–2012.

Variable		Max	Min	Mean	Std.dev
Inputs	Capital stock (billions of 1978 RMB)	34474.14	129.84	3427.17	4283.58
	Labor force (ten thousand)	6287.58	226.00	2265.64	1497.38
	Total energy consumption (10,000 tons of SCE)	28378.23	202.67	5735.71	4540.80
Desirable outputs	GDP (billions of 1978 RMB)	1070.87	41.04	415.67	240.81
Undesirable outputs	CO_2 emissions (10,000 tons)	82711.44	538.96	16564.17	13625.41

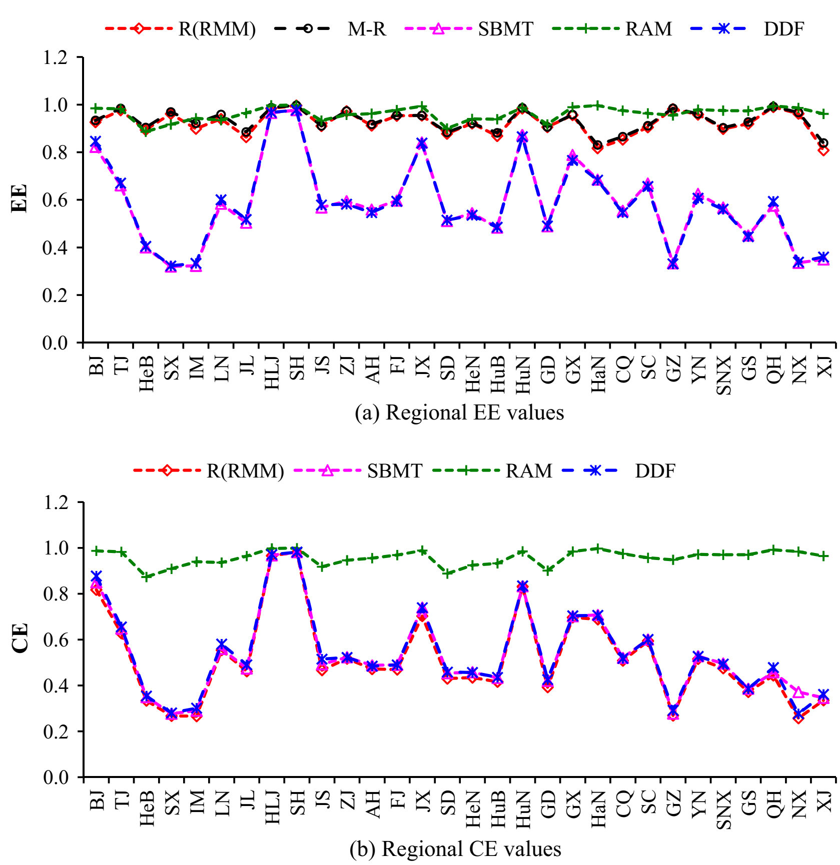


Fig. 7. China's regional EE&CE values based on different models, 2012.

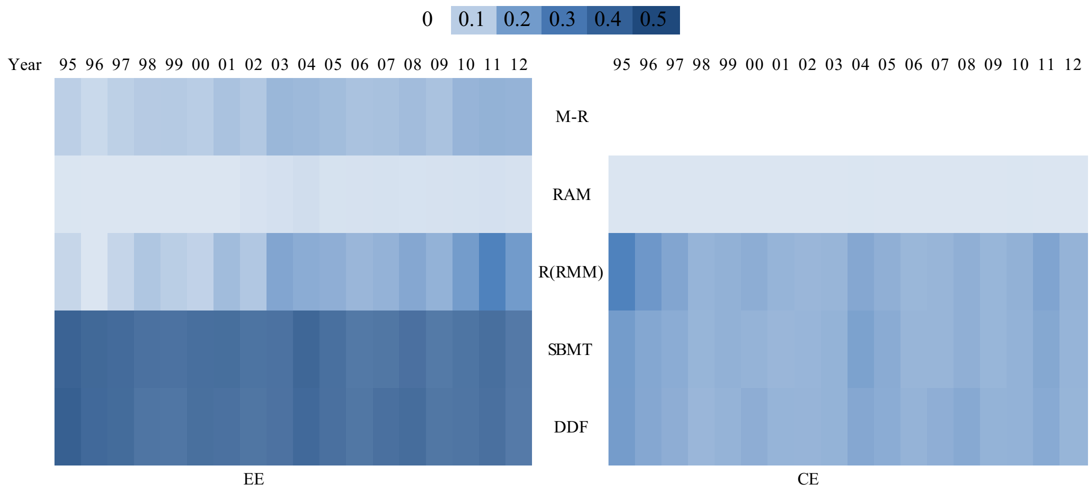


Fig. 8. Variance of China's EE and CE values across provinces/regions, 1995–2012.

by the SBMT and DDF models. For carbon emission efficiency, CE values derived from the RAM model are larger than the others; (3) these models may be classified into two or three categories due to the varying trend of efficiency values across the regions.

4.3. Statistical analysis of China's EE&CE values across regions

Based on the preliminary findings reported in Section 4.2, this subsection adopts some statistical approaches, e.g. the variance and box plots, to further analyze the distribution of EE&CE values across regions and the differences among different DEA models.

Fig. 8 shows the variance of China's EE and CE values across the regions from 1995 to 2012. Since there is no M-Radial type model for CE evaluation based on the assumption of weak disposability, the squares for the M-Radial model in CE assessment are blank. The square with darker color has the larger variance which reveals a relatively high level of data dispersion and strong discrimination power for a certain model. From Fig. 8, it is found that the variance of efficiency indices obtained by the RAM model is the lowest for both the EE and CE assessment cases. Focusing on EE measures, the highest variances come from the SBMT and DDF models, followed by the R(RMM) and M-Radial models. For CE measures, the variances of R(RMM), SBMT and DDF models give larger variance in regional efficiency values than does the RAM model. Based on this observation, the order of discrimination power for different models is SBMT, DDF > R(RMM), M-Radial > RAM.

Fig. 9 illustrates how the variances in China's regional efficiency scores vary with the models. In terms of EE measurements, the efficiency score for the SBMT model has the most widely fluctuating band. About 50% of the scores are concentrated between 0.485 and 0.667. The variance of EE for DDF model ranks the second with a very small gap with the SBMT model, followed by the R(RMM) and M-Radial models. In addition, the efficiency scores for the RAM model are the most concentrated. For the CE measurement, apart from the RAM model, other models (namely R(RMM), SBMT and DDF) have similar discrimination power due to their similar fluctuating band.

For the medians of efficiency scores shown in Fig. 9, the medians of the EE from the RAM model are the highest (around 0.97), followed by the R(RMM) and M-Radial models (around 0.92). On the other hand, SBMT and DDF models have the lowest medians of the EE (around 0.57). However, the medians of CE for the R (RMM) model are similar to those for the SBMT and DDF model (around 0.48).

In general, the efficiency scores calculated by the SBMT and DDF models are lower and more dispersed than those calculated by the

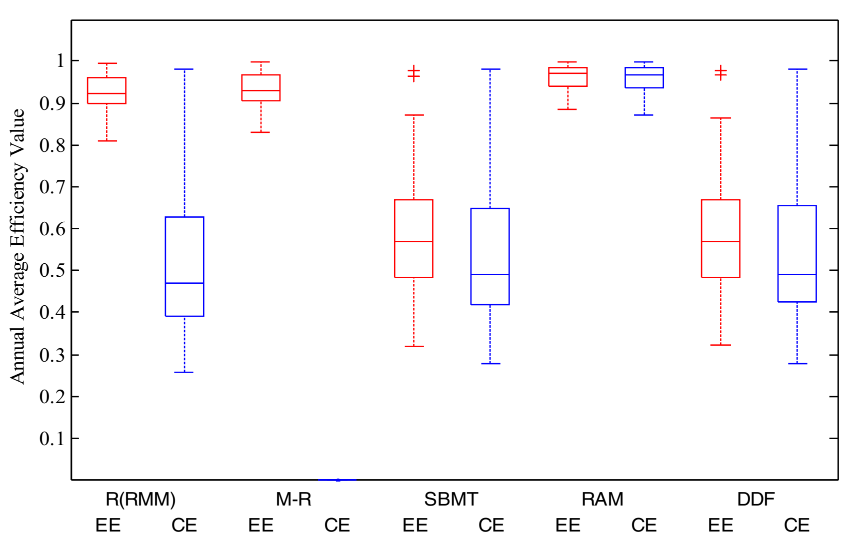


Fig. 9. Comparative box plots of China's regional EE and CE for 6 models.

R(RMM), M-Radial and RAM models. It is also worth noting that these models can be classified into several categories according to their similarities in data distribution.

Tables 7 and 8 further show the average EE&CE values by region and respective ranking using different models. Similar conclusion can be drawn from Table 7 that EE values obtained from R

Table 7
Annual average EE values and ranks across regions by different models.

Region	R(RMM)		M-R		SBMT		RAM		DDF	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
AH	0.912	18	0.917	19	0.559	17	0.962	18	0.546	18
BJ	0.926	15	0.934	15	0.823	5	0.985	9	0.846	4
CQ	0.853	28	0.866	28	0.554	18	0.975	13	0.547	17
FJ	0.953	13	0.955	13	0.597	11	0.977	12	0.594	12
GD	0.906	20	0.906	22	0.489	22	0.917	27	0.490	22
GS	0.919	17	0.927	16	0.450	24	0.974	15	0.445	24
GX	0.956	11	0.958	12	0.789	6	0.989	6	0.766	6
GZ	0.981	5	0.984	5	0.334	28	0.955	21	0.331	29
HaN	0.817	29	0.831	30	0.685	7	0.997	2	0.683	7
HeB	0.894	24	0.904	23	0.401	25	0.886	30	0.405	25
HeN	0.921	16	0.922	17	0.544	19	0.940	23	0.536	19
HLJ	0.984	3	0.987	3	0.965	2	0.997	2	0.967	2
HuB	0.868	26	0.882	27	0.484	23	0.939	24	0.485	23
HuN	0.983	4	0.986	4	0.873	3	0.988	7	0.865	3
IM	0.899	22	0.922	17	0.323	29	0.942	22	0.333	28
JL	0.864	27	0.885	25	0.504	21	0.965	16	0.518	20
JS	0.910	19	0.911	20	0.568	15	0.933	26	0.578	15
JX	0.954	12	0.955	13	0.841	4	0.993	5	0.839	5
LN	0.940	14	0.959	11	0.584	13	0.935	25	0.600	11
NX	0.962	8	0.968	9	0.336	27	0.986	8	0.338	27
QH	0.990	2	0.992	2	0.576	14	0.994	4	0.594	12
SaX	0.898	23	0.903	24	0.568	15	0.975	13	0.561	16
SC	0.905	21	0.911	20	0.669	8	0.963	17	0.656	9
SD	0.878	25	0.884	26	0.511	20	0.900	29	0.515	21
SH	0.996	1	0.997	1	0.977	1	0.998	1	0.977	1
SX	0.961	9	0.969	8	0.320	30	0.917	27	0.323	30
TJ	0.977	6	0.984	5	0.661	9	0.982	10	0.670	8
XJ	0.808	30	0.839	29	0.350	26	0.961	19	0.360	26
YN	0.959	10	0.961	10	0.625	10	0.979	11	0.607	10
ZJ	0.972	7	0.973	7	0.594	12	0.957	20	0.582	14

Table 8
Annual average CE values and ranks across regions by different models.

Region	R(RMM)		SBMT		RAM		DDF	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank
AH	0.472	15	0.487	17	0.955	19	0.484	18
BJ	0.817	4	0.850	3	0.987	6	0.878	3
CQ	0.508	13	0.521	13	0.974	11	0.518	13
FJ	0.470	16	0.490	16	0.969	15	0.490	16
GD	0.392	23	0.420	23	0.901	28	0.426	23
GS	0.372	24	0.386	24	0.970	13	0.386	24
GX	0.697	6	0.702	7	0.984	8	0.704	7
GZ	0.269	27	0.278	29	0.948	20	0.292	28
HaN	0.688	7	0.708	6	0.997	3	0.706	6
HeB	0.334	26	0.350	26	0.873	30	0.354	26
HeN	0.435	20	0.458	19	0.924	25	0.457	21
HLJ	0.966	2	0.967	2	0.998	1	0.971	2
HuB	0.416	22	0.433	22	0.933	24	0.436	22
HuN	0.832	3	0.833	4	0.985	7	0.835	4
IM	0.266	29	0.290	28	0.940	22	0.301	27
JL	0.462	18	0.474	18	0.964	17	0.490	16
JS	0.467	17	0.492	15	0.918	26	0.515	14
JX	0.703	5	0.740	5	0.988	5	0.739	5
LN	0.554	10	0.560	10	0.936	23	0.581	10
NX	0.257	30	0.372	25	0.984	8	0.277	30
QH	0.444	19	0.458	19	0.991	4	0.478	19
SaX	0.475	14	0.496	14	0.970	13	0.494	15
SC	0.594	9	0.601	9	0.956	18	0.601	9
SD	0.430	21	0.454	21	0.888	29	0.459	20
SH	0.980	1	0.982	1	0.998	1	0.982	1
SX	0.267	28	0.277	30	0.909	27	0.281	29
TJ	0.628	8	0.648	8	0.983	10	0.656	8
XJ	0.335	25	0.346	27	0.965	16	0.361	25
YN	0.516	12	0.528	11	0.972	12	0.527	11
ZJ	0.517	11	0.524	12	0.946	21	0.522	12

Table 9
Results of Kruskal-Wallis test.

Null hypothesis (H0)	Chi-square	*p*-Value	
Median(EE_R(RMM))=Median(EE_M-R) =Median(EE_RAM)	11.520	0.003	Reject H0
Median(CE_ R(RMM))=Median(CE_SBMT) =Median(CE_DDF)	0.681	0.712	Accept H0

Table 10
Results of Mann-Whitney *U* test.

Null hypothesis (H0)	Mann-Whitney U	*p*-Value	
Median(EE_ R(RMM))=Median (EE_M-R)	406.500	0.520	Accept H0
Median(EE_SBMT)=Median(EE_DDF)	455.000	0.941	Accept H0

(RMM), M-R and RAM models are larger than those computed by the SBMT and DDF models. When examining the rankings of the 30 regions using different models, it is found that Shanghai always ranks first. However, the rankings of some regions, e.g. Guizhou and Zhejiang, depend on the model selection. In fact, the above differences are mainly caused by the way in which the models project inefficient DMUs onto the production frontiers. Based on the similarities of regional EE rankings, these DEA models can be grouped into three categories: (i) R(RMM) and M-Radial Model; (ii) RAM Model and (iii) SBMT and DDF Model. As for CE assessment in Table 8, the R(RMM), SBMT and DDF Models can be put in the same group due to their similar CE values and rankings for different regions.

4.4. Statistical tests for China's regional EE&CE values across models

This subsection further uses the Kruskal-Wallis test and Mann-Whitney test to determine whether there are significant differences across the models in terms of EE and CE values. The Mann-Whitney test applies to only two independent samples, while the Kruskal-Wallis test is adopted when there are three or more samples. The results are shown in Tables 9 and 10 respectively.

Firstly, from the EE point of view as shown in Fig. 7, we assume no considerable differences in terms of EE between the R(RMM), M-Radial and RAM models. However, this hypothesis is rejected at the 5% level of significance as shown in Table 9. We therefore conduct the Mann-Whitney *U* test without considering the RAM model based on Fig. 7. From Table 10, it is found that the null hypotheses cannot be rejected at this level of significance, implying that there are no significant differences between the R(RMM) model and the M-Radial model when measuring China's regional EE, as with the SBMT model and DDF model. Thus, the six kinds of models can be grouped into three categories: (i) the R(RMM) model and M-Radial model; (ii) the RAM model and (iii) the SBMT model and DDF model. The reason may be that the R(RMM) model and M-Radial model both examine efficiency mainly via a radial coefficient. However, the SBMT model and DDF model construct the performance index by using non-radial items, such as slacks and other adjustable variables. As for the RAM model, even though

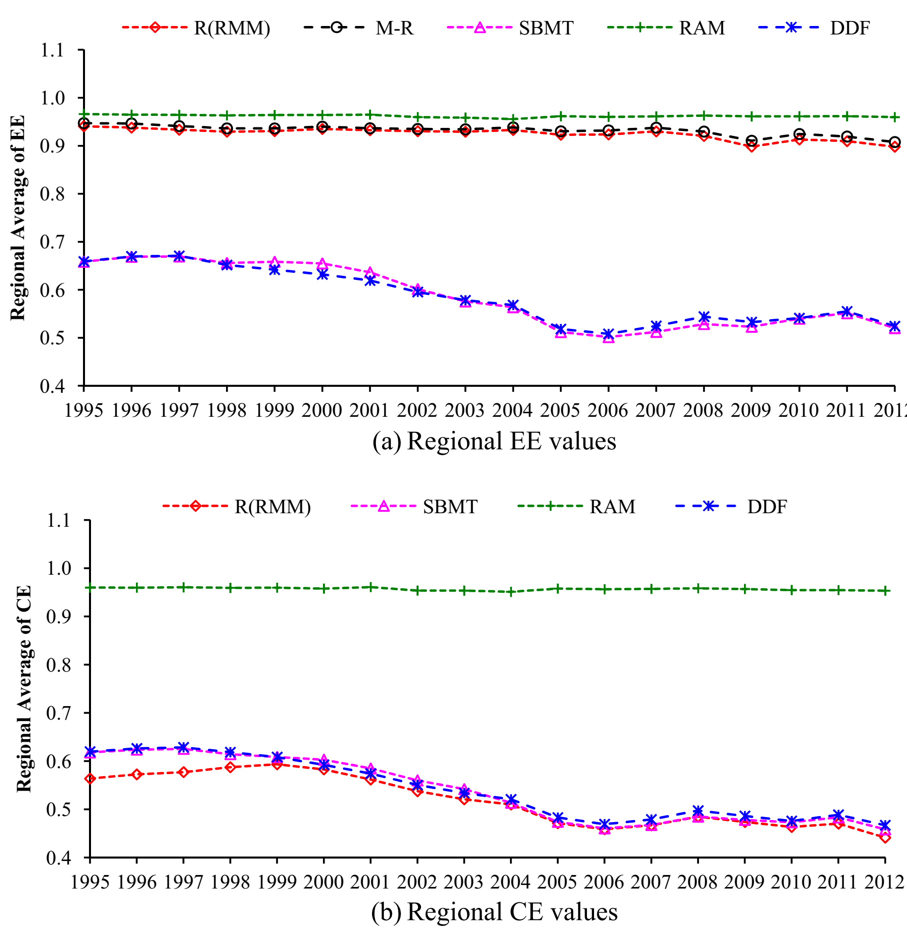


Fig. 10. Regional average value of EE and CE over time, 1995–2012.

Fig. 11. Division of China's economic regions.

it is also a non-radial model which applies slacks to construct the performance index, it includes only the slack of energy input. That is why it differs from the SBMT and DDF models and has weaker discrimination power.

Secondly, from the perspective of CE, it can be seen from Table 9 that the null hypothesis in terms of CE cannot be rejected since its *p*-value is larger than 0.05. This means that the efficiency scores obtained from the R(RMM) model, SBMT model and DDF model do not show considerable differences. Different from the case of EE, the R(RMM) model, SBMT model and DDF model can be regarded as a group. This may be due to the assumption of weak disposability on undesirable output in the R(RMM) model.

4.5. Discussions on China's regional EE&CE

After discussing the differences and similarities between different models in efficiency assessment based on efficiency scores obtained, this subsection focuses on the empirical results and the variations over time and space.

Fig. 10(a)–(b) depicts the trends in the regional average value of EE and CE from 1995 to 2012. From Fig. 10(a), the EE values in the R (RMM), M-Radial and RAM models are relatively stable, the pink[3] and blue lines show different trends more clearly than the red, black and green lines. China's energy efficiency remained stable during the 9th Five Year Plan period (1996–2000), and then decreased in the 10th Five Year Plan (2000–2005). After that, China's energy efficiency was on a relatively increasing trend in the 11th Five Year Plan period but dropped slightly in 2009 due to the global financial crisis.

[3] For interpretation of color in Fig. 10, the reader is referred to the web version of this article.

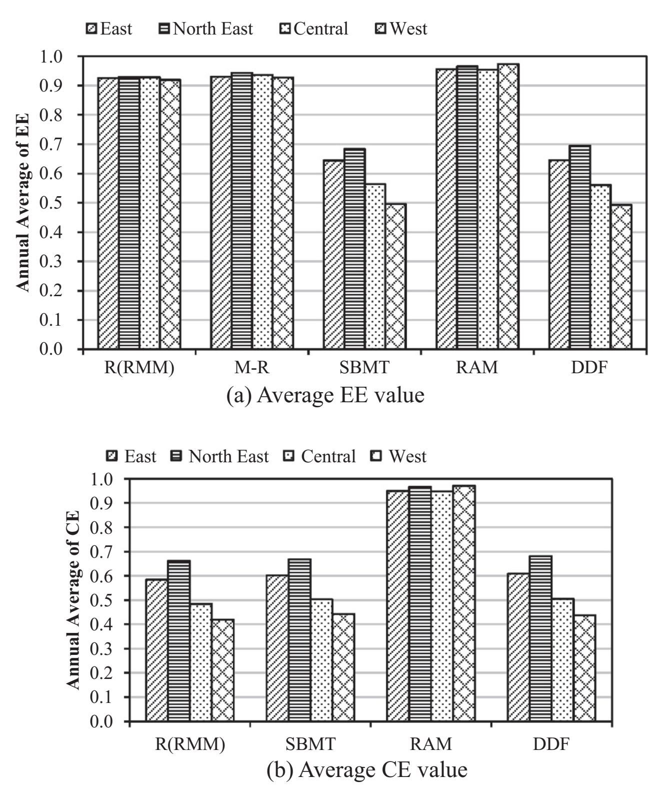


Fig. 12. Annual average value of EE and CE across region.

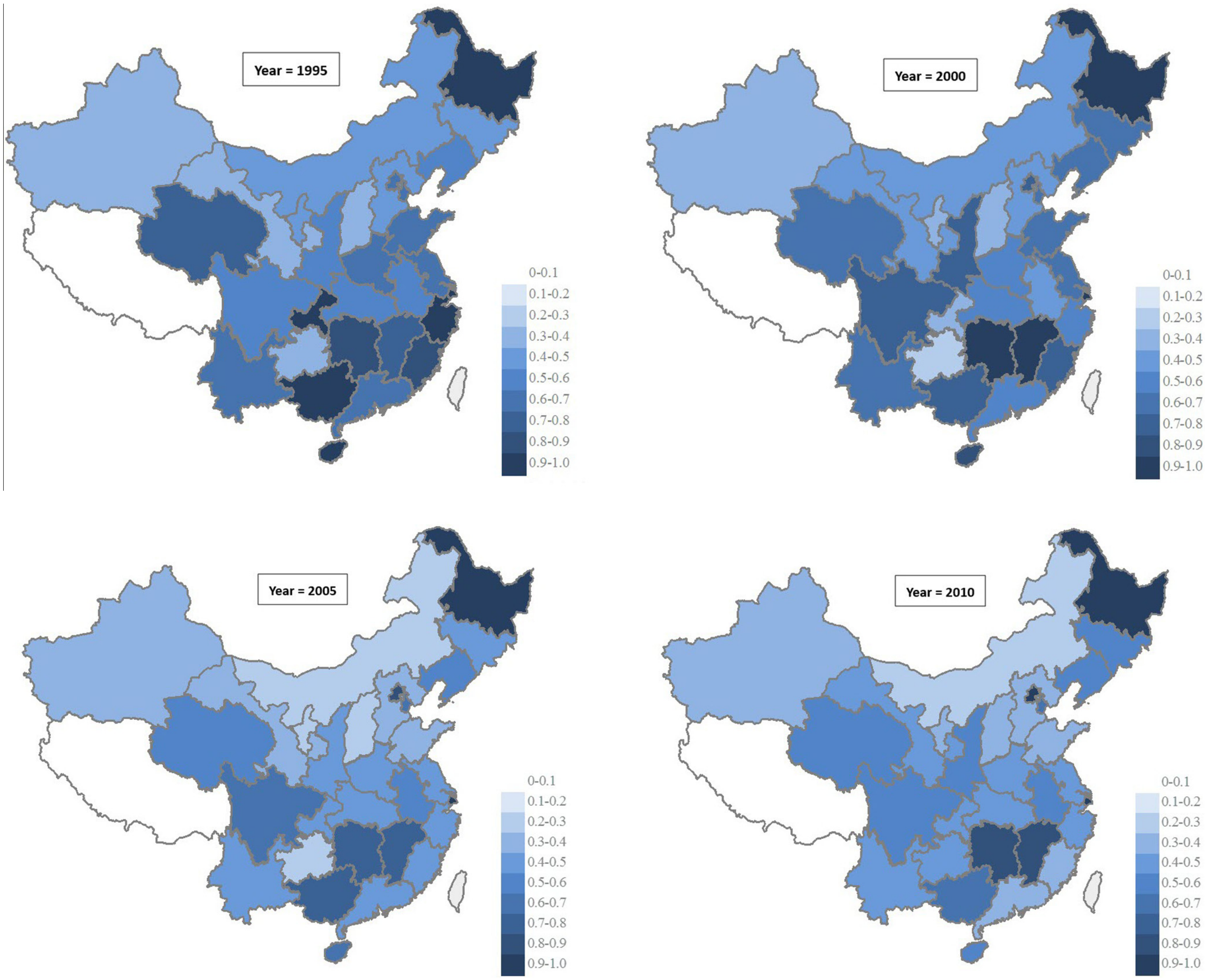


Fig. 13. EE values in 30 provinces/regions by DDF model.

As for carbon emission efficiency, the variance trend of the CE values obtained from the R(RMM) model, SBMT model and DDF model were very similar to those of the EE values illustrated by the pink and blue lines.

It is also interesting to examine China's regional EE and CE by four economic geographical regions as shown in Fig. 11. The east area includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Hainan and Guangdong; the northeast area includes Liaoning, Jilin and Heilongjiang; the central area includes Shanxi, Inner Mongolia, Anhui, Jiangxi, Henan, Hubei and Hunan; the west area includes Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. Fig. 12 shows the annual average value of EE and CE across the regions calculated by different models. It implies that apart from the RAM model, the models yield very similar conclusions, i.e., the northeast region of China has the highest energy and carbon emission efficiency, followed by the east region. And the west area exhibits the lowest average energy and carbon emission efficiencies.

Looking at time and space jointly, Fig. 13 exhibits the EE values in the 30 provinces/regions by the DDF model in 1995, 2000, 2005 and 2010 which are the final years of China's 8th, 9th, 10th and 11th Five Year Plans, respectively. Fig. 13 indicates that: (i) from the area perspective, the provinces/regions with high energy efficiency were always in east and northeast China, and the energy efficiency in central and west China was generally low. (ii) From the time perspective, the country as a whole obviously had a decreasing trend in energy efficiency during the 8th, 9th, 10th and 11th Five Year Plans, but a slightly increasing trend during the 11th Five Year Plan, coming mainly from the decline of EE in the east and south coast areas. (iii) The performance gap between the 30 provinces/regions was becoming narrow, revealing that China's regional energy efficiency is converging to some extent.

5. Conclusions

This paper provides a comprehensive survey of the studies published on China's regional energy and carbon emission efficiency (EE&CE) assessment using DEA-type models. It contributes to the literature in the following ways: (1) it is the first comprehensive review of DEA studies on China's regional EE&CE assessment; (2) it provides a helpful reference for model selection (only DEA models) from both theoretical and practical perspectives; (3) it investigates China's regional EE&CE using six types of DEA models based on the same data sets for China's 9th, 10th and 11th Five Year Plans, providing comparable empirical results from different models.

A total of six types of DEA models were employed in the previous studies, namely the Radial, M-Radial, RMM, SBMT, RAM and

DDF models. The major difference among these models is the way they adjust the inefficiency units. Each model has its application scopes, advantages and limits. From theoretical perspective, Radial model is the simplest and most popular model, because it proportionally adjust the inputs/outputs to the efficient targets. The other models can adjust inputs/outputs non-proportionally. On the other hand, input-/output-oriented should be presupposed for the Radial, M-Radial and RMM models, but is no necessary for the SBMT, RAM and DDF models whose inputs/outputs can be improved simultaneously using slacks or directional vectors. Moreover, the SBMT, RAM and DDF models can provide information about the amount of increase/decrease in inputs/outputs to the efficient targets. From practical perspective, empirical results show evidences that SBMT and DDF models have stronger discrimination power than others in China's regional EE&CE assessment. According to the aim of different studies, above conclusions provide useful reference for model selection.

Currently, most of the DEA empirical studies focus on the analysis at the country level. Considering the large regional diversities in China, it is important to measure its regional EE&CE to provide the guidance on their energy and emission performance improvement. Similar regional studies on China can be applied to other developed and developing world countries and regions. It should be noted that the EE&CE values obtained from the DEA models are relative efficiency values. For instance, Shanghai has a very high EE value relative to other regions in China. However, this conclusion may not retain when comparing with other more efficient countries/regions in the world. It would be interesting to include both national and regional level data in the DEA analysis. Such exercise can identify the efficiency improvement potential compared with not only China's regions but also the world countries/regions.

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Appendix A. Detailed datasets constructed and used in this paper

See Tables A.1–A.5.

Table 11
Labor force (Ten thousand).

Region	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BJ	2201.8	2497.7	2799.0	3175.0	3523.4	3901.3	4341.3	4912.8	5649.1	6457.9	7349.7	8312.6	9380.6	10071.9	11041.5	12257.4	13480.2	14984.1
TJ	602.3	673.4	753.5	849.6	935.6	1030.2	1145.7	1283.6	1468.3	1678.8	1938.9	2258.8	2665.2	3206.9	4006.4	4996.7	6139.9	7423.6
HeB	1314.0	1529.1	1785.0	2067.0	2367.7	2649.5	2932.7	3222.1	3594.1	4080.2	4742.8	5533.3	6465.6	7630.3	8989.5	10444.6	12229.1	14117.9
SX	616.1	650.1	701.3	782.7	868.3	956.5	1055.2	1177.6	1340.6	1560.7	1845.1	2196.9	2616.2	3050.9	3704.5	4448.7	5314.2	6152.9
IM	602.5	654.7	719.4	789.3	864.1	947.5	1048.2	1218.9	1547.2	2026.4	2726.0	3545.4	4557.9	5706.1	7323.9	9094.3	11042.3	13301.3
LN	1364.6	1456.5	1547.9	1653.0	1758.9	1893.6	2049.3	2230.3	2492.0	2906.3	3406.1	4057.9	4858.5	5856.9	6955.4	8287.6	9773.7	11358.6
JL	546.2	602.1	641.4	690.2	752.0	830.1	915.9	1020.7	1153.6	1329.9	1594.9	2039.5	2664.9	3481.4	4355.2	5368.0	6338.9	7366.5
HLJ	828.6	911.3	999.0	1110.6	1210.6	1313.0	1434.8	1569.5	1710.2	1878.1	2082.8	2353.4	2708.1	3124.6	3674.9	4297.4	4991.4	5813.8
SH	1630.2	1966.0	2291.2	2596.2	2881.1	3177.7	3490.9	3850.4	4238.4	4701.8	5248.2	5882.1	6614.4	7281.2	8167.0	8893.9	9552.5	10204.1
JS	3313.4	3793.2	4324.5	4956.7	5627.0	6373.2	7163.3	8029.5	9303.1	10787.4	12705.1	14831.7	17098.5	19519.5	22721.7	26376.6	30315.1	34474.1
ZJ	298.3	344.7	405.2	489.2	601.1	749.7	923.3	1131.9	1333.9	1549.9	2828.4	4141.6	5506.0	6819.0	8241.8	9800.0	11355.5	12924.8
AH	722.1	823.1	928.6	1034.5	1135.8	1245.4	1365.7	1500.6	1665.7	1908.0	2190.2	2527.2	2936.5	3418.6	3984.5	4668.7	5456.9	6332.4
FJ	509.6	604.7	707.8	831.0	951.1	1070.8	1189.3	1317.0	1479.0	1687.2	1964.8	2313.5	2757.4	3303.4	3937.2	4608.9	5386.3	6247.7
JX	754.6	844.6	956.8	1071.4	1190.8	1316.6	1469.6	1702.2	2023.3	2409.3	2857.5	3364.9	3915.5	4482.6	5302.8	6179.1	7145.9	8142.0
SD	1952.9	2157.3	2398.7	2686.5	3017.8	3418.5	3848.7	4373.2	5026.8	5874.7	6960.4	8209.2	9508.0	10920.5	12881.4	15051.8	17330.6	19745.8
HeN	1330.6	1522.4	1737.2	1982.4	2229.3	2489.7	2766.2	3089.4	3476.1	3963.4	4717.2	5751.1	7103.9	8689.2	10784.2	13168.7	15720.3	18561.1
HuB	949.7	1132.4	1323.8	1532.4	1744.8	1966.0	2208.2	2451.8	2703.1	3012.9	3395.3	3905.8	4518.7	5194.1	6078.2	7132.4	8420.1	9817.6
HuN	584.8	646.9	709.0	782.1	865.5	957.9	1063.3	1181.6	1318.5	1483.0	1705.5	1972.3	2296.6	2736.2	3265.7	3931.2	4671.5	5479.7
GD	2335.6	2720.3	3084.6	3529.7	4063.9	4594.9	5178.1	5880.2	6769.8	7752.8	9006.7	10409.7	12005.7	13600.5	15788.6	18267.0	20968.2	23931.6
GX	402.5	450.8	494.9	550.3	615.0	679.5	747.2	827.2	923.1	1053.7	1236.0	1480.1	1794.2	2153.5	2790.7	3675.6	4681.6	5694.0
HaN	169.0	181.8	192.8	205.1	218.9	232.3	246.1	262.6	282.8	306.0	334.8	369.8	408.3	470.8	543.2	642.2	756.6	914.1
CQ	442.8	468.6	507.7	570.2	635.4	705.7	793.8	906.8	1064.0	1250.5	1477.1	1726.7	2009.8	2298.6	2662.7	3097.5	3620.6	4156.4
SC	771.5	849.0	938.7	1050.6	1158.1	1282.5	1420.6	1581.9	1775.7	1998.8	2276.1	2633.0	3067.1	3543.6	4141.6	4838.8	5618.8	6467.9
GZ	310.4	332.8	363.3	404.6	455.5	512.9	590.7	680.2	780.4	884.3	1001.0	1135.7	1290.1	1466.2	1687.1	1957.1	2283.1	2718.1
YN	466.3	516.7	574.1	650.9	726.0	788.7	852.8	927.2	1028.0	1151.9	1317.3	1524.0	1765.6	1913.9	2223.0	2723.8	3337.1	4043.6
SaX	641.1	682.7	728.9	794.5	869.1	965.1	1065.5	1180.1	1347.5	1513.4	1738.4	2029.9	2406.8	2904.6	3504.8	4271.5	5106.6	6053.7
GS	376.5	396.7	425.3	459.3	504.5	560.0	632.4	717.1	813.3	926.8	1054.7	1198.3	1366.4	1611.6	1839.5	2113.1	2440.5	2811.2
QH	142.6	157.8	178.7	203.4	231.0	264.3	310.3	363.9	423.5	485.5	555.1	630.2	713.4	802.9	938.3	1121.7	1346.5	1667.6
NX	129.8	135.2	142.1	152.5	166.8	184.9	208.1	236.0	277.9	324.7	377.8	437.9	508.6	609.1	747.3	912.8	1070.1	1254.4
XJ	525.6	581.6	638.4	707.3	772.7	849.8	932.1	1037.3	1174.8	1322.6	1499.4	1699.6	1920.8	2120.4	2351.9	2669.8	3033.5	3597.2

Table 12
Capital stock (Billions of 1978 RMB).

Region	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BJ	669.5	660.9	660.8	624.3	621.9	622.1	629.5	798.9	858.6	895.0	920.4	1015.9	1111.4	1173.8	1255.1	1317.7	1366.4	1414.4
TJ	489.7	484.9	491.6	427.0	421.1	406.7	410.5	403.1	419.7	422.0	426.9	429.8	432.7	503.1	507.3	520.8	545.4	574.0
HeB	3367.3	3391.2	3415.0	3382.9	3399.9	3441.2	3379.6	3385.6	3389.5	3416.4	3467.3	3517.2	3567.2	3651.7	3899.7	3790.2	3885.6	4006.5
SX	1460.4	1478.0	1483.2	1429.0	1434.3	1419.1	1412.9	1417.3	1469.5	1474.6	1476.4	1513.3	1550.1	1583.5	1599.7	1665.1	1717.4	1768.1
IM	1024.5	1042.8	1050.3	1006.8	1017.0	1016.6	1013.3	1010.1	1005.2	1019.1	1041.1	1061.3	1081.5	1103.3	1142.5	1184.7	1249.3	1304.9
LN	2034.0	2030.9	2063.3	1818.2	1796.4	1812.6	1833.4	1842.0	1861.3	1951.6	1978.6	2024.9	2071.3	2098.2	2190.0	2238.1	2283.9	2340.8
JL	1254.5	1257.5	1237.3	1127.4	1102.8	1078.9	1057.3	1095.3	1044.6	1115.6	1099.4	1097.8	1096.2	1143.5	1184.7	1248.7	1273.6	1290.9
HLJ	1552.4	1567.4	1658.6	1723.0	1679.9	1635.0	1631.0	1626.5	1622.4	1623.3	1625.8	1642.8	1659.9	1670.2	1687.5	1743.4	1784.7	1829.8
SH	768.0	764.3	770.2	670.0	677.3	673.1	692.4	742.8	771.5	812.3	855.9	866.2	876.6	896.0	929.2	924.7	936.2	945.7
JS	3765.4	3747.7	3745.5	3635.0	3595.8	3558.8	3565.4	3505.6	3610.3	3719.7	3877.7	4035.4	4193.2	4384.1	4536.1	4731.7	4735.2	4736.5
ZJ	2700.7	2701.9	2700.3	2651.1	2660.9	2700.5	2772.0	2834.7	2961.9	3092.0	3202.9	3409.1	3615.4	3691.9	3825.2	3989.2	4031.0	4049.8
AH	3206.8	3246.1	3321.7	3311.0	3312.5	3372.9	3389.7	3403.8	3416.0	3453.2	3484.7	3541.2	3597.6	3594.6	3689.8	3846.8	3914.1	3995.7
FJ	1567.0	1593.5	1613.4	1621.9	1630.9	1660.2	1677.8	1711.3	1756.7	1817.5	1868.5	1933.7	1998.9	2079.8	2168.9	2181.3	2393.8	2499.8
JX	2059.2	2064.4	2077.7	1971.3	1961.3	1935.3	1933.0	1955.1	1972.3	2039.8	2107.5	2151.6	2195.7	2223.3	2244.2	2306.1	2337.3	2358.9
SD	4625.4	4649.7	4707.0	4657.2	4698.6	4661.8	4671.7	4751.9	4850.6	4939.7	5110.8	5186.5	5262.2	5352.5	5449.8	5654.7	5728.6	5789.3
HeN	4696.7	4829.2	5017.0	4999.6	5205.0	5571.7	5516.6	5522.0	5535.7	5587.4	5662.4	5717.6	5772.7	5835.5	5948.8	6041.6	6197.6	6287.6
HuB	2707.0	2692.3	2708.7	2616.3	2572.4	2507.8	2452.5	2467.5	2537.3	2588.6	2676.3	2719.7	2763.0	2875.6	3024.5	3116.5	3139.6	3152.4
HuN	3506.1	3547.4	3590.7	3498.5	3496.1	3462.1	3438.8	3468.7	3515.9	3599.6	3658.3	3703.8	3749.4	3811.0	3907.7	4007.7	4030.1	4044.5
GD	3656.8	3690.7	3784.3	3737.4	3760.5	3861.0	3962.8	3966.7	4119.5	4316.0	4702.1	4997.5	5292.8	5478.0	5643.3	5776.9	5865.7	5870.8
GX	2382.5	2416.8	2452.4	2470.9	2481.5	2530.4	2543.5	2570.5	2601.4	2649.1	2703.1	2731.4	2759.6	2807.2	2862.6	2945.3	2978.8	2808.3
HaN	335.3	335.0	330.9	320.8	326.2	333.7	339.7	341.7	353.8	366.5	377.7	396.3	414.8	412.1	431.5	445.7	465.5	490.6
CQ	1709.3	1719.4	1689.9	1645.1	1639.4	1636.5	1624.0	1640.2	1659.5	1689.5	1720.8	1755.2	1789.5	1837.1	1878.5	1912.1	1968.2	2027.8
SC	4626.0	4575.8	4617.6	4534.7	4482.3	4435.8	4414.6	4408.8	4449.6	4503.4	4603.5	4691.1	4778.6	4874.5	4945.2	4997.6	5011.2	5024.6
GZ	1857.1	1892.1	1927.1	1946.3	1975.9	2045.9	2068.3	2081.4	2118.4	2168.8	2215.8	2249.4	2283.1	2301.6	2341.1	2402.2	2431.9	2476.7
YN	2186.3	2213.8	2247.6	2270.3	2273.4	2295.4	2322.6	2341.0	2349.6	2401.4	2461.3	2531.1	2600.8	2679.5	2730.2	2814.1	2907.0	2932.1
SaX	1774.4	1797.8	1811.9	1802.0	1780.9	1812.8	1784.6	1873.1	1911.3	1884.7	1882.9	1902.5	1922.0	1946.6	1919.5	1952.0	1937.9	1939.8
GS	1159.4	1175.1	1185.9	1175.6	1185.6	1182.1	1187.2	1254.9	1304.0	1321.7	1347.6	1361.0	1374.4	1388.7	1406.6	1431.9	1432.6	1424.3
QH	226.0	231.9	235.4	230.4	241.2	238.6	240.3	247.3	254.3	263.1	267.6	271.9	276.3	276.8	285.5	294.1	295.6	297.2
NX	243.6	250.1	260.4	259.5	270.8	274.4	278.0	281.5	290.6	298.1	299.6	304.5	309.5	303.9	328.5	326.0	339.6	344.5
XJ	662.2	671.6	690.7	678.3	669.6	672.5	685.4	701.5	721.3	744.5	764.3	782.6	800.8	813.7	829.2	852.6	908.5	962.9

Table 13
Total energy consumption (10,000 tons of SCE).

Region	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BJ	2749.4	2915.3	3033.2	3089.0	3107.0	3236.3	3401.7	3513.7	3703.5	3974.0	4287.4	4592.5	4913.0	4868.8	5023.6	5258.8	5155.1	5316.6
TJ	1988.3	1822.9	1889.0	1943.6	1970.9	2167.2	2342.1	2482.5	2580.4	2900.2	3078.8	3362.0	3715.3	4074.8	4496.2	5250.8	5721.8	6273.8
HeB	6654.6	6561.4	6620.0	6832.3	6987.8	7375.6	7763.7	8572.1	9878.3	11084.1	14397.4	15636.9	16811.0	17871.5	18486.9	20613.1	23156.4	23788.7
SX	4529.0	4650.2	4556.2	4510.1	4436.6	4558.6	5571.2	6611.9	7367.7	7707.1	8037.0	8961.0	9682.4	10548.6	10567.6	11076.7	11903.4	12558.0
IM	2067.7	2165.9	2681.2	2414.6	2536.8	2676.3	2863.2	3127.9	3695.9	5712.0	6234.5	6935.9	7765.8	9278.6	10981.8	11660.9	13203.0	12935.1
LN	7318.7	6826.2	6674.0	6347.4	6198.1	7185.9	7138.1	7215.4	7549.1	7979.2	9386.8	10439.5	12025.0	12285.6	13483.8	15623.8	16564.7	17998.8
JL	3247.9	3332.1	3275.3	2818.6	2643.7	2781.2	2818.8	2971.2	3395.0	3631.5	4648.7	5375.0	5970.9	5758.5	6004.4	6704.2	7522.6	7500.1
HLJ	3910.3	3803.1	4028.4	3901.7	4095.5	4105.2	3924.7	4027.5	4195.9	4477.1	4803.1	5541.5	6004.2	5957.8	6540.2	6977.5	7759.4	8579.6
SH	3366.4	3460.4	3538.0	3600.1	3979.3	4108.0	4247.8	4464.5	4745.3	5392.7	6049.3	6879.8	7452.7	7613.4	7891.4	8713.3	8668.4	8766.7
JS	5954.1	5860.0	5808.7	5880.7	5799.5	5986.8	6006.0	6385.6	6663.9	9172.4	11382.2	12513.5	13876.9	15045.8	16149.5	17701.5	18858.5	19600.8
ZJ	4265.3	3412.6	3313.7	3644.2	3770.5	4085.2	4450.3	5020.4	5500.4	6681.4	8017.0	8814.7	9673.5	10195.4	10422.4	11127.3	11954.0	12334.1
AH	3256.0	3556.1	3497.0	3701.5	3768.8	3977.1	4225.0	4393.5	4667.3	4642.8	4895.2	5468.0	5898.0	6194.9	6641.5	7006.9	7732.4	8268.6
FJ	1573.6	1696.2	1767.1	1800.3	1918.8	2056.8	2079.2	2454.8	2763.7	3143.5	4512.7	4916.7	5367.9	5760.4	6362.9	7101.3	7485.5	7870.7
JX	1933.7	1745.2	1761.6	1731.1	1704.9	1671.4	1810.8	2014.6	2306.2	2476.8	2778.7	3218.8	3662.0	3927.8	4266.1	4606.6	4889.2	5276.7
SD	6250.6	6094.7	5922.4	6901.9	6831.4	6731.8	8389.1	8274.9	9167.8	11112.6	17017.6	18498.4	20526.2	22375.4	23215.0	24938.1	26935.4	28378.2
HeN	4648.8	4624.5	4726.4	4820.8	4886.1	5049.0	5311.5	5509.4	6010.9	7702.1	9851.4	11427.9	12566.4	12874.2	13656.2	14863.1	16006.7	15588.5
HuB	4485.8	4735.3	4886.0	4896.3	5126.1	5152.2	4962.9	5369.6	5926.9	6330.8	7273.0	8121.4	9009.5	9938.5	10836.1	11971.9	13649.9	14449.3
HuN	4153.4	4316.9	3698.4	3794.3	2988.6	2854.6	3265.7	3606.5	3793.1	4525.0	7224.3	7744.7	8301.8	9016.6	9607.7	10238.2	11257.7	11718.1
GD	5142.3	5366.7	5640.4	5955.6	6197.7	6480.7	6926.4	7428.0	9143.2	9590.9	11694.6	13159.8	14618.1	15617.4	16950.1	18203.6	19388.0	19758.9
GX	1884.8	1925.4	1878.6	1926.3	2003.5	2137.8	2273.1	2288.4	2715.0	3139.7	3408.7	3975.6	4621.4	4879.4	5369.4	5893.2	6606.1	7085.5
HaN	202.7	247.9	299.2	317.3	337.4	362.7	384.0	496.3	656.2	822.2	619.9	735.3	827.0	979.1	1023.6	1152.1	1498.0	1519.9
CQ	1057.5	1583.2	2046.8	2562.7	2794.1	3020.8	2479.9	2745.1	2239.3	2452.1	3258.7	3501.0	3710.5	4956.0	5277.4	5774.2	6359.8	6771.0
SC	5144.6	4752.3	4498.5	4577.2	4212.0	4075.5	4183.7	4641.3	5066.7	6451.5	6230.2	6807.4	7910.2	9233.8	10346.6	12083.8	14079.6	14859.3
GZ	2401.4	2565.2	2772.4	2944.8	2887.8	2875.1	3025.7	3225.9	3728.5	4259.0	4508.4	4923.2	4938.0	4732.0	5076.0	5319.0	5894.2	6832.7
YN	1961.9	2099.1	2176.6	2068.1	1906.1	2040.5	2216.5	2554.5	3035.8	2302.0	4678.1	4838.6	5188.1	5492.9	6062.4	6391.4	6841.8	6832.7
SaX	2327.7	2524.0	2267.7	2246.6	1920.3	1881.4	2658.8	2491.6	2585.4	3208.3	3964.0	4123.4	4528.3	5174.8	5612.1	6468.6	7226.5	7948.9
GS	1975.7	2026.1	1917.2	1968.3	2053.1	2156.1	2168.0	2103.9	2201.2	2716.2	3103.9	3354.3	3491.6	3706.7	3749.1	4144.0	4329.9	4919.8
QH	400.6	409.8	446.5	449.9	587.7	537.3	545.2	627.0	714.1	850.4	887.3	1114.5	1166.2	1422.9	1475.2	1560.4	1902.3	2177.6
NX	466.0	465.3	514.5	540.9	601.1	775.9	950.8	1125.6	1300.5	1344.2	1555.4	1706.7	1872.4	2053.4	2169.6	2455.7	2822.3	2955.1
XJ	2141.4	2443.6	2320.0	2356.6	2325.3	2413.2	2537.0	2615.3	2988.5	3377.1	3963.2	4368.8	4606.5	4994.2	5326.5	5759.7	6766.4	7974.2

Table 14
GDP (Billions of 1978 RMB).

Region	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BJ	301.9	328.7	346.3	362.1	367.9	388.5	408.3	427.3	446.6	472.2	479.9	485.7	510.0	524.7	551.7	580.9	618.8	631.9
TJ	219.3	231.0	232.3	231.0	229.3	234.7	236.2	234.9	245.3	255.6	264.9	271.8	274.3	296.2	301.0	314.4	331.1	331.6
HeB	543.2	580.0	590.3	574.0	558.1	569.4	573.0	570.3	587.7	637.6	669.6	673.5	710.8	762.4	737.9	778.2	840.5	831.1
SX	254.4	273.2	280.4	278.5	268.6	271.8	271.5	275.4	294.4	319.7	332.2	335.2	356.3	405.7	401.4	440.6	476.3	466.1
IM	171.5	179.0	182.1	180.1	180.8	182.1	183.2	183.2	191.3	202.1	209.1	218.4	230.7	250.8	269.3	280.6	302.0	299.6
LN	671.7	699.1	728.4	728.7	723.8	743.9	735.7	724.0	714.1	703.6	752.1	763.4	794.5	857.8	857.1	910.6	977.4	997.3
JL	252.9	263.8	263.2	259.8	256.1	272.1	270.5	273.2	281.4	294.1	304.3	312.4	332.7	348.6	347.7	363.8	389.8	393.3
HLJ	626.8	677.1	692.7	665.2	639.3	649.6	639.3	622.5	630.1	660.5	686.6	689.2	701.0	737.5	684.1	733.0	792.0	783.3
SH	569.8	596.1	614.5	615.8	614.7	630.8	623.3	617.1	640.8	676.6	691.4	698.3	718.3	735.9	747.1	772.7	798.6	781.4
JS	670.5	695.8	691.5	671.3	651.9	655.1	657.6	660.5	682.1	716.4	763.4	785.6	813.1	852.6	862.3	919.8	982.4	981.9
ZJ	392.5	410.0	412.9	404.0	395.7	402.1	408.4	420.9	444.9	466.4	477.0	490.6	510.3	530.2	521.0	561.4	600.4	596.4
AH	346.9	355.9	357.2	357.3	349.4	345.2	354.6	350.7	357.3	382.6	387.2	391.5	412.9	441.5	443.4	475.2	518.4	520.2
FJ	244.3	255.7	259.2	257.5	253.1	255.4	254.2	253.0	253.1	261.8	267.4	268.9	284.7	294.9	296.9	314.0	333.1	335.4
JX	253.4	273.4	277.4	277.4	277.3	277.5	277.0	282.3	286.3	311.4	323.9	332.1	346.1	362.2	378.3	409.7	450.9	449.7
SD	741.4	785.6	785.7	761.6	739.0	745.4	747.3	747.6	775.0	835.9	894.5	929.0	955.9	1020.4	992.1	1020.9	1066.1	1070.9
HeN	504.3	538.6	542.4	531.5	515.6	526.6	529.0	527.0	541.7	593.4	643.1	656.5	695.6	760.9	726.1	765.0	797.3	795.6
HuB	403.4	428.5	437.6	439.1	422.6	427.3	429.6	427.0	439.6	468.0	483.5	496.4	527.9	571.4	575.9	618.0	667.7	680.2
HuN	531.3	564.7	572.7	560.5	549.3	556.8	551.2	547.8	561.1	606.0	626.6	649.2	689.2	740.9	762.8	817.4	888.8	899.7
GD	575.7	596.0	609.7	603.8	594.6	619.3	628.3	627.0	640.7	664.5	692.4	706.7	732.3	764.2	770.5	798.9	839.8	832.8
GX	323.9	339.0	335.8	321.0	306.6	299.8	303.4	303.7	308.1	335.4	351.7	366.7	393.0	419.5	398.5	430.4	469.4	469.2
HaN	50.8	52.1	51.4	51.0	50.6	51.4	51.7	52.4	52.6	54.6	54.7	55.4	57.2	62.2	63.1	67.9	74.1	76.8
CQ	207.4	218.0	225.0	219.8	211.5	209.5	211.7	216.3	221.6	234.0	239.3	239.8	247.7	267.9	298.7	309.6	336.0	337.2
SC	529.9	563.1	575.0	561.9	553.6	549.4	551.0	550.0	557.5	591.6	608.2	627.6	668.5	726.7	718.1	757.7	806.1	813.2
GZ	145.4	151.8	155.2	152.3	152.9	155.0	156.7	157.6	164.2	173.4	183.3	188.5	200.1	220.8	232.6	242.6	261.3	276.5
YN	243.2	271.9	273.6	276.5	267.3	263.2	262.0	260.0	264.0	285.9	295.6	304.8	320.6	347.2	335.3	349.6	378.5	388.4
SaX	222.0	234.8	237.9	228.0	225.7	231.6	235.1	237.1	243.6	264.7	279.3	296.9	313.0	339.4	356.3	385.3	418.1	427.9
GS	135.6	156.8	157.9	161.0	159.1	159.6	155.5	154.9	158.9	171.9	176.1	185.9	196.6	209.7	202.7	220.6	238.8	238.8
QH	54.9	55.4	56.0	56.0	56.1	56.7	57.8	58.5	60.0	63.8	66.3	69.5	75.7	82.4	84.2	91.2	99.4	100.4
NX	41.0	42.9	44.0	44.2	43.7	44.2	45.9	46.5	49.9	52.9	53.8	56.0	62.2	68.5	75.4	82.9	92.0	91.9
XJ	134.5	139.6	148.7	147.2	144.0	155.3	156.5	156.3	164.4	172.9	183.8	193.6	199.6	214.6	202.0	232.1	252.0	255.5

Table 15
CO_2 emissions (10,000 tons).

Region	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BJ	7093.4	7603.0	7532.7	7725.5	7889.9	8239.4	8795.2	8801.9	9263.5	9862.4	10690.0	11580.7	12512.0	12516.2	13032.9	14857.6	13940.5	14365.1
TJ	5455.6	4943.7	5059.9	5159.1	5293.0	5896.2	6268.7	6329.9	6746.3	7781.2	8274.5	9257.6	10296.1	10876.5	11988.5	14169.0	15537.5	16742.0
HeB	18762.1	18562.2	18877.9	19198.0	19967.8	20916.3	22055.8	24608.6	28660.0	32398.9	41308.4	45720.1	49109.1	53118.8	55770.2	66318.6	72952.4	74986.1
SX	13116.7	13509.9	13477.5	13317.2	13193.6	13759.2	16824.1	19792.3	22134.6	22794.0	23020.2	25725.1	28202.6	30516.4	30567.2	32706.4	34935.8	37170.8
IM	5938.3	6199.9	7374.6	6680.8	7184.0	7580.2	8104.4	8937.2	10686.8	15919.4	17666.5	19686.5	22407.1	26071.6	29658.0	33592.6	40413.7	39858.9
LN	18470.6	16985.1	17454.4	16756.1	16920.0	19272.1	19145.2	19366.9	20141.2	21044.8	24225.3	26821.5	31683.6	32894.2	35674.4	46215.7	45046.0	47822.3
JL	8818.4	9118.2	8929.6	7279.6	7120.1	7514.5	7700.9	8096.6	9004.9	10026.5	12223.2	14233.9	15455.9	14913.1	15732.5	18580.0	21080.5	21796.1
HLJ	10174.4	9843.5	10556.2	10061.5	10438.2	10028.1	10004.0	10144.6	10592.4	11425.1	12167.6	13902.3	15114.0	15372.0	16329.4	17650.2	19979.7	22054.4
SH	8933.2	9331.3	9676.3	9966.0	10624.0	11142.4	11550.6	11934.0	12894.2	14470.9	15947.0	17132.1	18532.6	19220.8	19728.9	23805.4	23809.0	23824.5
JS	16463.5	16369.0	15777.8	16191.5	16448.8	16669.3	17178.3	18547.4	20254.9	27282.2	33687.1	37813.2	42522.1	45990.0	48680.4	58767.1	61452.8	64173.0
ZJ	11542.7	9947.9	9835.9	10592.9	11075.0	12096.2	13668.7	15366.8	17365.0	20900.2	24764.3	27597.5	30514.5	32191.7	33301.0	36733.5	39319.4	41010.0
AH	9037.2	10103.0	10153.5	10689.4	10936.3	11587.3	12225.2	12776.0	13653.9	13561.0	14153.6	15838.9	17302.8	18297.9	19567.8	21161.0	23408.1	25190.9
FJ	4813.6	5152.1	5393.6	5567.5	5918.7	6420.6	6570.3	7822.0	8915.5	9911.3	13510.9	14912.4	16318.1	17866.6	19666.6	21746.7	23402.6	24612.7
JX	5458.3	5033.8	5048.2	4949.4	4856.6	4797.4	5173.0	5707.8	6558.8	7403.0	8116.7	9362.2	10437.1	11189.5	12127.5	13640.5	15256.1	16153.4
SD	17192.0	17249.5	17612.7	19238.6	19013.1	19381.2	25690.2	23908.3	27072.9	32310.6	47635.1	52174.0	58002.9	62519.5	65427.3	72763.4	77948.3	82711.4
HeN	13717.2	13819.3	14046.6	14302.7	14423.5	14931.4	15842.9	16667.3	18408.9	23371.7	29402.0	34072.5	37831.3	39585.6	42039.7	47244.8	49822.8	49233.6
HuB	12589.6	13247.8	13633.9	13692.4	14327.4	14627.3	14502.7	15477.1	17174.0	18332.4	20420.5	22505.3	25264.9	26990.9	29212.1	35865.5	40715.2	42961.8
HuN	11912.0	12154.8	10550.4	10851.0	8729.4	8404.5	9681.2	10707.4	11357.6	13668.5	20159.0	21547.7	23292.5	25307.6	26507.1	28034.8	31002.3	31413.8
GD	14658.1	15347.2	15724.9	16638.1	17371.5	19388.9	20755.3	22753.2	27763.1	29736.9	35623.1	39758.2	44091.5	46676.7	49877.3	56768.9	60691.6	62364.0
GX	5495.9	5583.0	5553.8	5578.9	5794.9	6155.6	6487.2	6483.6	7565.9	8641.0	9919.1	11653.4	13291.9	14079.3	15702.9	18480.5	20002.4	21389.5
HaN	539.0	620.4	723.7	768.1	817.5	880.0	945.6	1180.4	1505.8	1937.0	1530.3	1773.4	2026.0	2379.8	2556.6	2932.8	3655.5	3876.7
CQ	2923.5	4455.0	5634.8	7320.7	7924.4	8412.2	6956.3	7651.0	6354.7	6939.0	8408.6	8990.5	9390.0	12504.5	13631.1	14903.4	16936.6	17952.3
SC	14223.2	13372.7	12824.3	12852.4	11743.8	11524.1	11878.6	13320.2	14607.5	18409.4	17963.4	19706.1	22480.0	26113.0	29181.4	34778.3	37782.0	40422.6
GZ	6940.8	7483.8	8078.0	8569.5	8509.5	8701.6	9486.6	10175.5	11689.1	13229.4	13765.9	15066.6	15194.9	14444.0	15594.9	16854.3	18999.4	21795.3
YN	5674.1	6224.7	6420.5	6181.2	5838.4	6242.1	6686.5	7744.0	8907.1	6686.9	13445.0	14238.9	15454.5	16667.8	18126.0	20301.9	22192.7	21795.3
SaX	6846.0	7401.3	6697.9	6538.4	5766.1	5694.0	6627.6	7374.4	7748.8	9242.8	11661.5	12074.3	12941.6	14768.1	16142.0	18767.7	21413.5	23299.1
GS	5780.0	5914.7	5576.7	5597.3	5875.8	6132.5	6209.8	6173.8	6695.3	7926.5	8835.6	9490.7	10284.1	10989.0	11193.5	13673.4	13973.7	16284.6
QH	1260.4	1276.3	1417.3	1439.4	1839.5	1732.2	1710.7	1937.7	2186.2	2635.5	2778.3	3461.9	3794.4	4450.0	4763.3	5553.2	6732.5	7525.5
NX	1521.0	1547.5	1689.6	1742.1	1926.3	2243.4	2560.6	2877.7	3194.9	4424.7	4950.2	5484.8	5756.5	6603.3	6968.6	7960.6	9724.5	10113.2
XJ	5658.2	6421.0	6052.3	6087.0	6063.0	6301.6	6448.1	6739.5	7366.0	8162.5	9063.2	10436.8	11285.7	12687.1	14149.6	15553.1	18530.0	22596.2

Note: BJ (Beijing), TJ (Tianjin), HeB (Hebei), SX (Shanxi), IM (Inner Mongolia), LN (Liaoning), JL (Jilin), HLJ (Heilongjiang), SH (Shanghai), JS (Jiangsu), ZJ (Zhejiang), AH (Anhui), FJ (Fujian), JX (Jiangxi), SD (Shandong), HeN (Henan), HuB (Hubei), HuN (Nunan), GD (Guandong), GX (Guangxi), HaN (Hainan), CQ (Chongqing), SC (Sichuan), GZ (Guizhou), YN (Yunnan), SaX (Shaanxi), GS (Gansu), QH (Qinghai), NX (Ningxia), and XJ (Xinjiang).

References

[1] Su B, Ang BW. Structural decomposition analysis applied to energy and emissions: Some methodological developments. Energy Econ 2012;34(1):177–88.
[2] Ang BW, Xu XY, Su B. Multi-country comparisons of energy performance: the index decomposition analysis approach. Energy Econ 2015;47:68–76.
[3] Su B, Ang BW. Multi-region comparisons of emission performance: the structural decomposition analysis approach. Ecol Ind 2016;67:78–87.
[4] Kao C. Network data envelopment analysis: a review. Eur J Oper Res 2014;239(1):1–16.
[5] Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. Eur J Oper Res 1978;2(6):429–44.
[6] Cook WD, Seiford LM. Data envelopment analysis (DEA)–Thirty years on. Eur J Oper Res 2009;192(1):1–17.
[7] Tyteca D. Linear programming models for the measurement of environmental performance of firms—concepts and empirical results. J Prod Anal 1997;8(2):183–97.
[8] Zaim O, Taskin F. Environmental efficiency in carbon dioxide emissions in the OECD: a non-parametric approach. J Environ Manage 2000;58(2):95–107.
[9] Boyd GA, Tolley G, Pang J. Plant level productivity, efficiency, and environmental performance of the container glass industry. Environ Resource Econ 2002;23(1):29–43.
[10] Färe R, Grosskopf S, Hernandez-Sancho F. Environmental performance: an index number approach. Resour Energy Econ 2004;26(4):343–52.
[11] Zhou P, Ang BW, Poh KL. A survey of data envelopment analysis in energy and environmental studies. Eur J Oper Res 2008;189(1):1–18.
[12] Zhou P, Ang BW, Han JY. Total factor carbon emission performance: a Malmquist index analysis. Energy Econ 2010;32(1):194–201.
[13] Zhang XP, Cheng XM, Yuan JH, et al. Total-factor energy efficiency in developing countries. Energy Policy 2011;39(2):644–50.
[14] Hu JL, Wang SC. Total-factor energy efficiency of regions in China. Energy Policy 2006;34(17):3206–17.
[15] Wang H, Zhou P, Zhou DQ. Scenario-based energy efficiency and productivity in China: a non-radial directional distance function analysis. Energy Econ 2013;40:795–803.
[16] Wang K, Lu B, Wei YM. China's regional energy and environmental efficiency: a range-adjusted measure based analysis. Appl Energy 2013;112:1403–15.
[17] Wang QW, Zhao ZY, Zhou P, et al. Energy efficiency and production technology heterogeneity in China: a meta-frontier DEA approach. Econ Model 2013;35:283–9.
[18] Zhang N, Kong F, Yu Y. Measuring ecological total-factor energy efficiency incorporating regional heterogeneities in China. Ecol Ind 2015;51:165–72.
[19] Wei YM, Liao H, Fan Y. An empirical analysis of energy efficiency in China's iron and steel sector. Energy 2007;32(12):2262–70.
[20] Shi GM, Bi J, Wang JN. Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. Energy Policy 2010;38(10):6172–9.
[21] Wu F, Fan LW, Zhou P, et al. Industrial energy efficiency with CO_2 emissions in China: a nonparametric analysis. Energy Policy 2012;49:164–72.
[22] Pan H, Zhang H, Zhang X. China's provincial industrial energy efficiency and its determinants. Math Comput Modell 2013;58(5):1032–9.
[23] Bi GB, Song W, Zhou P, et al. Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model. Energy Policy 2014;66:537–46.
[24] Zhang N, Wei X. Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. Appl Energy 2015;146:409–20.
[25] Zhou P, Ang BW, Poh KL. Measuring environmental performance under different environmental DEA technologies. Energy Econ 2008;30(1):1–14.
[26] Färe R, Grosskopf S, Lovell CAK, et al. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Rev Econ Stat 1989:90–8.
[27] Chang TP, Hu JL. Total-factor energy productivity growth, technical progress, and efficiency change: an empirical study of China. Appl Energy 2010;87(10):3262–70.
[28] Song M, Yang L, Wu J, et al. Energy saving in China: analysis on the energy efficiency via bootstrap-DEA approach. Energy Policy 2013;57:1–6.
[29] Choi Y, Zhang N, Zhou P. Efficiency and abatement costs of energy-related CO_2 emissions in China: a slacks-based efficiency measure. Appl Energy 2012;98:198–208.
[30] Wang K, Wei YM, Zhang X. A comparative analysis of China's regional energy and emission performance: which is the better way to deal with undesirable outputs? Energy Policy 2012;46:574–84.
[31] Wang QW, Zhou P, Zhou DQ. Efficiency measurement with carbon dioxide emissions: the case of China. Appl Energy 2012;90(1):161–6.
[32] Wang ZH, Zeng HL, Wei YM, et al. Regional total factor energy efficiency: an empirical analysis of industrial sector in China. Appl Energy 2012;97:115–23.
[33] Bian YW, He P, Xu H. Estimation of potential energy saving and carbon dioxide emission reduction in China based on an extended non-radial DEA approach. Energy Policy 2013;63:962–71.
[34] Yang L, Wang KL. Regional differences of environmental efficiency of China's energy utilization and environmental regulation cost based on provincial panel data and DEA method. Math Comput Modell 2013;58(5):1074–83.
[35] Zhou G, Chung W, Zhang X. A study of carbon dioxide emissions performance of China's transport sector. Energy 2013;50:302–14.
[36] Li LB, Hu JL. Ecological total-factor energy efficiency of regions in China. Energy Policy 2012;46:216–24.
[37] Rao X, Wu J, Zhang Z, et al. Energy efficiency and energy saving potential in China: an analysis based on slacks-based measure model. Comput Ind Eng 2012;63(3):578–84.
[38] Chang YT, Zhang N, Danao D, et al. Environmental efficiency analysis of transportation system in China: a non-radial DEA approach. Energy Policy 2013;58:277–83.
[39] Zhang N, Choi Y. Environmental energy efficiency of China's regional economies: a non-oriented slacks-based measure analysis. Soc Sci J 2013;50(2):225–34.
[40] Wang K, Wei YM. China's regional industrial energy efficiency and carbon emissions abatement costs. Appl Energy 2014;130:617–31.
[41] Li K, Lin B. Metafroniter energy efficiency with CO_2 emissions and its convergence analysis for China. Energy Econ 2015;48:230–41.
[42] Banker RD, Cooper WW, Seiford LM, et al. Returns to scale in different DEA models. Eur J Oper Res 2004;154(2):345–62.
[43] Wu J, Lv L, Sun J, et al. A comprehensive analysis of China's regional energy saving and emission reduction efficiency: from production and treatment perspectives. Energy Policy 2015;84:166–76.
[44] Färe R, Grosskopf S, Lovell CAK. Production frontiers. Cambridge University Press; 1994.
[45] Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manage Sci 1984;30(9):1078–92.
[46] Färe R, Lovell CAK. Measuring the technical efficiency of production. J Econ Theory 1978;19(1):150–62.
[47] Russell RR. Measures of technical efficiency. J Econ Theory 1985;35(1):109–26.
[48] Tone K. A slacks-based measure of efficiency in data envelopment analysis. Eur J Oper Res 2001;130(3):498–509.
[49] Cooper WW, Park KS, Pastor JT. RAM: a range adjusted measure of inefficiency for use with additive models, and relations to other models and measures in DEA. J Prod Anal 1999;11(1):5–42.
[50] Chung YH, Färe R, Grosskopf S. Productivity and undesirable outputs: a directional distance function approach. J Environ Manage 1997;51(3):229–40.
[51] Cooper WW, Seiford L M, Tone K. Introduction to Data Envelopment Analysis and its uses: with DEA-solver Software and References. Springer Science & Business Media; 2006.
[52] Hu JL, Kao CH. Efficient energy-saving targets for APEC economies. Energy Policy 2007;35(1):373–82.
[53] Chien T, Hu JL. Renewable energy and macroeconomic efficiency of OECD and non-OECD economies. Energy Policy 2007;35(7):3606–15.
[54] Zhang J, Wu GY, Zhang JP. The estimation of China's provincial capital stock: 1952–2000. Econ Res J 2004;10:35–44 [in Chinese].
[55] Charnes A, Cooper WW. Preface to topics in data envelopment analysis. Ann Oper Res 1984;2(1):59–94.
[56] Halkos GE, Tzeremes NG. Exploring the existence of Kuznets curve in countries' environmental efficiency using DEA window analysis. Ecol Econ 2009;68(7):2168–76.
[57] Sueyoshi T, Goto M, Sugiyama M. DEA window analysis for environmental assessment in a dynamic time shift: performance assessment of US coal-fired power plants. Energy Econ 2013;40:845–57.
[58] Färe R, Grosskopf S, Lindgren B, et al. Productivity developments in Swedish hospitals: a Malmquist output index approach. In: Data envelopment analysis: theory, methodology, and applications. Netherlands: Springer; 1994. p. 253–72.
[59] Guo XD, Zhu L, Fan Y, et al. Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA. Energy Policy 2011;39(5):2352–60.
[60] Zhou P, Sun ZR, Zhou DQ. Optimal path for controlling CO_2 emissions in China: a perspective of efficiency analysis. Energy Econ 2014;45:99–110.
[61] Wang Z, Feng C, Zhang B. An empirical analysis of China's energy efficiency from both static and dynamic perspectives. Energy 2014;74:322–30.
[62] Xue X, Wu H, Zhang X, et al. Measuring energy consumption efficiency of the construction industry: the case of China. J Clean Prod 2014;107:509–15.
[63] Zhou G, Chung W, Zhang Y. Measuring energy efficiency performance of China's transport sector: a data envelopment analysis approach. Expert Syst Appl 2014;41(2):709–22.
[64] Duan N, Guo JP, Xie BC. Is there a difference between the energy and CO_2 emission performance for China's thermal power industry? A bootstrapped directional distance function approach. Appl Energy 2015;162:1552–63.
[65] Pan X, Liu Q, Peng X. Spatial club convergence of regional energy efficiency in China. Ecol Ind 2015;51:25–30.
[66] Wang Z, Feng C. A performance evaluation of the energy, environmental, and economic efficiency and productivity in China: an application of global data envelopment analysis. Appl Energy 2015;147:617–26.
[67] Lin W, Yang J, Chen B. Temporal and spatial analysis of integrated energy and environment efficiency in China based on a green GDP index. Energies 2011;4(9):1376–90.
[68] Cui Q, Li Y. The evaluation of transportation energy efficiency: An application of three-stage virtual frontier DEA. Transp Res Part D: Transp Environ 2014;29:1–11.
[69] Wu H, Shi Y, Xia Q, et al. Effectiveness of the policy of circular economy in China: A DEA-based analysis for the period of 11th five-year-plan. Resour Conserv Recy 2014;83:163–75.

[70] Guo L, Wu C, Qu Y, et al. Evaluation of the energy-saving and emission-reduction potential for Chinese provinces based on regional difference coefficients. J Renew Sustain Energy 2015;7(4):043149.
[71] Lin B, Fei R. Regional differences of CO_2 emissions performance in China's agricultural sector: A Malmquist index approach. Eur J Agron 2015;70:33–40.
[72] Song X, Hao Y, Zhu X. Analysis of the environmental efficiency of the Chinese transportation sector using an undesirable output slacks-based measure data envelopment analysis model. Sustainability 2015;7(7):9187–206.
[73] Shen N, Zhou J, Zou W. Energy efficiency measures and convergence in China, taking into account the effects of environmental and random factors. Pol J Environ Stud 2015;24(1):257–67.
[74] Yao X, Zhou H, Zhang A, et al. Regional energy efficiency, carbon emission performance and technology gaps in China: a meta-frontier non-radial directional distance function analysis. Energy Policy 2015;84:142–54.