The comprehensive environmental efficiency of socioeconomic sectors in China: An analysis based on a non-separable bad output SBM

Qi He[a, b,]∗, Han Ji[c], Dabo Guan[d, e], Zhifu Mi[d,f], Hongyan Zhao[a], Qiang Zhang[a]

[a] Ministry of Education Key Laboratory for Earth System Modeling, Department of Earth System Science, Tsinghua University, Beijing 100084, China
[b] ESRC Centre for Climate Change Economics and Policy (CCCEP), School of Earth and Environment, University of Leeds, Leeds LS2 9JT, UK
[c] Agricultural Information Institute, Chinese Academy of Agricultural Sciences, Beijing 100081, China
[d] School of International Development, University of East Anglia, Norwich NR4 7JT, UK
[e] School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China
[f] The Bartlett School of Construction and Project Management, University College London, London, WC1E 7HB, UK

Abstract:

The increasingly high frequency of heavy air pollution in most regions of China signals the urgent need for the transition to an environmentally friendly production performance by socioeconomic sectors for the sake of people's health and sustainable development. Focusing on CO_2 and major air pollutants, this paper presents a comprehensive environmental efficiency index based on evaluating the environmental efficiency of major socioeconomic sectors, including agriculture, power, industry, residential and transportation, at the province level in China in 2010 based on a slack-based measure DEA model with non-separable bad output and weights determined by the coefficient of variation method. In terms of the environment, 5, 16, 6, 7 and 4 provinces operated along the production frontier for the agricultural, power, industrial, residential and transportation sectors, respectively, in China in 2010, whereas Shanxi, Heilongjiang, Ningxia, Hubei and Yunnan showed lowest efficiency correspondingly. The comprehensive environmental efficiency index varied from 0.3863 to 0.9261 for 30 provinces in China, with a nationwide average of 0.6383 in 2010; Shanghai ranked at the top, and Shanxi was last. Regional disparities in environmental efficiency were identified. Amore detailed inefficiency decomposition and benchmarking analysis provided insight for understanding the source of comprehensive environmental inefficiency and, more specifically, the reduction potential for CO_2 and air pollutants. Some specific academic implications were uncovered from this work.

Keywords:

Environmental efficiency, Air pollutants, Socioeconomic sectors, Data envelop analysis; Slack-based model, China

---

∗ Corresponding author. Phone: +86 180-1009-9257.
E-mail address: heqi0788@mail.tsinghua.edu.cn (Q. He); jihan@caas.cn(J. Han)

Nomenclature

BC	Black carbon	Mt	Megatons
CAY	China Agriculture Yearbook	NBSC	National Bureau of Statistics of China
CEADs	China Emission Accounts and Datasets	NMVOC	Non-methane volatile organic compounds
CEPY	China Electric Power Yearbook	NO_2	Nitrogen dioxide
CESY	China Energy Statistical Yearbook	OC	Organic carbon
CO	Carbon monoxide	PM	Particulate matter
CO_2	Carbon dioxide	PM10	Particulate Matter 10
DDF	Directional distance function	PM2.5	Particulate Matter 2.5
DEA	Data envelopment analysis	RAM	Range-adjusted measure
DMUs	Decision making units	SBMs	Slack-based models
Kt	Kilotons	SO_2	Sulfur dioxide
MCDB	Macro China Industry Database	tce	Tonne of coal equivalent
MEIC	Multi-resolution Emission Inventory for China		

1. Introduction

As the world's largest energy consumer as well as the leading emitter of carbon dioxide (Lin and Fei, 2015), China has been suffering from severe environmental pollution, especially air pollution, due to its energy-intensive industrial structure (Wang et al., 2016) and fossil fuel-based energy system, seriously restricting the sustainable development of its social economy and threatening the health of its citizens (MEP, 2012). During 2016, the air quality of 254 cities in China exceeded the National Ambient Air Quality Standards, accounting for 75.1% of 338 Chinese cities at the prefecture level and above, according to the annual report from the Ministry of Environmental Protection of China (MEP, 2017). Specifically, 71.5%, 58.3%, 17.5%, 3.0%, 16.9% and 3.0% cities suffered from air pollution due to PM2.5, PM10, O3, SO_2, NO_2 and CO, respectively (MEP, 2017).

Significant regional differences exist, and the air quality of northern China, especially that of the second- or third-tier cities in the Beijing-Tianjin-Hebei metropolis circle, is relatively heavier polluted, while people in the southeastern coastal cities enjoy cleaner air (MEP, 2017). This presents a dilemma for the Chinese government. On the one hand, rapidly growing demand in energy use with continued economic growth creates constant environmental pressure; on the other hand, the emergence of a growing middle class driven by economic growth in China increases the demand for air pollution control.

The Chinese government first committed to achieving a binding goal of reducing SO_2 emissions by 10% during its 11th Five-Year Period (2006-2010) (State Council, 2006). The prevention and control of air pollution targeting compound pollutants involving SO_2, NO_2, PM10 and PM2.5 in key regions of China was incorporated into the 12th Five-Year Plan(2011-2015)(MEP, 2012). In 2013, the State Council of China identified ten measures for the control of air pollution and established the goal of a 10% reduction in the nationwide concentration of PM (State Council, 2013). Accordingly, Beijing-Tianjin-Hebei, the Yangtze River Delta and the Pearl River Delta are recommended to cut concentration of PM by 25%, 20%, and 15%, respectively, from the 2012 levels by 2017 (State Council, 2013).

From the perspective of different sectors, taking 2010 as an example, for agriculture, its major air pollutant $NH_3$was estimated to be 9013.27 Kt according to the MEIC database[1], accounting for 92.35% of total national NH_3 emissions[2],without taking other greenhouse gases emitted from energy use or attributed to agricultural production into account. With regards to the power sector, China relies heavily on thermal power generation and mainly uses coal as its energy input, which inevitably produces large amounts of CO_2 and other air pollutants such as SO_2 andNO_2; these respectively accounted for 34.90%, 28.38% and 32.71% of the total amount in China. Furthermore, as a major supplier of most industrial products in the world, the energy

[1]See the detailed information for the MEIC in http://www.meicmodel.org/index.html. Emissions of air pollutants are all collected from the MEIC database, with energy consumption and corresponding CO2 emissions from the CEAD database; see http://www.ceads.net/.

[2]Here, the percentage of air pollutants is calculated by sectoral emission divided by aggregated emissions from agricultural, power, industry, residential and transportation sectors, and the same below.

consumption of China's industrial sector increased by 134% from 1996 to 2010 (Wang et al., 2016).The industrial sector represents51.00% of the total energy consumption in China and generates approximately 49.54% of CO_2 emissions as well as 58.60%of SO_2, 61.68% of NMVOC and 56.87% of PM10 in 2010. Although energy consumption and CO_2 emissions from the residential sector is relatively limited (both less than 10%), it produced 76552.02 (45.2%), 906.83(51.68%) and 2750.77 (81.41%) Kt of CO, BC and OC, respectively, in China in 2010, all of which are major precursors of PM and may increase rapidly with the rising standard of living. Meanwhile, the transportation sector's energy consumption is 268.73Mt standard coal (6.98%), with 536.66Mt (6.57%) of CO_2, 7000.87 Kt (24.54%) of NO_2, 273.65 (15.59%) Kt of BC and 20326.41Kt (11.95%) of CO. Infrastructure investment and energy consumption will be further stimulated by the huge transportation demand (Cui and Li, 2014).Therefore, the agricultural, power, industrial, residential and transportation sectors are all expected to play an important role in the reduction of air pollutant emissions in China. In the context of complex regional atmospheric pollution along with traditional coal-based air pollution, investigation into China's baseline environmental efficiency by major socioeconomic sector and a demonstration of regions with higher environmental efficiency is of great importance for the success of nationwide persistent air pollution governance in China.

Many studies are making an effort to incorporate data envelopment analysis (DEA)into the evaluation of environmental efficiency for China considering undesirable factors (see appendix Table A1) and are exploring environmental performance in different sectors, including agriculture (Lin and Fei, 2015; Fei and Lin, 2016, 2017), power generation (Zhou et al., 2013b; Bi et al., 2014; Lin and Yang, 2014; Song et al., 2017), industry (He et al., 2013; Zhou et al., 2013a; Wang and Wei, 2014; Wu et al., 2014; Bian et al., 2015; Xie et al., 2016) and transportation (Cui and Li, 2015; Zhang et al., 2015; Liu et al., 2016; Song et al., 2016), in addition to limited research regarding the residential sector without involving China (Haas, 1997; Grösche, 2009).

Most studies of agricultural efficiency evaluation target technical efficiency or energy efficiency related to CO_2 emissions reduction (Lin and Fei, 2015; Fei and Lin, 2016, 2017); however, these overlook the most significant air pollutant, NH_3, from agricultural sources as an undesirable output. Topics related to the industrial sectors of China include the evaluation of carbon efficiency (Emrouznejad and Yang, 2016; Zhang et al., 2016) and environmental efficiency taking NO_2 and SO_2(Wang et al., 2014; Wu et al., 2014; Bian et al., 2015) or waste gas, waste water and solid waste(He et al., 2013; Zhou et al., 2013a; Xie et al., 2016) as bad outputs, with decision making units (DMUs) varying from provinces to cities or firms in industrial sectors of China. In addition to studies considering CO_2 as an undesirable output (Lin and Yang, 2014),studies focusing on Chinese power sectors have given the most attention to emissions of SO_2 and NOx from thermal power generation (Zhou et al., 2013b; Bi et al., 2014; Song et al., 2017) Some studies confirm the need to evaluate environmental performance and sustainability in the residential sector (Haas, 1997; Grösche, 2009) but DEA analysis has not yet been applied to this sector in China, let alone taking air pollutants such as CO emitted from residents into consideration. Similarly, with the power and industrial sectors, a growing literature has examined carbon efficiency in the transportation sector of China (Cui and Li, 2015; Zhang et al., 2015; Liu et al., 2016), and some studies have incorporated air pollutants such as SO_2 (Song et al., 2016). However, based on the above, few studies have specialized in evaluating environmental efficiency considering the major air pollutants and providing a comprehensive decomposable picture of environmental efficiency based on the primary socioeconomic sectors of China for individual provinces.

In addition, although a series of DEA models have been employed in the literature for efficiency evaluation, such as the CCR model subject to the strong hypothesis of constant returns to scale and the DDF (He et al., 2013; Zhang et al., 2008), the BCC model (Xie et al., 2016) and the RAM model(Wang et al., 2016), as well as some developed SBMs, such as weighted, dynamic, super and network SBMs (Zhou et al., 2013a; Li and Shi, 2014; Lin and Yang, 2014; Wang and Feng, 2015; Song et al., 2017);these models cannot serve our purpose of identifying China's comprehensive provincial environmental efficiency performance in major sectors, especially considering that specific bad outputs such as PM are closely related (non-separable) to specific inputs such as coal consumption. Therefore, our paper tries to fill the gaps by employing a bad output model that takes into account non-separable situations related to inputs leading to undesirable outputs.

Thus, taking major air pollutants as an undesirable output in a non-separable bad output SBM model, this paper presents a comprehensive nationwide analysis of China's environmental efficiency based on a new comprehensive environmental efficiency index derived from evaluations of the primary socioeconomic sectors, including the agriculture, power, industry, residential and transport sectors, at the provincial level. The rest of this paper unfolds as follows. The second section introduces the methodology adopted in our paper. The variables and data information are described in the third section. The results and discussion are presented in Section 4. The final section concludes the paper and provides some research implications.

2. Methodology

With increasing environmental conservation awareness, the undesirable outputs of production and social activities, e.g., air pollutants and hazardous waste, are increasingly being recognized as dangerous and undesirable. Thus, the development of technologies emitting less undesirable outputs is an important subject of concern in every area of production and social life. The criterion of efficiency in DEA is usually to produce more outputs with lower resource inputs. In the presence of undesirable outputs, however, technologies with more good (desirable) outputs and fewer bad (undesirable) outputs relative to fewer inputs should be recognized as efficient. Thus, this paper addresses the Chinese environmental efficiency problem by applying a slack-based model, which is non-radial and non-oriented, and directly utilizing input and output slack to produce an efficiency measure, taking undesirable outputs into account based on Cooper et al.(2007); DEA Solver Pro 13.2 is used to perform the analysis.

2.1. An SBM with undesirable outputs

Suppose that there are n DMUs, each having three factors: inputs, good outputs and bad (undesirable) outputs, as represented by three vectors $x \in R^m$, $y^g \in R^{s_1}$ and $y^b \in R^{s_2}$, respectively. The matrices X, Y^g and Y^b are defined as follows. $X = [x_1, \cdots, x_n] \in R^{m\times n}$, $Y^g = [y_1^g, \cdots, y_n^g] \in R^{s_1\times n}$ and $Y^b = [y_1^b, \cdots, y_n^b] \in R^{s_2\times n}$. We assume that $X > 0$, $Y^g > 0$ and $Y^b > 0$.

The production possibility set (P) is defined by

$$P = \{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\} \tag{1}$$

Where $\lambda \in R^n$ is the intensity vector. This definition corresponds to the constant returns to scale technology.

Thus, a $DMU_o(x_o, y_o^g, y_o^b)$ is defined as being efficient in the presence of undesirable outputs if there is no vector $(x, y^g, y^b) \in P$ such that $x_o \geq x, y_o^g \leq y^g, y_o^b \geq y^b$ with at least one strict inequality.In accordance with this definition, the SBM is modified as follows:

[SBM-Undesirable] $$\rho^* = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{ro}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{ro}^b}\right)}$$

(2)

Subject to

$$x_o = X\lambda + s^- \tag{3}$$

$$y_o^g = Y^g\lambda - s^g \tag{4}$$

$$y_o^b = Y^b\lambda + s^b \tag{5}$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0$$

The vectors $s^- \in R^m$ and $s^b \in R^{s_2}$ correspond to excess inputs and badoutputs, respectively, while $s^g \in R^{s_1}$ expresses shortages in good outputs. Theobjective function (2) is strictly decreasing with respect to $s_i^-(\forall i), s_r^g(\forall r)$ and $s_r^b(\forall r)$, and the objective value satisfies $0 < \rho^* \leq 1$. Let an optimal solution of the above program be $(\lambda^*, s^{-*}, s^{g*}, s^{b*})$. Then, we have **Theorem1**:

The DMU_o is efficient in the presence of undesirable outputs if and only if $\rho^* = 1$, *i.e.*, $s^{-*} = 0.,\ s^{g*} = 0$ *and* $s^{b*} = 0$.

If the $\mathrm{DMU_o}$ is inefficient, *i.e.*, $\rho^* < 1$, it can be improved and become efficient by deleting the excess inputs and bad outputs and augmenting the shortfall in good outputs with the following SBM projection:

$$\widehat{\mathrm{x_o}} \leftarrow \mathrm{x_o} - s^{-*} \tag{6}$$

$$\widehat{\mathrm{y_o^g}} \leftarrow \mathrm{y_o^g} + s^{g*} \tag{7}$$

$$\widehat{\mathrm{y_o^b}} \leftarrow \mathrm{y_o^b} - s^{b*} \tag{8}$$

2.2. Non-separable ‘good’ and ‘bad’ output model

It is often observed that certain ‘bad’ outputs are not separable from the corresponding ‘good’ outputs; thus, reducing bad outputs inevitably results in a reduction in good outputs. In addition, a certain bad output is often closely related (non-separable)to a certain input. For example, in power generation, emissions of nitrogen oxides ($\mathrm{NO_x}$) and sulphur dioxide ($\mathrm{SO_2}$) (bad outputs) are proportional to the fuel inputs, which represents a non-separable case. To address this situation, Cooper et al. (2007) decomposed the set of good and bad outputs $(\mathrm{Y^g}, \mathrm{Y^b})$ into $(\mathrm{Y^{Sg}})$ and $(\mathrm{Y^{NSg}}, \mathrm{Y^{NSb}})$, where $\mathrm{Y^{Sg}} \in \mathrm{R}^{s_{11}\times n}$ and $(\mathrm{Y^{NSg}} \in \mathrm{R}^{s_{21}\times n}, \mathrm{Y^{NSb}} \in \mathrm{R}^{s_{22}\times n})$denote the separablegood outputsand non-separable good and bad outputs, respectively. The set of input X is decomposed into $(\mathrm{X^S}, \mathrm{X^{NS}})$, where $\mathrm{X^S} \in \mathrm{R}^{m_1\times n}$ and$\mathrm{X^{NS}} \in \mathrm{R}^{m_2\times n}$respectively denote the separable and non-separable inputs. For the separable outputs$\mathrm{Y^{Sg}}$, we have the same structure of production as $\mathrm{Y^g}$ inP. However, the non-separable outputs$(\mathrm{Y^{NSg}}, \mathrm{Y^{NSb}})$ need to be handled differently. The reduction of the bad outputs $\mathrm{y^{NSb}}$ is designated by $\alpha\mathrm{y^{NSb}}$, with $0 \le \alpha \le 1$;this is accompanied by proportionate reductions in the good outputs, $\mathrm{y^{NSg}}$, as denoted by $\alpha\mathrm{y^{NSg}}$and in the non-separable input, as denoted by $\alpha\mathrm{x^{NS}}$.

The new production possibility set $\mathrm{P_{NS}}$ under CRS is defined by

$$\mathrm{P_{NS}} = \left\{ \left(\mathrm{x^S}, \mathrm{x^{NS}}, \mathrm{y^{Sg}}, \mathrm{y^{NSg}}, \mathrm{y^{NSb}}\right) \middle| \begin{array}{l} \mathrm{x^S} \ge \mathrm{X^S}\lambda, \mathrm{x^{NS}} \ge \mathrm{X^{NS}}\lambda, \mathrm{y^{Sg}} \le \mathrm{Y^{Sg}}\lambda, \\ \mathrm{y^{NSg}} \le \mathrm{Y^{NSg}}\lambda, \mathrm{y^{NSb}} \ge \mathrm{Y^{NSb}}\lambda, \lambda \ge 0 \end{array} \right\} \tag{9}$$

Basically, this definition is a natural extension of P in(1). We alter the definition of the efficiency status in the non-separable case as follows:

A $\mathrm{DMU_o}\left(\mathrm{x_o^S}, \mathrm{x_o^{NS}}, \mathrm{y_o^{Sg}}, \mathrm{y_o^{NSg}}, \mathrm{y_o^{NSb}}\right)$ is calledNS-efficient if and only if (1) for any$\alpha$with$(0 \le \alpha < 1)$, we have$\left(\mathrm{x_o^S}, \mathrm{x_o^{NS}}, \mathrm{y_o^{Sg}}, \alpha\mathrm{y_o^{NSg}}, \alpha\mathrm{y_o^{NSb}}\right) \notin \mathrm{P_{NS}}$ and (2) there is no $\left(\mathrm{x^S}, \mathrm{x^{NS}}, \mathrm{y^{Sg}}, \mathrm{y^{NSg}}, \mathrm{y^{NSb}}\right) \in \mathrm{P_{NS}}$ such that $\mathrm{x_o^S} \ge \mathrm{x^S}, \mathrm{x_o^{NS}} = \mathrm{x^{NS}}$, $\mathrm{y_o^{Sg}} \le \mathrm{y^{Sg}}, \mathrm{y_o^{NSg}} = \mathrm{y^{NSg}}, \mathrm{y_o^{NSb}} = \mathrm{y^{NSb}}$ with at least one strict inequity.

An SBM with non-separable inputs and outputs can be implemented by the program in $(\lambda, \mathrm{s^{S-}}, \mathrm{s^{Sg}}, \alpha)$, as below:

[SBM-NS]

$$\rho^* = \min \frac{1 - \frac{1}{\mathrm{m}}\sum_{\mathrm{i=1}}^{\mathrm{m_1}} \frac{\mathrm{s_i^{S-}}}{\mathrm{x_{io}}} - \frac{\mathrm{m_2}}{\mathrm{m}}(1-\alpha)}{1 + \frac{1}{\mathrm{s}}\left(\sum_{\mathrm{r=1}}^{\mathrm{s_{11}}} \frac{\mathrm{s_r^{Sg}}}{\mathrm{y_{ro}^{Sg}}} + (\mathrm{s_{21}} + \mathrm{s_{22}})(1-\alpha)\right)} \tag{10}$$

Subject to

$$x_o^S = X^S\lambda + s^{S-} \quad (11)$$
$$\alpha x_o^{NS} \geq X^{NS}\lambda \quad (12)$$
$$y_o^{Sg} = Y^{Sg}\lambda - s^{Sg} \quad (13)$$
$$\alpha y_o^{NSg} \leq Y^{NSg}\lambda \quad (14)$$
$$\alpha y_o^{NSb} \geq Y^{NSb}\lambda \quad (15)$$
$$s^{S-} \geq 0, s^{Sg} \geq 0, \lambda \geq 0, 0 \leq \alpha \leq 1$$

where $m = m_1 + m_2$ and $s = s_{11} + s_{21} + s_{22}$.

The objective function is strictly monotone decreasing with respect to $s_i^{S-}(\forall i), s_r^{Sg}(\forall r)$ and α. Let an optimal solution for [SBM-NS] be $(\rho^*, \lambda^*, s^{S-*}, s^{Sg*}, \alpha^*)$, then we have $0 < \rho^* \leq 1$ and the following **Theorem 2** holds:

The DMUo is non-separable (NS)-efficient if and only if $\rho^* = 1$, *i.e.*, $s^{S-*} = 0, s^{Sg*} = 0, \alpha^* = 1$.

If the *DMU*$_o$ is NS-inefficient, *i.e.*, $\rho^* < 1$, it can be improved and become NS-efficient by the following NS projection:

$$\widehat{x_o}^S \leftarrow x_o^S - s^{S-*} \quad (16)$$
$$\widehat{x_o}^{NS} \leftarrow \alpha^* x_o^{NS} \quad (17)$$
$$\widehat{y_o}^{Sg} \leftarrow y_o^{Sg} + s^{Sg*} \quad (18)$$
$$\widehat{y_o}^{NSg} \leftarrow \alpha^* y_o^{NSg} \quad (19)$$
$$\widehat{y_o}^{NSb} \leftarrow \alpha^* y_o^{NSb} \quad (20)$$

It should be noted that it holds that

$$s^{NS-*} \equiv -\alpha^* x_o^{NS} + X^{NS}\lambda \geq 0 \quad (21)$$
$$s^{NSg*} \equiv -\alpha^* y_o^{NSg} + Y^{NSg}\lambda^* \geq 0 \quad (22)$$
$$s^{NSb*} \equiv \alpha^* y_o^{NSb} - Y^{NSb}\lambda^* \geq 0 \quad (23)$$

This means that some of the slack in non-separable inputs and outputs may remain positive even after the projection and that these slacks, if they exist, are not accounted for in the NS-efficiency score, since we assume a proportionate reduction (α^*) in these outputs. Thus, we apply the SBM for the separable outputs, whereas we employ the radial approach for the non-separable outputs.

In actual situations, it is often required that in addition to constraints (11)-(15), the total amount of good outputs should remain unchanged, and the expansion rate of separable good outputs should be bounded by an exogenous value. The former option is described as

$$\sum_{r=1}^{s_{11}}\left(y_{ro}^{Sg} + s_r^{Sg}\right) + \alpha\sum_{r=1}^{s_{21}} y_{ro}^{NSg} = \sum_{r=1}^{s_{11}} y_{ro}^{Sg} + \sum_{r=1}^{s_{21}} y_{ro}^{NSg} \quad (24)$$

where we assume that the measurement units are the same among all good outputs. The latter condition can be expressed as

$$\frac{s_r^{Sg}}{y_{ro}^{Sg}} \leq U, (\forall r) \quad (25)$$

where U is the upper bound to the expansion rate for the separable goodoutputs.

Furthermore, it is reasonable that the slacks in the non-separable (radial) bad outputs and non-separable inputs should affect the overall efficiency, since even the radial slacks are sources of inefficiency.

Summing all of these requirements, we have the following model for evaluating overall efficiency:

$$[\text{NS-Overall}] \qquad \rho^* = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m_1}\frac{s_i^{S-}}{x_{io}^{S}}-\frac{1}{m}\sum_{i=1}^{m_2}\frac{s_i^{NS-}}{x_{io}^{NS}}-\frac{m_2}{m}(1-\alpha)}{1+\frac{1}{s}\left(\sum_{r=1}^{s_{11}}\frac{s_r^{Sg}}{y_{ro}^{Sg}}+\sum_{r=1}^{s_{22}}\frac{s_r^{NSb}}{y_{ro}^{NSb}}+(s_{21}+s_{22})(1-\alpha)\right)} \tag{26}$$

Subject to

$$x_o^S = X^S\lambda + s^{S-} \tag{27}$$

$$\alpha x_o^{NS} = X^{NS}\lambda + s^{NS-} \tag{28}$$

$$y_o^{Sg} = Y^{Sg}\lambda - s^{Sg} \tag{29}$$

$$\alpha y_o^{NSg} \le Y^{NSg}\lambda \tag{30}$$

$$\alpha y_o^{NSb} = Y^{NSb}\lambda + s^{NSb} \tag{31}$$

$$\sum_{r=1}^{s_{11}}\left(y_{ro}^{Sg}+s_r^{Sg}\right)+\alpha\sum_{r=1}^{s_{21}}y_{ro}^{NSg} = \sum_{r=1}^{s_{11}}y_{ro}^{Sg}+\sum_{r=1}^{s_{21}}y_{ro}^{NSg} \tag{32}$$

$$\frac{s_r^{Sg}}{y_{ro}^{Sg}} \le U(\forall r) \tag{33}$$

$$s^{S-} \ge 0, s^{NS-} \ge 0, s^{Sg} \ge 0, s^{NSb} \ge 0, \lambda \ge 0, 0 \le \alpha \le 1$$

2.3. Decomposition of inefficiency

Using the optimal solution $\left(s^{S-*}, s^{NS-*}, s^{Sg*}, s^{NSb*}, \alpha^*\right)$ for [NS-Overall], we can decompose the overall efficiency indicator ρ^*into its respective inefficiencies as follows:

$$\rho^* = \frac{1-\sum_{i=1}^{m_1}\alpha_{1i}-\sum_{i=1}^{m_2}\alpha_{2i}}{1+\sum_{r=1}^{s_{11}}\beta_{1r}+\sum_{r=1}^{s_{21}}\beta_{2r}+\sum_{r=1}^{s_{22}}\beta_{3r}} \tag{34}$$

where

Separable input inefficiency: $\alpha_{1i} = \frac{1}{m}\frac{s_i^{S-*}}{x_{io}^{S}}$ $(i = 1,\cdots, m_1)$ (35)

Non-separable input inefficiency: $\alpha_{2i} = \frac{1}{m}(1-\alpha^*) + \frac{1}{m}\frac{s_i^{NS-*}}{x_{io}^{NS}} (i = 1,\cdots, m_2)$ (36)

Separable good output inefficiency:$\beta_{1r} = \frac{1}{s}\frac{s_r^{Sg*}}{y_{ro}^{Sg}} (r = 1,\cdots, s_{11})$ (37)

Non-separable good output inefficiency: $\beta_{2r} = \frac{1}{s}(1-\alpha^*)(r = 1,\cdots, s_{21})$ (38)

Non-separable bad output inefficiency:$\beta_{3r} = \frac{1}{s}(1-\alpha^*) + \frac{1}{s}\frac{s_r^{NSb*}}{y_{ro}^{NSb}} (r = 1,\cdots, s_{22})$ (39)

Expression (34) is useful for finding the sources of inefficiency and the magnitude of their influence on the efficiency score ρ^*.

2.4. A comprehensive environmental efficiency index

Suppose that there are k sectors of n provinces incorporated in this study; when we determine the environmental efficiency score vector $\rho_i^* \in R^k$ for each province i with the above non-separable ‘good’ and ‘bad’ output SBM, we can construct a comprehensive environmental efficiency index τ_i using the coefficient of variation method. The matrix P^* and the row vector τ are defined as follows: $P^* =$

$[\rho_1^*, \cdots, \rho_n^*] \in \mathrm{R}^{\mathrm{k}\times\mathrm{n}}$, $\tau = [\tau_1, \cdots, \tau_n] \in \mathrm{R}^{1\times\mathrm{n}}$.

The coefficient of variation CV_j for each sector j can be calculated as the ratio of the standard deviation to the mean of each row of matrix P^*; thus, the weight vector $\mathrm{W}=[\mathrm{w}_1, \cdots, \mathrm{w}_k] \in \mathrm{R}^{1\times\mathrm{k}}$ can be obtained (see the results of the weights in Table A2), where $\mathrm{w}_j = CV_j / \sum_{j=1}^{k} CV_j$, (j=1, ⋯,k). Finally, the comprehensive environmental efficiency index vector can be determine using the following relation: $\tau = WP^*$.

3. Variables and dataset

A total of 30 regions at the provincial level except for Tibet, due to partially missing environmental data, in Mainland China are selected as DMUs in this study, which is more than triple the number of inputs and outputs considered by Cooper et al. (2001). Variables involving inputs, desirable outputs and undesirable outputs are tailored based on the characteristics of different sectors, including agriculture, power, industry, residential and transport for provincial DMUs[3], with detailed definitions in Table 1. To examine the existence of the relationship among the inputs and outputs data set, we summarize the correlation analysis results in Table Axa-Axe of the appendix. The correlation coefficients between input indexes and output indexes are significantly positive, indicating an isotonic relationship. Also, the correlation coefficients between input indexes as well as output indexes show that they are not alternatives to each other and can be incorporated as inputs or outputs in the DEA framework simultaneously.

Table 1

Variables, definitions and data sources

Sector	Type	Indicator	Description	Data source
Agricultural	Inputs	Labour	Average annual number of employees in agricultural sector	Date's Data
		Capital	Fixed capital investment in agricultural sector	NBSC
		Fertilizer	Nitrogenous fertilizer used in agricultural sector	CAY
		Energy use	Energy use in agricultural sector	CEADs
	Desirable outputs	Value added	Agricultural value added	NBSC
	Undesirable outputs	CO_2	Direct CO_2 emissions from energy use in agricultural sector	CEADs
		NH_3	NH_3 emissions from agricultural sector	MEIC
Power	Inputs	Labour	Employment data of thermal power generation sector	MCDB
		Capital	Installed thermal generation capacity	MCDB
		Energy-related inputs	Coal inputs	Authors' calculation based on CESY
			Other fuel inputs	

[3] The reason these five sectors are selected and incorporated in our study is that they are regarded as major sources in the MEIC data base, which is where the emission data are derived. In particular, the residential sector data include air pollutants from both residential and commercial sectors, which cannot be divided manually.

	Desirable outputs	Power generation	Amount of generated thermal power	CESY CEPY
	Undesirable outputs	CO_2	CO_2 emissions from fossil fuel inputs in thermal power industry	Authors' calculation based on CEADs
		SO_2	SO_2 emissions from thermal power industry	MEIC
		NO_2	NH_3 emissions from thermal power industry	
		PM10	NH_3 emissions from thermal power industry	
Industry	Inputs	Labour	Annual average number of employees in agricultural industry	NBSC
		Capital	Fixed capital investment in industrial sector	
		Energy use	Energy use in industrial sector	CEADs
	Desirable outputs	Value added	Industrial value added	NBSC
	Undesirable outputs	CO_2	Direct CO_2 emissions from energy use in industrial sector and those from industrial processes	CEADs
		SO_2	SO_2 emissions from industrial sector	MEIC
		NMVOC	NMVOC emissions from industrial sector	
		PM10	PM10 emissions from industrial sector	
Residential	Inputs	Urban residential buildings	Floor space of urban residential buildings	Authors' calculation based on NBSC
		Rural residential buildings	Floor space of rural residential buildings	
		Appliances	Numbers of appliances in residential sector	Authors' calculation based on NBSC
		Energy use	Energy use in residential sector	CEADs
	Desirable outputs	Population	Provincial population by the end of 2010	NBSC
	Undesirable outputs	CO_2	Direct CO_2 emissions from energy use in residential sector	CEADs

		CO	CO emissions from industrial sector	MEIC
		BC	BC emissions from industrial sector	
		OC	OC emissions from industrial sector	
Transport	Inputs	Labour	Annual average number of employees in transportation, storage and post industries	NBSC
		Capital	Fixed capital investment in transportation, storage and post industries	
		Energy use	Energy use in transportation, storage and post industries	CEADs
	Desirable outputs	Value added	Value added in transportation, storage and post industries	NBSC
	Undesirable outputs	CO_2	Direct CO_2 emissions from energy use in transportation sector	CEADs
		NO_2	SO_2 emissions from transportation sector	MEIC
		CO	CO emissions from transportation sector	
		BC	BC emissions from transportation sector	

Notes: NBSC is available at http://www.stats.gov.cn/, MCDB at http://mcid.macrochina.com.cn/, Date’s Data at http://cndata.datesdata.com.cn/, CEADs at http://www.ceads.net/, MEIC at http://www.meicmodel.org/tools.html.

For the agricultural, power, industrial and transportation sectors, labour inputs are measured by the average annual number of employees in each sector (Zhang and Wei, 2015; Li and Lin, 2016). Capital inputs are indexed by the fixed capital investment in the agricultural, industrial and transportation sectors (Cui and Li, 2014; Wu et al., 2014) and measured by the installed thermal generating capacity in the power sector (Xie et al., 2012; Song et al., 2017).In addition, the amount of nitrogenous fertilizer used was regarded as an important input related to the pollution generated in the agricultural sector (Zhang et al., 2011).

In particular, energy-related input is regarded as an important resource for production as well as a major source of pollution for each sector (Choi et al., 2012; Du et al., 2016; Wu et al., 2016). In this paper, energy consumption involving 20 energy carriers such as coal, coke products, petroleum, natural gas, electricity and others are all converted into the standard coal equivalent. As 94.67% of thermal power generation was powered by coal in China in 2010, the energy-related inputs are divided into coal inputs and other fuel inputs to the power sector for each DMU. In addition, to evaluate the environmental efficiency of the residential sector, residential buildings, appliance usage[4]and residential energy use (Grösche, 2009) are taken as input variables.

The desirable output is expressed by the value added of the corresponding sector for agriculture, industry and transport (Wu et al., 2016),while the amount of power generation is considered for the power sector (Lin and Yang, 2014). In particular, with a certain amount of residential buildings, appliance usage and energy input, the larger the population being supported (Haas, 1997), the more efficient the DMU would be, and population has thus been treated as desirable output in this paper.

The undesirable outputs are considered to be twofold. On the one hand, CO_2 emissions are utilized to evaluate the environmental efficiency of each sector as associated with greenhouse gas emissions and climate change. On the other hand, confronting the greater and more serious air pollution within major economic circles such as Beijing-Tianjin-Hebei Region, nine types of air pollutants, including SO_2, NO_2, CO, NMVOC, NH_3, PM10, PM2.5, BC, OC(see detailed emission information in Table B1), are also considered in our study. However, due to total number limitations on inputs and outputs following the instructions of Cooper et al. (2001),we introduce a screening principle (see the screening results in Table B1) for air pollutant indicators in which the top three air pollutants are selected in accordance with the significance of the severity of the pollution in each sector. First, for a certain type of air pollutant, we calculate the % proportion of each sector in total emissions for each DMU. Then, the average value of this percentage within 30 DMUs can be easily obtained. Finally, the nine air pollutants are ranked by the value of the average proportion; for example, considering the industrial sector, SO_2, NMVOC and PM10 are selected as the top three significant pollutants emitted from industry. However, NH_3 is the only air pollutant indicator in the agricultural sector released by MEIC and is thus considered to be the most significant pollutant from agriculture (Wagner et al., 2017).

Data for the labour and capital input variables of each sector are collected from several sources, including the National Bureau of Statistics of China, Date's Data and the MCDB. The energy-related data of input variables are obtained from CEADs and the China Energy Statistical Yearbook. Data for desirable outputs such as the value added of each sector come from the National Bureau of Statistics of China. As for the undesirable outputs, CO_2 emissions are collected from CEADs and all other air pollutants are drawn from the MEIC dataset. All data are collected for the year 2010, and the descriptive statistics of the data set are summarized in Table B2 of Appendix B.

[4]Due to the various types of home appliances used in the residential sector and reported by the National Bureau of Statistics of China, here we calculate the principal component scores based on primary appliance data and then apply process normalization to satisfy the data demand of DEA, where the zero value was replaced by an infinitesimal 10^(-6) following the instruction of Cooper et al.(2007).

4. Results and discussion

4.1. Environmental efficiency analysis by sectors

Some findings can be observed from the sectoral results based on the non-separable bad output SBM shown in Fig.1 (detailed results can be seen in Table B3,and results from a conventional SBM with undesirable outputs are shown in Table B4for reference). For the agricultural sector, the environmental efficiency is relatively low, with a nationwide average score at 0.6035. Five provinces (Shanghai, Jiangsu, Hainan, Guangxi, Guangdong) operated along the production frontier in 2010,and all five lie in the coastal area of China (Qin et al., 2017).First, generally, the modernization level is higher in the eastern coastal areas of China, where agriculture has been gradually modernizing with the increased application of efficient agricultural technology (Zhai et al., 2009).Furthermore, the emerging middle class of China are concentrated in the developed eastern coastal provinces, which have a higher demand for green and ecological agriculture (Shi et al., 2011),giving birth to a new agricultural pattern with mutual assistance between urban and rural areas and citizen participation. Second, it can be found that most provinces with higher rankings in environmental efficiency have low proportions of animal husbandry in agriculture, generally less than 20% (MA, 2011), with the exception of Guangxi. Guangxi developed a circular economy in agriculture by promoting a series of measures such as standardization farming, water-saving irrigation, soil testing, formulated fertilization, nutrition diagnosis, waste disposal, biogas engineering, and breeding technology (MA, 2011). Taking soil testing and formulated fertilization as examples, these have been adopted in more than 90% of the administrative villages in Guangxi, and this has effectively reduced fertilizer use and agricultural costs (MA, 2011).

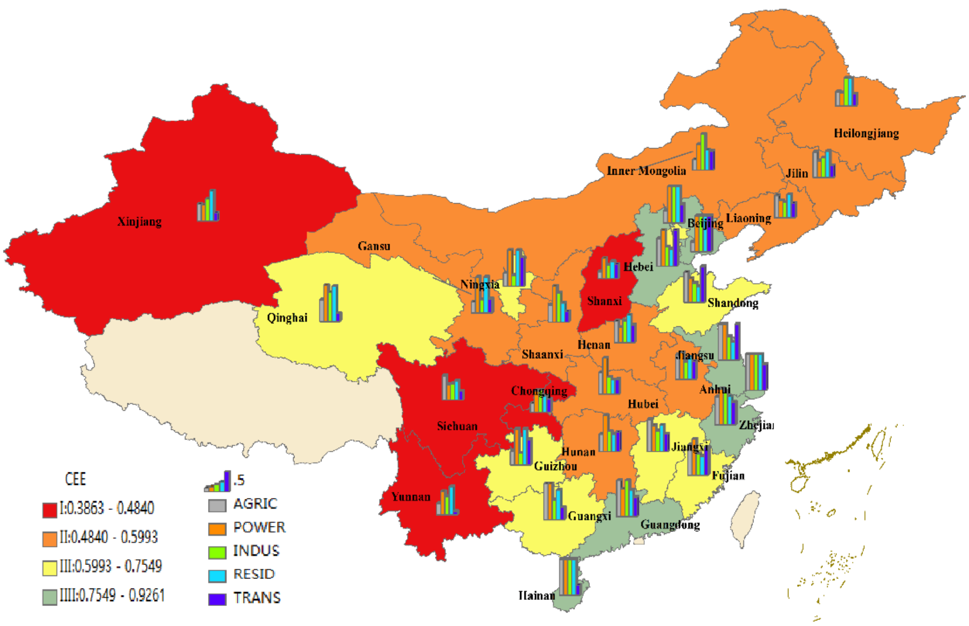

Fig. 1.Sectoral and Comprehensive environmental efficiency of China in 2010

Note: AGRIC, POWER, INDUS, RESID and TRANS represent the sectoral environmental efficiency of the agricultural, power, industry, residential and transportation sectors, respectively; CEE denotes the comprehensive environmental efficiency, which was categorized into 4 groups, where 'I' represent the lowest environmental efficiency based on natural breaks (Jenks) in ArcGIS 10.

Second, the thermal power industry of China had an average environmental efficiency score of 0.8014 in 2010, with more than half of the provinces operating along the production frontier; this group interestingly contains developed as well as less developed provinces, consistent with the results from Bi et al. (2014). The thermal power industry has achieved significant environmental development in China on account of the promotion of clean coal technology since 1997[5] and of flue gas desulphurization in thermal power plants during the11th Five-Year Plan[6]. As for the environmentally efficient DMUs, on the one hand, electricity consumption in the eastern coastal provinces of China largely rely on transfers from central and western regions, which have higher emissions and lower environmental efficiency, resulting in better energy-environmental performance per se (Bi et al., 2014). On the other hand, taking some provinces in northeast and central China as an example, the blind pursuit of capacity without considering the balance between supply and demand results in a heavy market with oversupply and a generator set with low energy efficiency (Lu et al., 2011)for low environmental efficiency over the long term.

Considering the industrial sector, the average environmental efficiency score in 2010 was 0.6471, indicating high potential for efficiency improvement. Only six provinces (Tianjin, Shanghai, Beijing, Inner Mongolia, Hainan, Guangdong) were shown to be environmentally efficient, with an efficiency score of 1, in 2010. Most of the environmentally efficient DMUs in industry have been experiencing a transition since 2000,as Tianjin has been focusing on the development of strategic emerging industries involving high-end equipment manufacturing, the new generation of information technology, energy conservation and environmental protection industries. Similarly, Shanghai has gradually been transforming its industry into cleaner high-tech based industries through the promotion of electronic information and high-end equipment manufacturing in addition to conducting sewage removal and replacing coal-fired boilers with alternative clean energy sources within traditional energy intensive industries. To facilitate energy conservation and emissions reduction, Guangdong has closed down backward and excess production facilities in energy intensive industries. The Beijing government has tried to lead the tertiary industry to dominate by shutting down or transferring environmentally polluting industrial enterprises. In particular, despite a weak foundation in industry, the development mode in Hainan is not at the expense of environment pollution, as it has assumed positioning as an international tourism island since 2010.

---

[5]See "The 9th Five-Year Plan of Chinese Clean Coal Technology and Development Outline in 2010" (In Chinese) in http://www.coal.com.cn/coalnews/articledisplay_82257.html.

[6]See the "The 11th Five-Year Plan for SO2 Treatment of Existing Coal-fired Power Plants" (In Chinese) in http://www.gov.cn/gzdt/2007-03/27/content_562672.htm.

The nationwide average score for environmental efficiency is 0.7196 for the residential sectors in China. The analysis shows that there are seven provinces (Tianjin, Shanghai, Beijing, Ningxia, Hainan, Gansu, Guizhou) with an environmental efficiency score of 1 in 2010. On the one hand, developed provinces including Tianjin, Shanghai and Beijing have a higher income level and standard of living, and the residential buildings in these provinces may be utilized with higher efficiency due to the concentration of population in these megacities. The second group includes Ningxia, Gansu, Guizhou and Hainan, which have less developed economies. Thus, the energy use per capita in their residential sectors would be much lower than the average national level due to limited purchasing power for domestic appliances and commercial energy products.

The average environmental efficiency score is shown to be low in the transportation sector, at 0.5179 for China in 2010, exhibiting the largest variation out of the five sectors. Tianjin, Shandong, Jiangsu, and Hebei are found to be operating along the production frontier in 2010.It is known that some provinces have taken a leading role in the development of green transportation, such as Tianjin, Shandong, Jiangsu and some cities in Hebei, where the construction of urban rail transit, number of electric buses and highway quality is among the best[7], and as a result, these have been selected to be pilot and demonstration provinces (cities) in China in 2015.

4.2. Comprehensive environmental efficiency and regional disparities

The results of the weighting of the sectoral efficiency using the coefficient of variation method are shown in Fig. 1 as well, and the details are summarized in Table B3. The index score of the comprehensive environmental efficiency for 30 DMUs varies from 0.3863 to 0.9261;the nationwide average score is 0.6383. Shanghai ranks at the top, while Shanxi is last. The best five following Shanghai are Jiangsu, Tianjin, Hainan and Zhejiang, while Yunnan, Chongqing, Sichuan, and Xinjiang follow Shanxi at the bottom. Taking Shanghai as an example, it operated along the production frontier (in an environmental context) in most sectors, including agriculture, power, industry and residential, with a transport efficiency score of 0.7203.

To examine the comprehensive environmental efficiency variation in different Chinese regions in 2010, the 30 provinces of China[8]are grouped into 7 areas, which are termed east (Anhui, Fujian, Jiangsu, Shandong, Shanghai, and Zhejiang), south (Guangdong, Guangxi, and Hainan), central (Henan, Hubei, Hunan, and Jiangxi), north (Beijing, Hebei, Inner Mongolia, Shanxi, and Tianjin), northwest (Gansu, Ningxia, Qinghai, Shaanxi, and Xinjiang), southwest (Chongqing, Guizhou, Sichuan, and Yunnan) and northeast (Heilongjiang, Jilin, and Liaoning),according to the history of administrative and geographical regionalization of China. A total of 30 DMUs are

[7] See more information on green transportation in Tianjin inhttp://www.chinahighway.com/news/2013/780610.php; Shandong in http://my.icxo.com/4056579/viewspace-1325981.html; and Jiangsu inhttp://news2.jschina.com.cn/system/2012/12/07/015471064.shtml. (In Chinese)

[8] Tibet, Taiwan, Hong Kong and Macao are not included in our analysis due to data limitations.

classified in accordance with the abovementioned pattern to study the differences in average efficiency across the seven areas; this is shown in Fig. 2.Someinteresting regional differences can be observed from the regionally averaged environmental efficiencies in China based on our evaluation.

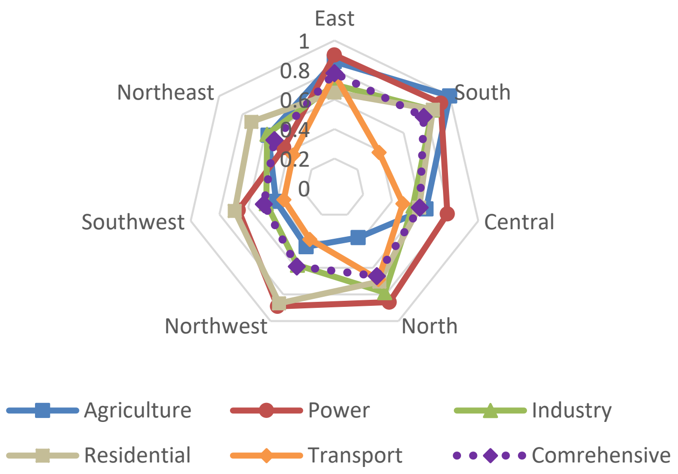

Fig. 2.Average efficiencies across seven regions of China.

Eastern China has the best comprehensive environmental performance, with an average score of 0.7789, followed by southern China, which has a score of 0.7746. Although the difference in the average index score is small, the potential reasons for the better environmental performance in eastern China may depend on the sector evaluation. In particular, eastern China has the highest economic development level, the greatest density of residents and, accordingly, the highest demand for transportation infrastructure; it therefore shows the best environmental performance in transportation in 2010. Green transportation and rail transit construction in eastern China has been at the forefront of the country since the 11th Five-Year Plan. For example, Jiangsu has been taking the lead in the reform of a major traffic management system, promoting the construction of comprehensive transportation systems to explore modernization and realize the preliminary implementation of an intelligent traffic system and green circulating low-carbon technology.

For southern China, agriculture in all three provinces operated along the production frontier; most areas within southern China have a tropical climate with good rainfall conditions. Thus, fertilizer inputs have a higher utilization efficiency. In addition, seaside locations contribute through the development of marine fishery and sea farming to low energy use and low emissions. The industrial sector of southern China is the most environmentally friendly and operates at the forefront of energy conservation and emissions reduction in China. Taking some southern provinces as examples, Hainan has targeted the international tourism market since 2010, while Guangdong has closed inefficient and outdated production facilities.

In contrast, southwestern, northeastern and northwestern China exhibit the worst performance, with average comprehensive environmental efficiencies of 0.4909, 0.5893 and 0.5212, respectively. Taking the industrial sector of southwestern China as an example, due to lying on the Qinghai-Tibet Plateau and within the Hengduan Mountains, provinces in southwestern China has the weakest industrial conditions and the lowest starting point of industrialization. In addition, the sulphur content in the coal of southwestern China is extremely high, making theSO_2 emissions per unit of industrial value added reach2.37 and2.91 (Kt/billion RMB), which is almost triple the national average (0.86 Kt/billion RMB).In addition, power generation in northeastern China has the lowest environmental efficiency. According to the National Energy Administration of China, there is a phenomenon called "Nest Electricity"[9], which is a serious issue in northeastern China that stems from limitations in the coupling components between the generator set, power plants, or local power grid. In these cases, extra power cannot be transferred to the major grid, leading to huge amounts of wasted electricity, which further indicates a lag of construction in power delivery.

4.3. Inefficiency decomposition and benchmarking analysis

Due to the application of an SBM in our study, in which an inefficient DMU can reduce its input and undesirable output simultaneously if it intends to achieve efficiency (Chen and Jia, 2017), the inefficiency score and the benchmarks for each DMU to be efficient by sector have been summarized in TablesB5-B9 in the appendix.

Taking Shanxi, which had the lowest comprehensive environmental efficiency in 2010, as an example, it ranks 30th, 24th, 27th, 25th and 19th out of 30 DMUs in the agriculture, power, industry, residential and transport sectors, respectively. Regarding agriculture in Shanxi, the inefficiencies are attributed to capital input that is higher than the effective level, and this should correspondingly be reduced by 15.35 billion RMB in 2010. Meanwhile, NH3 should be reduced by 17.81 tons in order to realize environmental efficiency in Shanxi. As a province located in the transition zone between cropping and nomadic areas, Shanxi should probably consider improving its feed nutrition formula and the development of a circular economy based on nitrogen uptake and utilization.

Ningxia, Guizhou, Gansu, Shanxi and Liaoning have the lowest environmental efficiency in the industrial sector in 2010. Ningxia, for example, should decrease labour, capital and energy use by 3.50 thousand people, 57.33 billion RMB and 10.33 tce, respectively, by benchmarking. Correspondingly, SO_2, PM10 and CO_2 should be reduced by 150.81 Kt, 43.94 Kt and 56.00 Mt.

For one of northeastern provinces, Heilongjiang, which was discussed above in terms of its low environmental efficiency in the power sector due to an over-supply problem, the power sector should be decreased by 95.48 thousand employees, 2594.0483 thousand kw of generation capacity, and 0.19 million tce of other fuel inputs to attain efficiency in power generation. In addition, it should also decrease its SO_2, NO_2, PM10 and CO_2 emissions by 29.03 Kt, 22.85 Kt, 28.46 Kt and 1.28 Mt, respectively, based on undesirable outputs.

According to the environmental evaluation of the residential sector, people in

[9] For more information, seehttp://zfxxgk.nea.gov.cn/auto84/201607/t20160711_2274.htm?keywords= (In Chinese).

Hubei, Shandong, Chongqing, Hebei and Hunan live a less environmentally friendly lifestyle; these are all provinces with a large population in China. For example, Hubei is shown to be in excess of the benchmark number of urban and rural residential buildings as well as appliances. In addition, CO, BC, OC and CO_2should respectively be reduced by 800.77 Kt, 12.41 Kt, 1.93 Kt and 1.68 Mt. Potentially, a high number of residential building per capita may lead to low efficiency in energy and resource utilization for the area and thus low environmental efficiency, where Hunan ranks top in the number of urban residential buildings, and all five provinces have rural residential buildings that are larger than the national average level per capita.

Yunnan has the second lowest comprehensive environmental efficiency, and it is the most environmentally inefficient in the transportation sector. To reach the benchmark in transportation, Yunnan would need decrease labour, capital and energy inputs by 129.27 thousand people, 78.00 billion RMB and 2.41 million tce, respectively, as well as reduce emissions by 15.88 Kt NO_2, 133.01 Kt CO and 5.05 Mt CO_2.

In particular, Fig. 3 shows the potential emissions reduction for CO_2 and three major air pollutants (SO_2, NO_2, PM10) for 30 DMUs based on the slack results for bad output excess in 2010. As for CO_2, the provinces in the north of China show the most reduction potential based on the benchmarking results. Without reducing desirable output, Shandong, Shanxi, Hebei, Henan and Liaoning can respectively reduce 352, 308, 306, 297 and 246 Mt CO_2 from the five socioeconomic sectors compared to 2010. With regard to pollution emissions, Shandong shows the greatest potential to reduce the most pollutants, with 1515, 121 and 752 Kt of SO_2, NO_2 and PM10, respectively, in order to reach its ideal benchmark point at the frontier of best practices, followed by Shanxi, Hubei, Chongqing and Henan for SO_2 reduction; Zhejiang, Anhui, and Guangdong for NO_2 reduction; and Henan, Shanxi, Hebei and Hunan for PM10 reduction. In particular, Inner Mongolia has the largest potential out of 30 DMUs for NO_2 reduction (170 Kt) from power generation and transportation. However, SO_2 and PM10 pollution is relatively more serious than NO_2 emissions, which implies that abatement measures need to be further taken to control the SO_2 and PM10 emissions to solve the increase in serious air pollution in China.

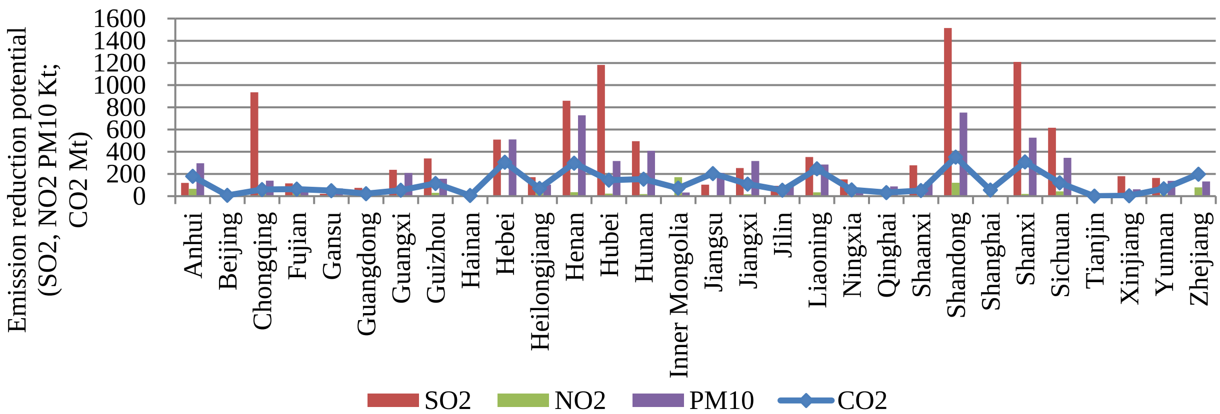

Fig. 3. Emission reduction potential for major air pollutants.

5. Conclusions and research implications

This paper presents a comprehensive environmental efficiency index based on evaluating environmental performance as related to the major air pollutant emissions of China's five socioeconomic sectors and weighting based on the coefficient of variation method. A non-separable bad output SBM model is adopted to investigate the variation in air pollutant emission performance across provinces to capture environmental efficiency by sector. In 2010, for the agricultural, power, industrial, residential and transportation sectors of China, 5, 16, 6, 7 and 4 provinces are at the production frontier. Particularly, the comprehensive environmental efficiency index for 30 provinces varied from 0.3863 to 0.9261, with a nationwide average score of 0.6383; Shanghai and Shanxi perform the best and worst, respectively. Based on an inefficiency decomposition and a benchmarking analysis, it can be found that inefficient DMUs can realize environmental efficiency by increasing their labour, capital, energy and other sector-specific inputs while decreasing undesirable air pollutants. In particular, it is shown that provinces in the north of China have the greatest potential for the emissions reduction of CO_2, while Shandong has potential forSO_2 and PM10 reduction and Inner Mongolia for NO_2 reduction.

From a regional perspective, it can be seen that there are great differences in the air pollutants emission performance by sector in the seven regions of China. In particular, southern China dominates in the agricultural, power and industrial sectors while eastern China has the best environmental performance in transportation. However, northeastern China show the largest improvement in environmental efficiency for power generationa long with southwestern China in industry. Less obvious differences in regional environmental efficiency can be observed in the residential sector. To conclude, given a target of maintaining nationwide sustainable development, the Chinese government should tailor emission reduction policies based on the environmental performance of different regions by sector, especially for those with the lowest comprehensive environmental efficiency. According to the analysis in this study, it is important to prioritize improvement in environmental efficiency for northeastern and southwestern China as well as to enhance the benchmarking effect of southern and eastern China in specific sectors.

However, it is advisable to recognize some limitations to this research and thus to follow those directions as future possible extensions. In the first place, only five major socioeconomic sectors have been incorporated at this point, leaving the commercial and construction sectors, among others, out of this accounting. Accordingly, it is important to acknowledge that the results should be interpreted with some caution where reduction potentials need to be considered as partial amounts and as a bottom line. Second, no attempt is made to measure environmental efficiency over time, which is certainly of great significance. Another limitation of the study is that the DMUs and input–output indicators were selected at the province level, but more targeted implications can be provided if air pollutant data aggregated at the city level or below by sector can be reported and analysed for China. Furthermore, there is a need for investment in certain sectors to improve their environmental efficiency; there is also a need for research to understand these actions. A logical extension of the present study would be to measure the relationship between the potential abatement actions by sector and a realistic improvement in environmental efficiency, which would make the evidence for reduction potential and strategies more convincing.

Acknowledgements

The research was funded by the National Key R&D Program of China (2016YFA0602604, 2016YFC0208801), China Postdoctoral Science Foundation (2016M591143) and the Basic Research Fund of Chinese Academy of Agricultural Sciences (2017). The authors would also like to thank the support from ESRC Centre for Climate Change Economics and Policy (CCCEP), University of Leeds as well as anonymous reviewers for their time and effort to improve this publication.

Appendices

Please see the online version of the article.

References

Bi, G.B., Song, W., Zhou, P., Liang, L., 2014. Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model. Energy Policy 66(C), 537-546. https://doi.org/10.1016/j.enpol.2013.10.056

Bian, Y., Liang N., Xu, H., 2015. Efficiency evaluation of Chinese regional industrial systems with undesirable factors using a two-stage slacks-based measure approach. J. Clean. Prod. 87(1), 348-356. https://doi.org/10.1016/j.jclepro.2014.10.055

Chen, L., Jia, G., 2017. Environmental efficiency analysis of China's regional industry: a data envelopment analysis (DEA) based approach. J. Clean. Prod. 142, 846-853. https://doi.org/10.1016/j.jclepro.2016.01.045

Choi, Y., Zhang, N., Zhou, P., 2012. Efficiency and abatement costs of energy-related CO_2, emissions in China: a slacks-based efficiency measure. Appl. Energy98(5), 198-208. https://doi.org/10.1016/j.apenergy.2012.03.024

Cooper, W.W., Li, S.L., Seiford, L.M., Tone, K., Thrall, R.M., Zhu, J., 2001. Sensitivity and stability analysis in DEA: some recent developments. J. Prod. Anal. 15(3), 217-246. http://www.jstor.org/stable/41770045

Cooper, W.W., Seiford, L.M., Tone, K., 2007. Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software, 2nd ed. Springer Science + Business Media, LLC.

Cui, Q., Li, Y., 2014. The evaluation of transportation energy efficiency: an application of three-stage virtual frontier DEA. Transport. Res. D-Tr. E. 29(6), 1-11. https://doi.org/10.1016/j.trd.2014.03.007

Cui, Q., Li, Y., 2015. An empirical study on the influencing factors of transportation carbon efficiency: evidences from fifteen countries. Appl. Energy 141, 209-217. https://doi.org/10.1016/j.apenergy.2014.12.040

Du, H., Matisoff, D.C., Wang, Y., Liu, X., 2016. Understanding drivers of energy efficiency changes in China. Appl. Energy 184, 1196-1206. https://doi.org/10.1016/j.apenergy.2016.05.002

Emrouznejad, A., Yang, G.L., 2016. A framework for measuring global Malmquist–Luenberger productivity index with CO_2, emissions on Chinese manufacturing industries. Energy 115, 840-856. https://doi.org/10.1016/j.energy.2016.09.032

Fei, R., Lin, B., 2016. Energy efficiency and production technology heterogeneity in China's agricultural sector: a meta-frontier approach. Technol. Forecast. Soc. 109, 25-34. https://doi.org/10.1016/j.techfore.2016.05.012

Fei, R., Lin, B., 2017. Technology gap and CO_2, emission reduction potential by technical efficiency measures: a meta-frontier modeling for the Chinese agricultural sector. Ecol. Indic. 73, 653-661. https://doi.org/10.1016/j.ecolind.2016.10.021

Grösche, P., 2009. Measuring residential energy efficiency improvements with DEA. J. Prod. Anal. 31(2), 87-94. DOI: 10.1007/s11123-008-0121-7

Haas, R., 1997. Energy efficiency indicators in the residential sector: What do we know and what has to be ensured? Energy Policy 25(7-9), 789-802. https://doi.org/10.1016/S0301-4215(97)00069-4

He, F., Zhang, Q., Lei, J., Fu, W., Xu, X., 2013. Energy efficiency and productivity change of China's iron and steel industry: accounting for undesirable outputs. Energy Policy54(54), 204-213. https://doi.org/10.1016/j.enpol.2012.11.020

Li, H., Shi, J.F., 2014. Energy efficiency analysis on Chinese industrial sectors: an improved Super-SBM model with undesirable outputs, J. Clean. Prod. 65(4), 97-107. https://doi.org/10.1016/j.jclepro.2013.09.035

Li, K., Lin, B., 2016. Impact of energy conservation policies on the green productivity in China's manufacturing sector: evidence from a three-stage DEA model. Appl. Energy 168, 351-363. https://doi.org/10.1016/j.apenergy.2016.01.104

Lin, B., Fei, R., 2015. Regional differences of CO_2, emissions performance in China's agricultural sector: a Malmquist index approach. Eur. J. Agron. 70, 33-40. https://doi.org/10.1016/j.eja.2015.06.009

Lin, B., Yang, L., 2014. Efficiency effect of changing investment structure on China's power industry. Renew. Sust. Energ. Rev. 39, 403-411. https://doi.org/10.1016/j.rser.2014.07.018

Liu, Z., Qin, C.X., Zhang, Y.J., 2016. The energy-environment efficiency of road and railway sectors in China: evidence from the provincial level. Ecol. Indic. 69, 559-570. https://doi.org/10.1016/j.ecolind.2016.05.016

Lu, R., Hou, X.G., Zhang, S.H., Zhang L.Y., Zhang, R.Q., 2011. Establishment of the evaluation index system of coal-fired power plants out-dated capacity and case research. Energy Conserv. 10, 32-38. (In Chinese)

Ministry of Agriculture (MA) of the People's Republic of China, 2011. China Agriculture Yearbook 2011. China Agriculture Press: Beijing.

Ministry of Environmental Protection (MEP) of the People's Republic of China, 2012. National Development and Reform Commission and Ministry of Finance of the People's Republic of China, Atmospheric pollution control plan of key regions for the 12th Five Years (In Chinese), see also: [EB/OL. http://www.zhb.gov.cn/gkml/hbb/bwj/201212/t20121205_243271.htm.]

Ministry of Environmental Protection (MEP) of the People's Republic of China, 2017. China Environmental State Bulletin 2016 (In Chinese), see also: [EB/OL.http://www.zhb.gov.cn/hjzl/zghjzkgb/lnzghjzkgb/201706/P020170605833655914077.pdf.]

Qin, Q., Li, X., Li, L., Zhen, W., Wei, Y.M., 2017. Air emissions perspective on energy efficiency: An empirical analysis of China's coastal areas. Appl. Energy 185, 604-614. https://doi.org/10.1016/j.apenergy.2016.10.127

Shi, Y., Cheng, C.W., Lei, P., Wen, T.J., Merrifield, C., 2011. Safe food, green food, good food: Chinese community supported agriculture and the rising middle class. Int. J. Agr. Sustain 9(4), 551-558. http://dx.doi.org/10.1080/14735903.2011.619327

Song, M., Zhang, G., Zeng, W., Liu, J., Fang, K., 2016. Railway transportation and environmental efficiency in China. Transport. Res. D-Tr. E. 48, 488-498. https://doi.org/10.1016/j.trd.2015.07.003

Song, W., Bi, G.B., Wu, J., Yang, F., 2017. What are the effects of different tax policies on China's coal-fired power generation industry? An empirical research from a network slacks-based measure perspective. J. Clean. Prod. 142, 2816-2827. https://doi.org/10.1016/j.jclepro.2016.10.187

State Council of the People's Republic of China, 2006. The 11th Five-Year Plan of national economic and social development of the People's Republic of China (In Chinese), see also: [EB/OL. http://www.gov.cn/gongbao/content/2006/content_268766.htm.]

State Council of the People's Republic of China, 2013. The action plan for the prevention and control of atmospheric pollution (In Chinese), see also: [EB/OL. http://zfs.mep.gov.cn/fg/gwyw/201309/t20130912_260045.shtml.]

Wagner, S., Angenendt, E., Beletskaya, O., Zeddies, J., 2017. Assessing ammonia emission abatement measures in agriculture: Farmers' costs and society's benefits – a case study for Lower Saxony, German. Agr. Syst. 157, 70-81. https://doi.org/10.1016/j.agsy.2017.06.008

Wang, J., Zhao, T., Zhang, X., 2016. Environmental assessment and investment strategies of provincial industrial sector in China — analysis based on DEA model. Environ. Imp. Assess. Rev. 60, 156-168. https://doi.org/10.1016/j.eiar.2016.05.002

Wang, K., Wei, Y.M., 2014. China's regional industrial energy efficiency and carbon emissions abatement costs. Appl. Energy 130, 617-631. https://doi.org/10.1016/j.apenergy.2014.03.010

Wang, Z., Feng, C., 2015. A performance evaluation of the energy, environmental, and economic efficiency and productivity in China: an application of global data envelopment analysis. Appl. Energy 147, 617-626. https://doi.org/10.1016/j.apenergy.2015.01.108

Wu, J., An, Q., Yao, X., Wang, B., 2014. Environmental efficiency evaluation of industry in China based on a new fixed sum undesirable output data envelopment analysis. J. Clean. Prod. 74(7), 96-104. https://doi.org/10.1016/j.jclepro.2014.03.054

Wu, J., Zhu, Q., Liang, L., 2016. CO_2, emissions and energy intensity reduction allocation over provincial industrial sectors in China. Appl. Energy 166, 282-291. https://doi.org/10.1016/j.apenergy.2016.01.008

Xie, B.C., Fan, Y., Qu, Q.Q., 2012. Does generation form influence environmental efficiency performance? An analysis of China's power system. Appl. Energy 96(1), 261-271. https://doi.org/10.1016/j.apenergy.2011.11.011

Xie, X.M., Zang, Z.P., Qi, G.Y., 2016. Assessing the environmental management efficiency of manufacturing sectors: evidence from emerging economies. J. Clean. Prod. 112, 1422-1431. https://doi.org/10.1016/j.jclepro.2015.08.006

Zhai, R., Liu, Y., 2009. Dynamic evolvement of agricultural system and typical patterns of modern agriculture in coastal China: a case of Suzhou. Chin. Geogra. Sci. 19(3), 249-257. DOI:10.1007/s11769-009-0249-z

Zhang, B., Bi, J., Fan, Z., Yuan, Z., Ge, J., 2008. Eco-efficiency analysis of industrial system in China: a data envelopment analysis approach. Ecol. Econ. 68(1-2), 306-316. https://doi.org/10.1016/j.ecolecon.2008.03.009

Zhang, N., Wei, X., 2015. Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. Appl. Energy 146, 409-420. https://doi.org/10.1016/j.apenergy.2015.01.072

Zhang, N., Zhou, P., Kung, C.C., 2015. Total-factor carbon emission performance of the Chinese transportation industry: a bootstrapped non-radial Malmquist index analysis. Renew. Sust. Energ. Rev. 41, 584-593. https://doi.org/10.1016/j.rser.2014.08.076

Zhang, Y., Luan, S., Chen, L., Shao, M., 2011. Estimating the volatilization of ammonia from synthetic nitrogenous fertilizers used in China. J. Environ. Manage. 92(3), 480-493. https://doi.org/10.1016/j.jenvman.2010.09.018

Zhang, Y.J., Hao, J.F., Song, J., 2016. The CO_2, emission efficiency, reduction potential and spatial clustering in China's industry: evidence from the regional level. Appl. Energy 174, 213-223. https://doi.org/10.1016/j.apenergy.2016.04.109

Zhou, Y., Liang, D., Xing, X., 2013a. Environmental efficiency of industrial sectors in China: An improved weighted SBM model. Math. Comput. Model. 58(5-6), 990-999. https://doi.org/10.1016/j.mcm.2012.09.021

Zhou, Y., Xing, X., Fang, K., Liang, D., Xu, C., 2013b. Environmental efficiency analysis of power industry in China based on an entropy SBM model. Energy Policy 57(7), 68-75. https://doi.org/10.1016/j.enpol.2012.09.060