Oper Res Int J (2017) 17:715–735
DOI 10.1007/s12351-015-0203-z

ORIGINAL PAPER

Measuring energy and environmental performance for regions in China by using DEA-based Malmquist indices

Jie Wu[1] · Qingyuan Zhu[1] · Pengzhen Yin[1] · Malin Song[2]

Received: 19 May 2015 / Revised: 28 August 2015 / Accepted: 7 September 2015 /
Published online: 16 September 2015
© Springer-Verlag Berlin Heidelberg 2015

Abstract China's rapid economic development has intensified the country's many problems in the areas of energy shortage and environmental pollution. However, little research has been done which pays close attention to the evaluation of energy and environmental performance even though such evaluation is considered a crucial method in the fight to save energy, protect the environment, and mitigate global climate change. In this study, we utilize improved data envelopment analysis (DEA) models to evaluate the regional total-factor energy and environmental efficiency of China during the 11th 5-year plan period (2006–2010). The total-factor energy and environmental efficiency is considered using a joint production framework of both non-energy inputs and energy inputs, as well as desirable outputs and undesirable outputs. In addition, the DEA-based Malmquist index is applied to evaluate the dynamic productivity change considering the undesirable outputs and energy inputs. An empirical study is done on 30 of mainland China's provincial-level regions, showing that most of them have low energy and environmental efficiency. On average, eastern China had the highest energy and environmental efficiency, followed by central China, with the efficiency of western China being the worst.

✉ Jie Wu
jacky012@mail.ustc.edu.cn

Qingyuan Zhu
zqyustc@mail.ustc.edu.cn

Pengzhen Yin
yinpz@mail.ustc.edu.cn

Malin Song
songmartin@163.com

[1] School of Management, University of Science and Technology of China, Hefei 230026, Anhui Province, People's Republic of China

[2] School of Statistics and Applied Mathematics, Anhui University of Finance and Economics, Bengbu 233030, Anhui Province, People's Republic of China

Considering the Malmquist index, most regions' productivity improved each year of 2006–2010. In addition, most regions had a declining trend in technical efficiency even though most regions had an increasing trend in technical progress.

Keywords Data envelopment analysis · Undesirable outputs · Energy and environmental performance · Malmquist index

1 Introduction

Since mainland China's economic reform and opening policy started in 1978, China's economy has seen remarkable development. According to the National Bureau of Statistics of China (NBSC), the average annual growth rate of China's gross domestic product (GDP) has increased 15.73 % from 1979 to 2013. This increasing trend has made China the second largest economy in the world following the United States (Bi et al. 2012). With the rapid development of its economy, China's energy consumption is also growing rapidly. For example, Wang (2010) indicated that China has already overtaken the United States to become the world's largest energy consumer. The rapidly increasing energy consumption inevitably has caused serious environmental problems (Wang et al. 2007, 2013a; Song et al. 2014; Wu et al. 2015). Therefore, the energy shortage and environmental problems have already become significant difficulties for the economic growth and societal development of China (Zhou et al. 2008a; Wu et al. 2013, 2014a, b; Saharidis 2015).

In order to balance rational utilization of energy, environmental pollution, and sustainable development, many energy and environmental regulations have been strengthened by the Chinese government. For example, for the 11th 5-year plan effective from 2006 to 2010, China's central government set a target of reducing the energy consumption of per unit of GDP by 20 % and the main pollutant total emissions by 10 %. Evaluating energy and environmental performance has attracted increasing interest in recent years since it is considered a crucial method to save energy, protect the environment, and mitigate global climate change (Wang et al. 2013a). Since different regions of China may have different energy consumption structures and different environmental protection policies, the regional energy and environmental performances within China may have big differences across different regions (Wang et al. 2013b). Hence, in order to save energy and protect the environment, it is necessary to evaluate China's regional energy and environmental efficiency.

Traditionally, there are two main approaches for measuring efficiency. One is the parametric stochastic frontier analysis (SFA) approach; the other is the nonparametric data envelopment analysis (DEA) approach (Coelli et al. 2005). Wu et al. (2014a, b) indicated that the SFA approach is suitable only for one-output scenarios and the results largely depend on the predicted forms of the production functions. Therefore, incorrect results may be obtained due to using an incorrect form of production function. Developed by Charnes et al. (1978), DEA is a programming-based technique for measuring the relative efficiency of a group of homogenous decision making units (DMUs) (Cooper et al. 2007; Song et al. 2013; Cook and

Seiford 2009; Sharma and Yu 2013; Yang et al. 2015a, b). As a nonparametric technique, DEA does not need any prior functional form of the production frontier and can effectively measure the efficiency of a system with multiple inputs and multiple outputs (Smirlis et al. 2012; Panta et al. 2013; Huang et al. 2015; Wu et al. 2009). In the past years, DEA has been extensively applied in the performance evaluation and benchmarking of hospitals (e.g. Karagiannis and Velentzas 2012; Dimas et al. 2012), supply chains of enterprises (e.g. Chen et al. 2006), and other entities (e.g. Halkos et al. 2015; Shabani et al. 2012; Ibanez and McCalley 2011; Tsolas and Charles 2015). Since any economic activity is a joint production process using energy resources (coal, oil, etc.) and other non-energy resources (capital, labor, etc.) to produce desirable outputs (GDP) and undesirable outputs (CO_2, wastes, etc.), DEA is used to construct the framework of total-factor efficiency evaluation in this paper.

Recently, DEA has been widely applied to studying energy and environmental efficiency. As for energy efficiency, Ramanathan (2000) compared the energy efficiencies of alternative transport modes by using DEA. Hu and Wang (2006) applied DEA models to analyze the total factor energy efficiency index of 29 administrative regions in China for the period 1995–2002. Hu and Lee (2008) employed DEA methods to measure the energy utility efficiency of China. Yeh et al. (2010) measured the technical efficiency of energy utilization in the Chinese mainland and Taiwan by using the traditional BCC model (Banker et al. 1984). Wu (2012) presented several DEA models to evaluate industrial energy efficiency in 28 of China's regions.

As for environmental efficiency, Färe et al. (1989) made the first attempt to deal with undesirable outputs while using nonlinear programming. Seiford and Zhu (2002) applied a radial DEA model, considering undesirable outputs, to improve the environmental efficiency by decreasing undesirable outputs and increasing desirable outputs. Using DEA techniques, Zhou et al. (2008b) divided outputs into desirable and undesirable to calculate the carbon emission efficiency of eight world regions. Song and Wang (2014) calculated China's regional environmental efficiency for 1992, 1999, 2007, and 2012, and then decomposed the provincial environmental efficiency from the perspective of government regulation and technological progress. Yang et al. (2015a, b) measured the environmental efficiency of China based on an environmental super-efficiency DEA model using data of 30 provinces in China during the period 2000–2010.

In addition, there is also some literature that directly addresses combined energy and environmental efficiency. For example, Bian and Yang (2010) employed several DEA models for estimating resource efficiencies and environment efficiencies simultaneously. Shi et al. (2010) measured the energy and environmental overall technical efficiency, pure technical efficiency, and scale efficiency of 28 administrative regions in China based on three extended DEA models. Wang et al. (2012) established several DEA efficiency models based on environmental production technology to estimate the environmental efficiency, economic efficiency, and economic-environmental efficiency of 28 provinces in China. Wang et al. (2013a) applied the range-adjusted measure based on a nonparametric approach to evaluate the regional energy and environmental efficiency of China over the period 2006–2010. Wang et al. (2013b) utilized a DEA window analysis technique to measure the energy and environmental efficiency in cross-sectional and time-varying data of 29 administrative regions of China during the period 2000–2008.

In this paper, following Bian and Yang (2010) and Wang et al. (2013b), we propose an improved DEA model to measure the total-factor energy and environmental efficiency of 30 provincial-level regions in mainland China during the 11th 5-year plan period (2006–2010). In particular, our proposed total-factor energy and environmental efficiency measure considers a joint production framework of non-energy inputs (labor and capital) and energy input (total energy consumption), as well as a desirable output (GDP) and an undesirable output (waste gas). In addition, in order to reflect the dynamic efficiency and productivity change considering the undesirable output and energy input, a DEA-based Malmquist index method is utilized in our paper. The Malmquist index is further classified into the change in technical efficiency (TEC) and the change in technical progress (TPC) in order to reflect the trends of those two aspects.

The structure of this paper is as follows. Section 2 presents the methodology of our study. Then the energy and environmental efficiency and Malmquist index of different regions and areas in China during the period 2006–2010 are analyzed in Sect. 3. Finally conclusions are shown in Sect. 4.

2 Methodology

In this section, we firstly present a non-radial DEA model to evaluate the total-factor energy and environmental efficiency. Then we explore the total-factor energy and environmental efficiency by applying DEA-based Malmquist indices to analyze the efficiency and productivity changes over time.

2.1 DEA model for evaluating the energy and environmental performance

Suppose that there are n DMUs denoted by DMU_j ($j = 1,\ldots,n$), and each of them represents an administrative region of China. Each DMU_j ($j = 1,\ldots,n$) consumes m non-energy inputs denoted by $\mathbf{X} = (X_{1j}, X_{2j}, \ldots, X_{mj})^T$ and d energy inputs denoted by $\mathbf{E} = (E_{1j}, E_{2j}, \ldots, E_{dj})^T$ to produce s desirable outputs denoted by $\mathbf{Y} = (Y_{1j}, Y_{2j}, \ldots, Y_{sj})^T$ along with p undesirable outputs denoted by $\mathbf{F} = (F_{1j}, F_{2j}, \ldots, F_{pj})^T$.

In the DEA literature, there have been a variety of approaches to dealing with undesirable outputs, which can be mainly divided into two categories (Song et al. 2012; Chen and Delmas 2012). The first one is based on the weak disposability assumption of undesirable outputs (Färe et al. 1989, 2005; Zhou et al. 2012) and the second category on the strong disposability assumption on undesirable output. Two ways for treating undesirable output under this latter assumption have been proposed. One way treats undesirable outputs as inputs (Tyteca 1997; Shi et al. 2010; Macpherson et al. 2013); the other way is a transformation method which contains a non-linear or linear monotonic decreasing transformation (Scheel 2001; Seiford and Zhu 2002). In this paper, the weak disposability assumption of undesirable outputs is chosen for building our new DEA models since it is prevalent in DEA literature. The corresponding DEA production technology T exhibiting constant returns to scale (CRS) can be characterized as follows:

$$
\begin{aligned}
T = \{(\mathbf{X},\mathbf{E},\mathbf{Y},\mathbf{F})| \quad & \sum_{j=1}^{n}\lambda_j X_{ij} \le \mathbf{X_i}, && i = 1,\ldots,m \\
& \sum_{j=1}^{n}\lambda_j E_{kj} \le \mathbf{E_k}, && k = 1,\ldots,d \\
& \sum_{j=1}^{n}\lambda_j Y_{rj} \ge \mathbf{Y}_r, && r = 1,\ldots,s \\
& \sum_{j=1}^{n}\lambda_j F_{gj} = \mathbf{F}_g, && g = 1,\ldots,p \\
& \lambda_j \ge 0, && j = 1,\ldots,n\}
\end{aligned}
\tag{1}
$$

In this study, the undesirable outputs are generated by fuel combustion during the industrial production process. The corresponding undesirable outputs should be reduced if energy consumption is reduced. Therefore, following Shi et al. (2010) and Wang et al. (2013b), we first provide the following radial DEA-based model for evaluating the DMU_0's total-factor energy and environmental performance as

$$
\begin{aligned}
Min \quad & \theta \\
s.t. \quad & \sum_{j=1}^{n}\lambda_j X_{ij} \le X_{i0}, && i = 1,\ldots,m \\
& \sum_{j=1}^{n}\lambda_j E_{kj} \le \theta E_{k0}, && k = 1,\ldots,d \\
& \sum_{j=1}^{n}\lambda_j Y_{rj} \ge Y_{r0}, && r = 1,\ldots,s \\
& \sum_{j=1}^{n}\lambda_j F_{gj} = \theta F_{g0}, && g = 1,\ldots,p \\
& \lambda_j \ge 0, && j = 1,\ldots,n
\end{aligned}
\tag{2}
$$

Note that model (2) proportionally decreases the amounts of energy inputs and undesirable outputs as much as possible for a given level of non-energy inputs and desirable outputs. Obviously, the index θ for energy and environmental efficiency is between 0 and 1. The larger the index, the better the corresponding region performs both in saving energy and protecting the environment.

Once the optimal solutions (θ^*, λ_j^*) are obtained by solving model (2), we can determine each DMU's efficient targets for all inputs/outputs as $\left(\sum_{j=1}^{n}\lambda_j^* X_{ij}, \sum_{j=1}^{n}\lambda_j^* E_{kj}, \sum_{j=1}^{n}\lambda_j^* Y_{rj}, \sum_{j=1}^{n}\lambda_j^* F_{tj}\right)$.

The above total-factor energy and environmental efficiency measure is a kind of radial DEA efficiency index. Zhou et al. (2007) and Zhou and Ang (2008) indicated that this radial measure may have weak discriminating power in energy and environmental efficiency comparisons. Therefore, following Bian and Yang (2010) and Wang et al. (2013b), we extend the radial energy and environmental efficiency measure to the following non-radial measure.

$$
\begin{aligned}
& Min \quad \frac{1}{2}\left(\frac{1}{d}\sum_{k=1}^{d}\theta_k+\frac{1}{p}\sum_{g=1}^{p}\theta_g\right) && \\
& s.t. \quad \sum_{j=1}^{n}\lambda_j X_{ij}\le X_{i0}, && i=1,\ldots,m \\
& \qquad \sum_{j=1}^{n}\lambda_j E_{kj}\le \theta_k E_{k0}, && k=1,\ldots,d \\
& \qquad \sum_{j=1}^{n}\lambda_j Y_{rj}\ge Y_{r0}, && r=1,\ldots,s \\
& \qquad \sum_{j=1}^{n}\lambda_j F_{gj}= \theta_g F_{g0}, && g=1,\ldots,p \\
& \qquad \lambda_j\ge 0, && j=1,\ldots,n
\end{aligned}
\tag{3}
$$

Model (3) can evaluate the energy and environmental efficiency by using different non-proportional adjustments for any energy inputs and undesirable outputs. In other words, this measure can account for energy input mix effects and undesirable output mix effects when measuring DMU energy and environmental efficiency. In addition, we should point out that the energy and environmental efficiency is measured by using different non-proportional adjustments and the unified efficiency is calculated through a decision maker specified weight assigned to each of these two efficiency scores. Similar to Bian and Yang (2010) and Wang et al. (2013b), the weights are both set to 1/2 in this paper, but the decision makers also could assign different weights to these scores to represent different preferences between energy utilization performance and environmental protection performance.

2.2 DEA-based Malmquist index for evaluating the dynamic performance

In this study, we evaluate the energy and environmental efficiency of different regions in China not only for a single year but for the 11th 5-year plan from 2006 to 2010, which may be considered a dynamic evaluation and could provide us with more useful information about efficiency changes. Developed by Malmquist (1953), the Malmquist index has been widely applied in DEA literature for evaluating dynamic efficiency (e.g. Färe et al. 1994; Mahadevan 2002; Chen and Ali 2004; Camanho and Dyson 2006). Therefore, we extend the Malmquist index analysis for use in the dynamic evaluation of energy and environmental performance.

Let $(\mathbf{X}^t, \mathbf{E}^t, \mathbf{Y}^t, \mathbf{F}^t)$ denote the production process of period t, $t = 1,\ldots,T$. Then the Malmquist index can be defined using the results of the following four steps.

1. Compare $(\mathbf{X}_0^t, \mathbf{E}_0^t, \mathbf{Y}_0^t, \mathbf{F}_0^t)$ to the empirical production frontier (EPF) at time t, i.e., calculate $\theta_0^t(\mathbf{X_0^t}, \mathbf{E_0^t}, \mathbf{Y_0^t}, \mathbf{F_0^t})$ via the following linear program:

$$\begin{aligned}
\theta_0^t\left(\mathbf{X_0^t},\mathbf{E_0^t},\mathbf{Y_0^t},\mathbf{F_0^t}\right) = Min\frac{1}{2}&\left(\frac{1}{d}\sum_{k=1}^{d}\theta_k+\frac{1}{p}\sum_{g=1}^{p}\theta_g\right)\\
s.t.\quad &\sum_{j=1}^{n}\lambda_j X_{ij}^t \le X_{i0}^t, \qquad i=1,\ldots,m\\
&\sum_{j=1}^{n}\lambda_j E_{kj}^t \le \theta_k E_{k0}^t, \quad k=1,\ldots,d\\
&\sum_{j=1}^{n}\lambda_j Y_{rj}^t \ge Y_{r0}^t, \qquad r=1,\ldots,s\\
&\sum_{j=1}^{n}\lambda_j F_{gj}^t = \theta_g F_{g0}^t, \quad g=1,\ldots,p\\
&\lambda_j \ge 0, \qquad j=1,\ldots,n
\end{aligned} \tag{4}$$

2. Compare $(\mathbf{X}_0^{t+1},\mathbf{E}_0^{t+1},\mathbf{Y}_0^{t+1},\mathbf{F}_0^{t+1})$ to the empirical production frontier (EPF) at time $t+1$, i.e., calculate $\theta_0^{t+1}(\mathbf{X_0^{t+1}},\mathbf{E_0^{t+1}},\mathbf{Y_0^{t+1}},\mathbf{F_0^{t+1}})$ via the following linear program:

$$\begin{aligned}
\theta_0^{t+1}\left(\mathbf{X_0^{t+1}},\mathbf{E_0^{t+1}},\mathbf{Y_0^{t+1}},\mathbf{F_0^{t+1}}\right) = Min\frac{1}{2}&\left(\frac{1}{d}\sum_{k=1}^{d}\theta_k+\frac{1}{p}\sum_{g=1}^{p}\theta_g\right)\\
s.t.\quad &\sum_{j=1}^{n}\lambda_j X_{ij}^{t+1} \le X_{i0}^{t+1}, \qquad i=1,\ldots,m\\
&\sum_{j=1}^{n}\lambda_j E_{kj}^{t+1} \le \theta_k E_{k0}^{t+1}, \quad k=1,\ldots,d\\
&\sum_{j=1}^{n}\lambda_j Y_{rj}^{t+1} \ge Y_{r0}^{t+1}, \qquad r=1,\ldots,s\\
&\sum_{j=1}^{n}\lambda_j F_{gj}^{t+1} = \theta_g F_{g0}^{t+1}, \quad g=1,\ldots,p\\
&\lambda_j \ge 0, \qquad j=1,\ldots,n
\end{aligned} \tag{5}$$

3. Compare $(\mathbf{X}_0^t,\mathbf{E}_0^t,\mathbf{Y}_0^t,\mathbf{F}_0^t)$ to the empirical production frontier (EPF) at time $t+1$, i.e., calculate $\theta_0^{t+1}(\mathbf{X_0^t},\mathbf{E_0^t},\mathbf{Y_0^t},\mathbf{F_0^t})$ via the following linear program:

$$\begin{aligned}
\theta_0^{t+1}\left(\mathbf{X_0^t},\mathbf{E_0^t},\mathbf{Y_0^t},\mathbf{F_0^t}\right) &= Min\frac{1}{2}\left(\frac{1}{d}\sum_{k=1}^{d}\theta_k+\frac{1}{p}\sum_{g=1}^{p}\theta_g\right)\\
s.t.\quad & \sum_{j=1}^{n}\lambda_j X_{ij}^{t+1}\le X_{i0}^{t}, \qquad i=1,\ldots,m\\
& \sum_{j=1}^{n}\lambda_j E_{kj}^{t+1}\le \theta_k E_{k0}^{t}, \quad k=1,\ldots,d\\
& \sum_{j=1}^{n}\lambda_j Y_{rj}^{t+1}\ge Y_{r0}^{t}, \qquad r=1,\ldots,s\\
& \sum_{j=1}^{n}\lambda_j F_{gj}^{t+1}= \theta_g F_{g0}^{t}, \quad g=1,\ldots,p\\
& \lambda_j\ge 0, \qquad j=1,\ldots,n
\end{aligned} \tag{6}$$

4. Compare $(\mathbf{X}_0^{t+1},\mathbf{E}_0^{t+1},\mathbf{Y}_0^{t+1},\mathbf{F}_0^{t+1})$ to the empirical production frontier (EPF) at time $t+1$, i.e., calculate $\theta_0^{t}(\mathbf{X_0^{t+1}},\mathbf{E_0^{t+1}},\mathbf{Y_0^{t+1}},\mathbf{F_0^{t+1}})$ via the following linear program:

$$\begin{aligned}
\theta_0^{t}\left(\mathbf{X_0^{t+1}},\mathbf{E_0^{t+1}},\mathbf{Y_0^{t+1}},\mathbf{F_0^{t+1}}\right) &= Min\frac{1}{2}\left(\frac{1}{d}\sum_{k=1}^{d}\theta_k+\frac{1}{p}\sum_{g=1}^{p}\theta_g\right)\\
s.t.\quad & \sum_{j=1}^{n}\lambda_j X_{ij}^{t}\le X_{i0}^{t+1}, \qquad i=1,\ldots,m\\
& \sum_{j=1}^{n}\lambda_j E_{kj}^{t}\le \theta_k E_{k0}^{t+1}, \quad k=1,\ldots,d\\
& \sum_{j=1}^{n}\lambda_j Y_{rj}^{t}\ge Y_{r0}^{t+1}, \qquad r=1,\ldots,s\\
& \sum_{j=1}^{n}\lambda_j F_{gj}^{t}= \theta_g F_{g0}^{t+1}, \quad g=1,\ldots,p\\
& \lambda_j\ge 0, \qquad j=1,\ldots,n
\end{aligned} \tag{7}$$

Then the Malmquist index is defined as:

$$M_0=\left[\frac{\theta_0^{t}\left(\mathbf{X_0^{t+1}},\mathbf{E_0^{t+1}},\mathbf{Y_0^{t+1}},\mathbf{F_0^{t+1}}\right)}{\theta_0^{t}\left(\mathbf{X_0^{t}},\mathbf{E_0^{t}},\mathbf{Y_0^{t}},\mathbf{F_0^{t}}\right)}\frac{\theta_0^{t+1}\left(\mathbf{X_0^{t+1}},\mathbf{E_0^{t+1}},\mathbf{Y_0^{t+1}},\mathbf{F_0^{t+1}}\right)}{\theta_0^{t+1}\left(\mathbf{X_0^{t}},\mathbf{E_0^{t}},\mathbf{Y_0^{t}},\mathbf{F_0^{t}}\right)}\right]^{1/2} \tag{8}$$

The Malmquist index M_0 measures the efficiency and productivity changes between periods t and $t+1$. Productivity declines if $M_0 < 1$, remains unchanged if $M_0 = 1$, and improves if $M_0 > 1$.

According to Färe et al. (1994), the Malmquist index M_0 can be divided into two components:

$$M_0 = \frac{\theta_0^{t+1}\left(\mathbf{X_0^{t+1}}, \mathbf{E_0^{t+1}}, \mathbf{Y_0^{t+1}}, \mathbf{F_0^{t+1}}\right)}{\theta_0^{t}\left(\mathbf{X_0^{t}}, \mathbf{E_0^{t}}, \mathbf{Y_0^{t}}, \mathbf{F_0^{t}}\right)} \times \left[\frac{\theta_0^{t}\left(\mathbf{X_0^{t+1}}, \mathbf{E_0^{t+1}}, \mathbf{Y_0^{t+1}}, \mathbf{F_0^{t+1}}\right)}{\theta_0^{t+1}\left(\mathbf{X_0^{t+1}}, \mathbf{E_0^{t+1}}, \mathbf{Y_0^{t+1}}, \mathbf{F_0^{t+1}}\right)} \frac{\theta_0^{t}\left(\mathbf{X_0^{t}}, \mathbf{E_0^{t}}, \mathbf{Y_0^{t}}, \mathbf{F_0^{t}}\right)}{\theta_0^{t+1}\left(\mathbf{X_0^{t+1}}, \mathbf{E_0^{t+1}}, \mathbf{Y_0^{t+1}}, \mathbf{F_0^{t+1}}\right)}\right]^{1/2}$$

where the first component on the right hand side measures the change in technical efficiency (TEC) between periods t and $t+1$, denoted as follows.

$$TEC_0 = \frac{\theta_0^{t+1}\left(\mathbf{X_0^{t+1}}, \mathbf{E_0^{t+1}}, \mathbf{Y_0^{t+1}}, \mathbf{F_0^{t+1}}\right)}{\theta_0^{t}\left(\mathbf{X_0^{t}}, \mathbf{E_0^{t}}, \mathbf{Y_0^{t}}, \mathbf{F_0^{t}}\right)} \tag{9}$$

Technical efficiency declines if $TEC_0 < 1$, remains unchanged if $TEC_0 = 1$, and improves if $TEC_0 > 1$. The second component, which is the geometric mean, measures the change in technical progress (TPC) between periods t and $t+1$, denoted as follows.

$$TPC_0 = \left[\frac{\theta_0^{t}\left(\mathbf{X_0^{t+1}}, \mathbf{E_0^{t+1}}, \mathbf{Y_0^{t+1}}, \mathbf{F_0^{t+1}}\right)}{\theta_0^{t+1}\left(\mathbf{X_0^{t+1}}, \mathbf{E_0^{t+1}}, \mathbf{Y_0^{t+1}}, \mathbf{F_0^{t+1}}\right)} \frac{\theta_0^{t}\left(\mathbf{X_0^{t}}, \mathbf{E_0^{t}}, \mathbf{Y_0^{t}}, \mathbf{F_0^{t}}\right)}{\theta_0^{t+1}\left(\mathbf{X_0^{t}}, \mathbf{E_0^{t}}, \mathbf{Y_0^{t}}, \mathbf{F_0^{t}}\right)}\right]^{1/2} \tag{10}$$

Technical progress declines if $TPC_0 < 1$, remains unchanged if $TPC_0 = 1$, and improves if $TPC_0 > 1$.

3 Empirical studies

3.1 Data description

This section describes how to use our developed approach to evaluate the energy and environmental efficiencies of 30 provincial-level regions in mainland China

Table 1 Variables of inputs and outputs

Input/output	Variable	Units
Non-energy input	Labor	10 Thousand persons
	Capital	100 Million RMB
Energy input	Energy	10 Thousand tons of coal equivalent (10,000 tce)
Desirable output	GDP	100 Million RMB
Undesirable output	Waste gas	100 Million cu.m

during the 11th 5-year plan period (2006–2010). As Golany and Roll (1989) indicated, the number of evaluated DMUs should be more than five times the total selected number of inputs and outputs, otherwise the validity and credibility of the results will be seriously compromised. Hence, following many studies (Wang et al. 2013a, b; Li et al. 2013), our study selects five factors as inputs and outputs. We employ labor and investment of fixed assets (namely capital) as two non-energy inputs, energy consumption as the only energy input, GDP as one desirable output, and industrial waste gas emissions as one undesirable output. The input–output measures that are used in this study are summarized in Table 1.

Table 2 Descriptive statistics of the raw data

Variables	Input			Desirable output	Undesirable output
	Labor	Investment	Energy	GDP	Waste gas
2006					
Mean	245.20967	378.40	9684.57	11,032.63	7750.82
Median	133.055	367.5	6948.5	7614	5528.375
SD	271.93735	210.21522	6167.393748	8619.6952	6289.1881
Max.	1203.58	941	26,759	39,254	26,587.76
Min.	12.2	58	920	860	648.5
2007					
Mean	262.439	440.63	10,632.47	12,938.50	9313.16
Median	141.835	377	7663	9372	6763.59
SD	295.71637	245.02	6764.41	9840.34	7475.62
Max.	1307.4	1197	29,177	48,036	31,777.01
Min.	12.33	27	1057	1115	797.35
2008					
Mean	294.52833	522.43	11,256.77	13,461.77	11,097.30
Median	167.275	531.5	8289.5	9477.5	8405.285
SD	339.63043	308.43	7068.77	9963.18	8729.27
Max.	1493.38	1550	30,570	40,219	36,796.71
Min.	12.61	36	1135	1345	1018.62
2009					
Mean	294.31767	619.53	11,907.93	14,535.03	12,162.08
Median	159.71	548.5	8906	11,002.5	9163.625
SD	326.2036	364.34	7435.20	10,499.63	9499.96
Max.	1436.02	1880	32,420	50,779	39,482.56
Min.	12	56	1233	1353	1081.27
2010					
Mean	318.09333	690.37	12,983.70	17,305.07	14,551.15
Median	175.12	591.5	9758	13,687.5	11,020.3
SD	353.64423	433.57	8035.07	11,964.98	11,118.84
Max.	1568	2093	34,808	56,324	46,013.06
Min.	12.44	61	1359	1360	1350.43

We use the data of the 11th 5-year plan period (2006–2010). Unfortunately, the data for the Tibet Autonomous Region are incomplete and so it is not considered in the current study. The data are derived from the "China Statistical Yearbook" and "China Energy Statistical Yearbook". A statistical description of data is shown in Table 2.

3.2 Results and discussion of regional energy and environmental efficiency

We apply our methodology provided in Sect. 2 to calculate the energy and environmental efficiencies of 30 provincial-level regions in mainland China during

Table 3 The energy and environmental efficiency of 30 regions of China

Regions	2006	2007	2008	2009	2010	Average
1. Beijing	1	1	1	1	1	1
2. Tianjin	0.553	0.588	0.574	0.574	0.535	0.565
3. Hebei	0.274	0.258	0.270	0.245	0.243	0.258
4. Shanxi	0.199	0.197	0.194	0.184	0.179	0.190
5. Inner Mongolia	0.237	0.253	0.253	0.243	0.242	0.246
6. Liaoning	0.322	0.337	0.285	0.325	0.332	0.320
7. Jilin	0.486	0.498	0.456	0.441	0.434	0.463
8. Heilongjiang	0.549	0.497	0.444	0.378	0.400	0.454
9. Shanghai	0.753	0.753	0.654	0.664	0.600	0.685
10. Jiangsu	0.657	1.000	0.635	0.621	0.619	0.706
11. Zhejiang	0.720	0.693	0.641	0.620	0.633	0.661
12. Anhui	0.511	0.449	0.412	0.425	0.430	0.445
13. Fujian	0.700	0.653	0.603	0.582	0.554	0.618
14. Jiangxi	0.640	0.615	0.550	0.524	0.528	0.571
15. Shandong	0.529	0.497	0.467	0.458	0.428	0.476
16. Henan	0.481	0.476	0.443	0.426	0.436	0.453
17. Hubei	0.444	0.480	0.441	0.443	0.454	0.453
18. Hunan	0.623	0.541	0.509	0.481	0.449	0.520
19. Guangdong	1.000	0.947	0.794	0.749	0.743	0.846
20. Guangxi	0.471	0.429	0.425	0.403	0.409	0.427
21. Hainan	1	1	1	1	1	1
22. Chongqing	0.427	0.411	0.408	0.345	0.370	0.392
23. Sichuan	0.472	0.357	0.425	0.426	0.380	0.412
24. Guizhou	0.216	0.208	0.244	0.231	0.215	0.223
25. Yunnan	0.389	0.368	0.349	0.326	0.316	0.349
26. Shaanxi	0.520	0.504	0.427	0.409	0.407	0.453
27. Gansu	0.307	0.290	0.277	0.264	0.282	0.284
28. Qinghai	0.211	0.205	0.188	0.184	0.187	0.195
29. Ningxia	0.157	0.156	0.159	0.160	0.131	0.152
30. Xinjiang	0.355	0.330	0.300	0.265	0.260	0.302

the 11th 5-year plan period (2006–2010). By firstly employing model (3), the evaluated results are listed in Table 3. In Table 3, columns 3–7 show the energy and environmental efficiencies of the 30 regions from 2006 to 2010 and column 8 lists the average energy and environmental efficiencies for these 5 years.

It should be noted that the higher the value of energy and environmental efficiency is, the more efficient the region is. From Table 3, the following conclusions can be drawn. Firstly, Beijing and Hainan performed well from 2006 to 2010. Their energy and environmental efficiencies were all equal to 1, i.e. they were all efficient in these 5 years. Secondly, Ningxia performed the worst since the energy and environmental efficiencies for the 5 years were 0.157, 0.156, 0.159, 0.160 and 0.131, and its average efficiency over these 5 years was 0.152. Thirdly, more than half of the 30 regions did not perform well during the 11th 5-year plan. For example, there are 20 regions which had average energy and environmental efficiency below 0.5, including Hebei with 0.258, Shanxi with 0.19, Inner Mongolia with 0.246, Liaoning with 0.32, and Jilin with 0.463. Fourthly, the energy and environmental efficiency trend was not promising since the energy and environmental efficiency of most regions did not show any obvious increasing trend during the 5 years. In fact, they actually had a decreasing trend in some regions. Take Xinjiang for example. Its energy and environmental efficiency diminished from 0.355 to 0.330 (2006–2007), from 0.330 to 0.3 (2007–2008), from 0.3 to 0.265 (2008–2009), and from 0.265 to 0.26 (2009–2010). Finally, we know that the developed regions generally performed better than those less developed regions. For example, the average energy and environmental efficiencies of developed regions like Beijing, Shanghai, Jiangsu, and Guangdong were 1, 0.685, 0.706, and 0.846 receptively. This result shows us that the energy and environmental efficiency of provincial-level regions in China are not cause for optimism and so more actions need to be taken, by both national and regional governments, to practically handle the problems of energy shortage and environmental pollution.

To analyze the energy and environmental efficiency on a relatively larger scale, we group the 30 provincial-level regions into three categories: eastern area, central area, and western area. These areas and their constituent regions are listed in Table 4.

From Table 4, we know there are 11, 10, and 9 regions in the east, center, and west of China respectively. In the past 30 years, the eastern area has experienced the fastest economic growth in China. Along with a dense population, this area is home to the most light industry and foreign trade firms. Due to its convenient transportation and developed infrastructure, this area also attracts the most foreign

Table 4 Areas of China and constituent provincial-level regions

Area	Regions
East	Beijing, Tianjin, Hebei, Liaoning, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan
Central	Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi
West	Chongqing, Sichuan, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang

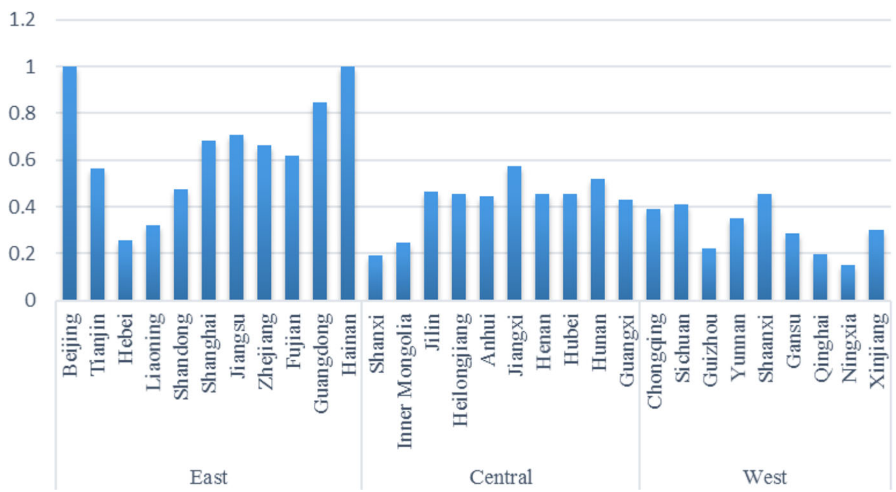

Fig. 1 Regional energy and environmental efficiency of China

Table 5 Energy and environmental efficiency of the three big areas

Area	2006	2007	2008	2009	2010	Average
East	0.683	0.702	0.629	0.622	0.608	0.649
Central	0.464	0.443	0.413	0.395	0.396	0.422
West	0.339	0.314	0.309	0.290	0.283	0.307
Whole country	0.507	0.500	0.461	0.446	0.440	0.471

investment and the best technology. The central area has a total population of 361 million, which accounts for 28 % of the national population. This area shows a lower level of development than the eastern area. The western region accounts for 71 % of the total area of China. Economic development in this area is lagging behind that of the eastern area and central area. Next we illustrate the average energy and environmental efficiencies of the three areas and 30 regions of China in Fig. 1.

From Fig. 1, the following conclusions can be drawn. Firstly, in the eastern area, 3 out of 11 regions (Beijing, Guangdong, and Hainan) are highly energy and environmentally efficient with average efficiency scores above 0.8, and 7 out of 11 regions (Tianjin, Liaoning, Shandong, Shanghai, Jiangsu, Zhejiang, and Fujian) have average efficiency scores between 0.3 and 0.8, with only one region (Hebei) having average efficiency score below 0.3. Secondly, in the central area, Jiangxi has the highest average efficiency and its score is no more than 0.8, which means no region in this area has high energy and environmental efficiency. All the average efficiency scores of the other regions in this area are below 0.6, and Shanxi has the lowest average efficiency score of 0.190, followed by Inner Mongolia with 0.246. Thirdly, in the western area, all of the 9 regions have low efficiencies below 0.5.

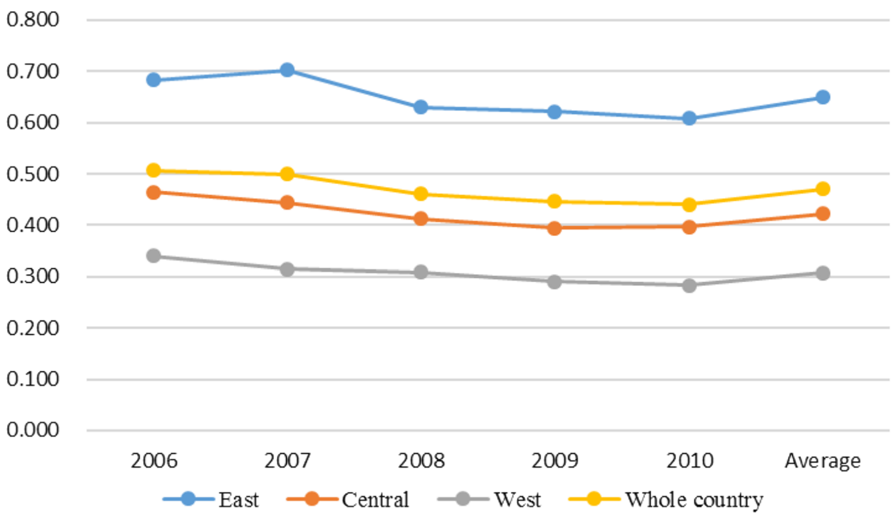

Fig. 2 Average energy and environmental efficiency of China and its three areas

We also calculate the average efficiencies of the three larger areas and the whole country for each year from 2006 to 2010; the results are shown in Table 5.

In order to clearly reflect the difference of the three areas, we illustrate the energy and environmental efficiencies of Table 5 in the following Fig. 2. From Fig. 2, we have the following conclusions. Firstly, from an area perspective considering each year during 2006–2010, the eastern area achieved the highest average energy and environmental efficiency score, followed by the central area and then the western area, but the efficiency scores of the central and western areas are both below the average efficiency at the whole country level. Secondly, all of these three areas had similar increasing and decreasing trends during the years 2007–2010. Finally, the energy and environmental efficiency of the whole country had a decreasing trend from 2006 to 2009. After that, the efficiency began to present an increasing trend from 2009 to 2010.

3.3 Results and discussion of Malmquist index

In order to dynamically analyze the productivity changes for each region during our study period and give a more detailed and clear demonstration, we show 30 provincial-level regions' Malmquist indices for 2006–2007, 2007–2008, 2008–2009, and 2009–2010. Applying models (4)–(8) to the data in Table 2, the Malmquist indices M can be calculated. Table 6 reports the Malmquist index of 30 regions of China over the 5-year period.

From Table 6, we can draw the following conclusions. Firstly we know that the values of the Malmquist index of the 30 regions are mostly greater than 1 for the reported period, which indicates that most regions' productivity improved during each year of the period 2006–2010. Consider, for example, Beijing. Its productivity

Table 6 Malmquist indices of 30 regions of China

Area	Regions	2006–2007 M	2007–2008 M	2008–2009 M	2009–2010 M	Region average	Area average
East	Beijing	1.063	1.293	1.144	1.026	1.132	1.084
	Tianjin	1.185	1.176	1.060	1.016	1.110	
	Hebei	1.059	1.239	0.959	1.086	1.086	
	Liaoning	1.170	0.998	1.207	1.116	1.123	
	Shandong	1.031	1.136	1.038	1.018	1.056	
	Shanghai	0.920	1.141	1.075	0.968	1.026	
	Jiangsu	1.393	1.080	1.036	1.065	1.144	
	Zhejiang	1.054	1.133	1.026	1.113	1.081	
	Fujian	1.022	1.112	1.023	1.037	1.049	
	Guangdong	1.027	1.027	0.999	1.080	1.033	
	Hainan	1.050	1.166	1.135	1.230	1.145	
Central	Shanxi	1.093	1.178	1.003	1.061	1.084	1.078
	Inner Mongolia	1.199	1.196	1.014	1.090	1.125	
	Jilin	1.135	1.117	1.025	1.073	1.088	
	Heilongjiang	1.000	1.097	0.902	1.153	1.038	
	Anhui	0.979	1.086	1.092	1.104	1.065	
	Jiangxi	1.067	1.073	1.007	1.101	1.062	
	Henan	1.095	1.124	1.019	1.117	1.089	
	Hubei	1.199	1.120	1.065	1.114	1.125	
	Hunan	0.957	1.156	1.002	1.018	1.033	
	Guangxi	1.026	1.166	1.004	1.107	1.076	
West	Chongqing	1.074	1.192	0.896	1.171	1.083	1.075
	Sichuan	0.841	1.433	1.062	0.973	1.077	
	Guizhou	1.075	1.411	1.003	1.013	1.125	
	Yunnan	1.055	1.143	0.990	1.058	1.061	
	Shaanxi	1.073	1.023	1.014	1.086	1.049	
	Gansu	1.047	1.151	1.012	1.164	1.094	
	Qinghai	1.084	1.101	1.033	1.111	1.082	
	Ningxia	1.099	1.225	1.065	0.890	1.070	
	Xinjiang	1.037	1.111	0.935	1.069	1.038	

improved 6.3 % for 2006–2007, 29.3 % for 2007–2008, 14.4 % for 2008–2009, and 2.6 % for 2009–2010. A few regions have a Malmquist index lower than 1, as seen by the Malmquist index for Hebei being 0.959 for 2008–2009 and for Shanghai being 0.92 for 2006–2007. These rare Malmquist indices lower than 1 indicate the decline of productivity in these few regions from 2006 to 2010. Secondly, the maximum value of Malmquist index for the 30 regions during 2006–2010 is 1.433 for Sichuan for 2007–2008, which had also the minimum value of Malmquist index (0.841) for 2006–2007. Thirdly, the average values of Malmquist index for the 30 regions are all greater than 1 during 2006–2010, which indicates the improvement in

Table 7 TEC and TPC of Malmquist index

Regions	2006–2007		2007–2008		2008–2009		2009–2010		Average	
	TEC	TPC	TEC	TPC	TEC	TPC	TEC	TPC	TEC	TPC
East										
Beijing	1.000	1.063	1.000	1.293	1.000	1.144	1.000	1.026	1.000	1.132
Tianjin	1.064	1.114	0.975	1.206	1.001	1.060	0.932	1.090	0.993	1.118
Hebei	0.943	1.123	1.046	1.184	0.906	1.058	0.994	1.092	0.972	1.114
Liaoning	1.048	1.117	0.844	1.183	1.141	1.058	1.024	1.090	1.014	1.112
Shandong	0.938	1.099	0.940	1.208	0.979	1.060	0.934	1.090	0.948	1.114
Shanghai	0.999	0.921	0.869	1.313	1.015	1.060	0.905	1.070	0.947	1.091
Jiangsu	1.521	0.916	0.635	1.702	0.978	1.059	0.998	1.067	1.033	1.186
Zhejiang	0.962	1.096	0.925	1.225	0.968	1.059	1.021	1.090	0.969	1.117
Fujian	0.933	1.096	0.923	1.205	0.966	1.059	0.951	1.090	0.943	1.113
Guangdong	0.947	1.085	0.839	1.224	0.942	1.060	0.992	1.089	0.930	1.114
Hainan	1.000	1.050	1.000	1.166	1.000	1.135	1.000	1.230	1.000	1.145
Central										
Shanxi	0.990	1.104	0.987	1.194	0.948	1.058	0.972	1.092	0.974	1.112
Inner Mongolia	1.068	1.123	1.002	1.194	0.958	1.058	0.999	1.091	1.007	1.117
Jilin	1.024	1.108	0.915	1.220	0.967	1.061	0.985	1.089	0.973	1.120
Heilongjiang	0.905	1.105	0.894	1.226	0.851	1.061	1.059	1.089	0.927	1.120
Anhui	0.877	1.116	0.918	1.183	1.033	1.058	1.012	1.092	0.960	1.112
Jiangxi	0.960	1.111	0.895	1.199	0.952	1.059	1.009	1.091	0.954	1.115
Henan	0.990	1.107	0.930	1.209	0.961	1.060	1.025	1.090	0.977	1.116
Hubei	1.082	1.108	0.919	1.220	1.004	1.060	1.023	1.089	1.007	1.119
Hunan	0.868	1.102	0.941	1.228	0.945	1.061	0.935	1.089	0.922	1.120
Guangxi	0.913	1.124	0.989	1.180	0.949	1.058	1.014	1.092	0.966	1.113
West										
Chongqing	0.963	1.115	0.991	1.202	0.846	1.059	1.073	1.091	0.969	1.117
Sichuan	0.757	1.110	1.190	1.204	1.002	1.061	0.894	1.089	0.961	1.116
Guizhou	0.963	1.116	1.173	1.202	0.946	1.060	0.930	1.090	1.003	1.117
Yunnan	0.945	1.117	0.948	1.206	0.934	1.059	0.970	1.090	0.949	1.118
Shaanxi	0.968	1.108	0.848	1.207	0.957	1.059	0.995	1.091	0.942	1.116
Gansu	0.946	1.107	0.954	1.207	0.955	1.060	1.068	1.090	0.981	1.116
Qinghai	0.973	1.115	0.918	1.199	0.976	1.059	1.018	1.091	0.971	1.116
Ningxia	0.992	1.107	1.023	1.198	1.006	1.059	0.815	1.093	0.959	1.114
Xinjiang	0.929	1.116	0.911	1.220	0.882	1.060	0.981	1.089	0.926	1.121

productivity of each region during the 11th 5-year plan of China. Fourthly, the average Malmquist indices of the eastern area, central area, and western area are 1.084, 1.078, and 1.075 respectively, which means the productivity in those areas during 2006–2010 improved 8.4, 7.8, and 7.5 % respectively. This result indicates that the eastern area had the highest improvement of productivity during the 11th 5-year plan, followed by central area and then the western area. Lastly, we find that the values of Malmquist index of all the 30 regions does not show any obvious increasing or decreasing trend during the four periods. Moreover, we know that the productivity of most regions had an increasing trend during 2006–2008 and 2008–2010 since the values of Malmquist index of most regions for 2007–2008 (2009–2010) are bigger than the values for 2006–2007 (2008–2009). However, the productivity of most regions had a decreasing trend during 2007–2009 since the values of Malmquist index of most regions for 2008–2009 are smaller than the values for 2007–2008. Take Hainan for example. All of its values of Malmquist index are bigger than 1, that is, its productivity improved each year, however its improving trend is not increasing since its values of Malmquist index are 1.05 (2006–2007), 1.166 (2007–2008), 1.135 (2008–2009), and 1.23 (2009–2010). To be more precise, Hainan's productivity had an increasing trend during 2006–2008 (from 1.05 to 1.166) and 2008–2010 (from 1.135 to 1.23), but a decreasing trend during 2007–2009 (from 1.166 to 1.135).

Applying models (9) and (10) from Sect. 2, we divide the Malmquist index into the change in technical efficiency (TEC) and the change in technical progress (TPC). The corresponding results are shown in Table 7.

From Table 7, we have the following conclusions. Firstly, during each year of the period 2006–2010, the values of TECs for most regions are lower than 1, while the values of TPCs for most regions are higher than 1. For example, there are 22 regions which have the values of TEC lower than 1 and just 8 regions with the values of TEC higher than 1 for 2006–2007. In contrast, there are only two regions (Shanghai and Jiangsu) which have values of TPC lower than 1 for 2006–2007. These results indicate a decline of technical efficiency and an improvement of technical progress. Secondly, from the average values of TEC and TPC during the period 2006–2010, there are 23 regions which have a declining trend of technical efficiency (that is the value of TEC is lower than 1) while all the 30 regions have an increasing trend of technical progress (that is the value of TPC is higher than 1). Thirdly, combining Tables 6 and 7, we know which values of TEC and TPC led to the higher or lower Malmquist index. Take Anhui for example. Its value of Malmquist index for 2006–2007 is 0.979 which indicates that the productivity of Anhui declined 2.1 %. This result was caused by the changes of technical efficiency, where the value of TEC is lower than 1 in corresponding time period, whereas the technical progress improved since the value of TPC is greater than 1 for 2006–2007. Finally, considering the various trends of TECs, we know that the technical efficiency did not have an increasing or decreasing trend for most regions during the period 2006–2010, that is, it does not present any regular changes. Although the technical progress also did not have an increasing or decreasing trend for most regions during the whole period 2006–2010, the regions did have identical trends during parts of the period. For example, the technical progress of all regions has an increasing trend for 2006–2008 (2008–2010) since the values of TPCs of all regions for 2007–2008 (2009–2010) are all higher than their values for 2006–2007 (2008–2009). In addition, the technical progress of all regions has a decreasing trend for 2007–2009 since the values of TPCs of all regions for 2008–2009 are all lower than their values for 2007–2008.

4 Conclusions

During the last three decades, the economy of China has been increasing rapidly. The fast economic progress has led to the growth of GDP accompanied by serious problems such as energy shortage and environmental pollution. Naturally, it is desirable to evaluate the energy and environmental performance of provincial-level regions of China.

Based on the above-mentioned context, in this paper we apply DEA models to evaluate the total-factor efficiency of energy and environment of 30 provincial-level regions and three areas in mainland China during China's 11th 5-year plan period (2006–2010). In particular, this study measures a joint production framework of non-energy inputs (labor and capital) and an energy input (total energy consumption), as well as a desirable output (GDP) and an undesirable output (waste gas). In addition, this study applies a DEA-based Malmquist index to evaluate the dynamic productivity change considering the undesirable output and energy input.

The major empirical results of this study show that: (1) Two regions, namely Beijing and Hainan, had the highest total-factor energy and environmental efficiency during the period 2006–2010. In addition, most regions had poor energy and environmental efficiency. Thus, these two regions could be seen as the benchmarks for inefficient regions to bring about energy and environmental efficiency improvement. (2) From an area perspective, China's eastern area had the highest energy and environmental efficiency, followed by the central area, with the efficiency of the western area being the worst. The efficiency differences of the three areas may arise from the imbalance of economic development. (3) From the Malmquist index, we know that productivity in most regions improved during each year of the period 2006–2010. The eastern area had the highest improvement of productivity during the 11th 5-year plan, followed by the central area and then the western area. (4) Dividing the Malmquist index into the change in technical efficiency (TEC) and the change in technical progress (TPC), we know that most regions had a declining trend in technical efficiency while most regions had an increasing trend in technical progress.

Acknowledgments The research is supported by National Natural Science Funds of China (No. 71222106, 71110107024, and 7150189), Research Fund for the Doctoral Program of Higher Education of China (No. 20133402110028), Foundation for the Author of National Excellent Doctoral Dissertation of P. R. China (No. 201279) and The Fundamental Research Funds for the Central Universities (No. WK2040160008).

References

Banker RD, Charnes A, Cooper WW (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manag Sci 30(9):1078–1092. doi:10.1287/mnsc.30.9.1078

Bi G, Luo Y, Ding J, Liang L (2012) Environmental performance analysis of Chinese industry from a slacks-based perspective. Ann Oper Res 228(1):65–80. doi:10.1007/s10479-012-1088-3

Bian Y, Yang F (2010) Resource and environment efficiency analysis of provinces in China: a DEA approach based on Shannon's entropy. Energy Policy 38(4):1909–1917. doi:10.1016/j.enpol.2009.11.071

Camanho AS, Dyson RG (2006) Data envelopment analysis and Malmquist indices for measuring group performance. J Prod Anal 26(1):35–49. doi:10.1007/s11123-006-0004-8
Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2(6):429–444. doi:10.1016/0377-2217(78)90138-8
Chen Y, Ali AI (2004) DEA Malmquist productivity measure: new insights with an application to computer industry. Eur J Oper Res 159(1):239–249. doi:10.1016/S0377-2217(03)00406-5
Chen CM, Delmas MA (2012) Measuring eco-inefficiency: a new frontier approach. Oper Res 60(5):1064–1079. doi:10.1287/opre.1120.1094
Chen Y, Liang L, Yang F (2006) A DEA game model approach to supply chain efficiency. Ann Oper Res 145(1):5–13. doi:10.1007/s10479-006-0022-y
Coelli TJ, Prasada Rao DS, O'Donnell CJ (2005) An introduction to efficiency and productivity analysis. Springer, New York
Cook WD, Seiford LM (2009) Data envelopment analysis (DEA)—thirty years on. Eur J Oper Res 192(1):1–17. doi:10.1016/j.ejor.2008.01.032
Cooper WW, Seiford LM, Tone K (2007) Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software. Springer, New York
Dimas G, Goula A, Soulis S (2012) Productive performance and its components in Greek public hospitals. Oper Res 12(1):15–27. doi:10.1007/s12351-010-0082-2
Färe R, Grosskopf S, Lovell CK, Pasurka C (1989) Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Rev Econ Stat 71(1):90–98. doi:10.2307/1928055
Färe R, Grosskopf S, Lindgren B, Roos P (1994) Productivity developments in Swedish hospitals: a Malmquist output index approach. In: Charnes A, Cooper W, Lewin AY, Seiford M (eds) Data envelopment analysis: theory, methodology, and applications. Springer, Boston, pp 253–272
Färe R, Grosskopf S, Noh DW, Weber W (2005) Characteristics of a polluting technology: theory and practice. J Econom 126(2):469–492. doi:10.1016/j.jeconom.2004.05.010
Golany B, Roll Y (1989) An application procedure for DEA. Omega 17(3):237–250. doi:10.1016/0305-0483(89)90029-7
Halkos GE, Tzeremes NG, Kourtzidis SA (2015) Regional sustainability efficiency index in Europe: an additive two-stage DEA approach. Oper Res 15(1):1–23. doi:10.1007/s12351-015-0170-4
Hu JL, Lee YC (2008) Efficient three industrial waste abatement for regions in China. Int J Sustain Dev World Ecol 15(2):132–144. doi:10.1080/13504500809469778
Hu JL, Wang SC (2006) Total-factor energy efficiency of regions in China. Energy Policy 34(17):3206–3217. doi:10.1016/j.enpol.2005.06.015
Huang CY, Chiou CC, Wu TH, Yang SC (2015) An integrated DEA-MODM methodology for portfolio optimization. Oper Res 15(1):115–136. doi:10.1007/s12351-014-0164-7
Ibanez E, McCalley JD (2011) Multiobjective evolutionary algorithm for long-term planning of the national energy and transportation systems. Energy Syst 2(2):151–169. doi:10.1007/s12667-011-0031-z
Karagiannis R, Velentzas K (2012) Productivity and quality changes in Greek public hospitals. Oper Res 12(1):69–81. doi:10.1007/s12351-010-0080-4
Li H, Fang K, Yang W, Wang D, Hong X (2013) Regional environmental efficiency evaluation in China: analysis based on the super-SBM model with undesirable outputs. Math Comput Model 58(5):1018–1031. doi:10.1016/j.mcm.2012.09.007
Macpherson AJ, Principe PP, Mehaffey M (2013) Using Malmquist Indices to evaluate environmental impacts of alternative land development scenarios. Ecol Indic 34:296–303. doi:10.1016/j.ecolind.2013.05.009
Mahadevan R (2002) A DEA approach to understanding the productivity growth of Malaysia's manufacturing industries. Asia Pac J Manag 19(4):587–600. doi:10.1023/A:1020577811369
Malmquist S (1953) Index numbers and indifference surfaces. Trabajos de Estadistica y de Investigacion Operativa 4(2):209–242. doi:10.1007/BF03006863
Panta M, Smirlis Y, Sfakianakis M (2013) Assessing bids of Greek public organizations service providers using data envelopment analysis. Oper Res 13(2):251–269. doi:10.1007/s12351-011-0108-4
Ramanathan R (2000) A holistic approach to compare energy efficiencies of different transport modes. Energy Policy 28(11):743–747. doi:10.1016/S0301-4215(00)00072-0
Saharidis GK (2015) Environmental externalities score: a new emission factor to model green vehicle routing problem. Energy Syst. doi:10.1007/s12667-015-0147-7

Scheel H (2001) Undesirable outputs in efficiency evaluations. Eur J Oper Res 132(2):400–410. doi:10.1016/S0377-2217(00)00160-0
Seiford LM, Zhu J (2002) Modeling undesirable factors in efficiency evaluation. Eur J Oper Res 142(1):16–20. doi:10.1016/S0377-2217(01)00293-4
Shabani Z, Rafiee S, Mobli H, Khanalipur E (2012) Optimization in energy consumption of carnation production using data envelopment analysis (DEA). Energy Syst 3(4):325–339. doi:10.1007/s12667-012-0059-8
Sharma MJ, Yu SJ (2013) Multi-stage data envelopment analysis congestion model. Oper Res 13(3):399–413. doi:10.1007/s12351-012-0128-8
Shi GM, Bi J, Wang JN (2010) Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. Energy Policy 38(10):6172–6179. doi:10.1016/j.enpol.2010.06.003
Smirlis YG, Zeimpekis V, Kaimakamis G (2012) Data envelopment analysis models to support the selection of vehicle routing software for city logistics operations. Oper Res 12(3):399–420. doi:10.1007/s12351-010-0100-4
Song ML, Wang SH (2014) DEA decomposition of China's environmental efficiency based on search algorithm. Appl Math Comput 247:562–572. doi:10.1016/j.amc.2014.09.050
Song M, Guo X, Wu K, Wang G (2014) Driving effect analysis of energy-consumption carbon emissions in the Yangtze River Delta region. J Clean Prod 103:620–628. doi:10.1016/j.jclepro.2014.05.095
Song M, An Q, Zhang W, Wang Z, Wu J (2012) Environmental efficiency evaluation based on data envelopment analysis: a review. Renew Sutain Energy Rev 16(7):4465–4469. doi:10.1016/j.rser.2012.04.052
Song ML, Yang L, Wu J, Lv WD (2013) Energy saving in China: analysis on the energy efficiency via bootstrap-DEA approach. Energy Policy 57:1–6. doi:10.1016/j.enpol.2012.11.001
Tsolas IE, Charles V (2015) Green exchange-traded fund performance appraisal using slacks-based DEA models. Oper Res 15(1):51–77. doi:10.1007/s12351-015-0169-x
Tyteca D (1997) Linear programming models for the measurement of environmental performance of firms—concepts and empirical results. J Prod Anal 8(2):183–197. doi:10.1023/A:1013296909029
Wang Q (2010) Effective policies for renewable energy—the example of China's wind power—lessons for China's photovoltaic power. Renew Sustain Energy Rev 14(2):702–712. doi:10.1016/j.rser.2009.08.013
Wang K, Wang C, Lu X, Chen J (2007) Scenario analysis on CO2 emissions reduction potential in China's iron and steel industry. Energy Policy 35(4):2320–2335. doi10.1016/S0377-2217(03)00406-5
Wang Q, Zhou P, Zhou D (2012) Efficiency measurement with carbon dioxide emissions: the case of China. Appl Energy 90(1):161–166. doi:10.1016/j.apenergy.2011.02.022
Wang K, Yu S, Zhang W (2013a) China's regional energy and environmental efficiency: a DEA window analysis based dynamic evaluation. Math Comput Model 58(5):1117–1127. doi:10.1016/j.mcm.2011.11.067
Wang K, Lu B, Wei YM (2013b) China's regional energy and environmental efficiency: a range-adjusted measure based analysis. Appl Energy 112:1403–1415. doi:10.1016/j.apenergy.2013.04.021
Wu Y (2012) Energy intensity and its determinants in China's regional economies. Energy Policy 41:703–711. doi:10.1016/j.enpol.2011.11.034
Wu J, Liang L, Yang F (2009) Achievement and benchmarking of countries at the Summer Olympics using cross efficiency evaluation method. Eur J Oper Res 197(2):722–730. doi:10.1016/j.ejor.2008.06.030
Wu J, An Q, Xiong B, Chen Y (2013) Congestion measurement for regional industries in China: a data envelopment analysis approach with undesirable outputs. Energy Policy 57:7–13. doi:10.1016/j.enpol.2012.02.062
Wu HQ, Shi Y, Xia Q, Zhu WD (2014a) Effectiveness of the policy of circular economy in China: a DEA-based analysis for the period of 11th five-year-plan. Resour Conserv Recycl 83:163–175. doi:10.1016/j.resconrec.2013.10.003
Wu J, An QX, Yao X, Wang B (2014b) Environmental efficiency evaluation of industry in China based on a new fixed sum undesirable output data envelopment analysis. J Clean Prod 74:96–104. doi:10.1016/j.jclepro.2014.03.054
Wu J, Zhu Q, Chu J, Liang L (2015) Two-stage network structures with undesirable intermediate outputs reused: a DEA based approach. Comput Econ. doi:10.1007/s10614-015-9498-3
Yang B, Zhang Y, Zhang H, Zhang R, Xu B (2015a) Factor-specific Malmquist productivity index based on common weights DEA. Oper Res. doi:10.1007/s12351-015-0185-x

Yang L, Ouyang H, Fang K, Ye L, Zhang J (2015b) Evaluation of regional environmental efficiencies in China based on super-efficiency-DEA. Ecol Indic 51:13–19. doi:10.1016/j.ecolind.2014.08.040

Yeh TL, Chen TY, Lai PY (2010) A comparative study of energy utilization efficiency between Taiwan and China. Energy Policy 38(5):2386–2394. doi:10.1016/j.enpol.2009.12.030

Zhou P, Ang BW (2008) Linear programming models for measuring economy-wide energy efficiency performance. Energy Policy 36(8):2911–2916. doi:10.1016/j.enpol.2008.03.041

Zhou P, Poh KL, Ang BW (2007) A non-radial DEA approach to measuring environmental performance. Eur J Oper Res 178(1):1–9. doi:10.1016/j.ejor.2006.04.038

Zhou P, Ang BW, Poh KL (2008a) A survey of data envelopment analysis in energy and environmental studies. Eur J Oper Res 189(1):1–18. doi:10.1016/j.ejor.2007.04.042

Zhou P, Ang BW, Poh KL (2008b) Measuring environmental performance under different environmental DEA technologies. Energy Econ 30(1):1–14. doi:10.1016/j.eneco.2006.05.001

Zhou P, Ang BW, Wang H (2012) Energy and CO_2 emission performance in electricity generation: a non-radial directional distance function approach. Eur J Oper Res 221(3):625–635. doi:10.1016/j.ejor.2012.04.022