ECOLOGICAL ECONOMICS 68 (2008) 306–316

available at www.sciencedirect.com

ScienceDirect

www.elsevier.com/locate/ecolecon

ANALYSIS

Eco-efficiency analysis of industrial system in China: A data envelopment analysis approach

Bing Zhang[a], *Jun Bi*[a,*], *Ziying Fan*[b], *Zengwei Yuan*[a], *Junjie Ge*[a]

[a]*State Key Laboratory of Pollution Control & Resource Reuse, School of Environment, Nanjing University, Nanjing 210093, PR China*
[b]*China Center for Economic Studies (CCES), Fudan University, 220 Handan Road, Shanghai 200433, PR China*

ARTICLE INFO

Article history:
Received 29 November 2006
Received in revised form
11 March 2008
Accepted 11 March 2008
Available online 2 May 2008

Keywords:
Eco-efficiency
Industrial system
Data envelopment analysis (DEA)
China

ABSTRACT

Eco-efficiency is an instrument for sustainability analysis, indicating how efficient the economic activity is with regard to nature's goods and services. This paper conducts an eco-efficiency analysis for regional industrial systems in China by developing data envelopment analysis (DEA) based models. Using real data of 30 provinces in China, an empirical study is employed to illustrate the pattern of regional industrial systems' eco-efficiency. The results indicate that Tianjing, Shanghai, Guangdong, Beijing, Hainan and Qinghai are relatively eco-efficient. The results also show that, provinces with higher level GDP per capita will have higher eco-efficiency relatively with an exception of Hainan and Qinghai. The study provides deeper insights into the causes of eco-inefficiency, and gives further implications on environmental protection strategies in China. In the article, we also discuss the advantages and disadvantages of using DEA in eco-efficiency analysis and areas that require further work are presented.
© 2008 Elsevier B.V. All rights reserved.

1. Introduction

Since 1979, China has maintained a high rate of economic growth with the adoption of economic reform policies, opening up to the outside world, and transition to a market economy. For a long time, China's scale-driven economic development led to inefficient natural resource utilization and energy use in the production process, as well as high volume of pollution emission. From 1981 to 2004, China's Gross Domestic Product (GDP) had increased 8.91 times, while energy consumption in 2004 was 3.42 times that of 1981. Volumes of industrial solid wastes produced, Sulphur Dioxide (SO_2) emission and wastewater discharge in 2004 were 3.19, 1.64 and 1.65 times that of 1981, respectively (see Fig. 1).

Since United Nations Conference on Environment and Development (UNCED) in 1992, sustainable development has been adopted as a fundamental development strategy by many countries, including China. While sustainable development has been widely adopted as a goal, it does not, in itself provide the means by which an unsustainable development could be transformed into a sustainable one. On the other hand, the UNCED also stated quite clearly that the main cause of global pollution is the continued use of natural resources at previous levels. Acceptance of this fact by the international community helped promote the discussion of specific measures to ensure sustainable economic development. In this connection, strategies for optimizing the use of resources or environment as expressed in more efficient way play a particularly important role. Eco-efficiency, which is an instrument for sustainability analysis, indicating an empirical relation in economic activities between environmental cost or value and environmental impact, has been proposed as a route to promote such a transformation (Mickwitz et al., 2006).

The concept of eco-efficiency can be traced back to 1970s as the concept of "environmental efficiency" (Freeman et al., 1973; McIntyre and J.R, 1974; McIntyre and Thornton, 1978). In the

* *Corresponding author*. Tel.: +86 25 83592841; fax: +86 25 83595207.
E-mail address: jbi@nju.edu.cn (J. Bi).

0921-8009/$ – see front matter © 2008 Elsevier B.V. All rights reserved.
doi:10.1016/j.ecolecon.2008.03.009

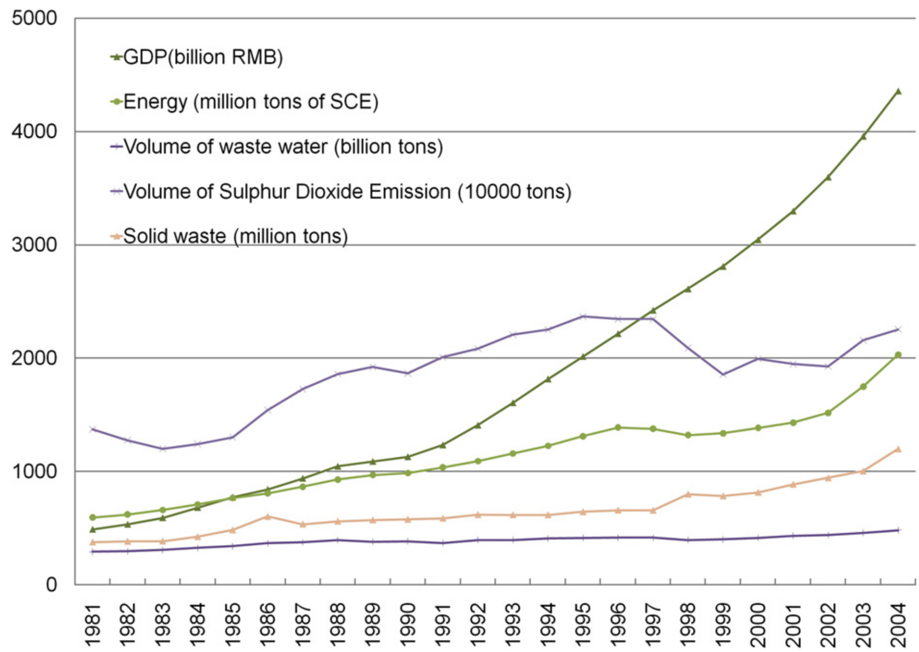

Fig. 1 – Economic development, energy consumption and pollution emissions in China from 1981 to 2004.

1990s, Schaltegger and Sturm (1990) introduced eco-efficiency as a "business link to sustainable development". Later, it was popularized by the World Business Council for Sustainable Development (WBCSD) (Schmidheiny, 1992). Not surprisingly, eco-efficiency has received significant attention in the sustainable development literature (Choucri, 1995; Cramer, 1997; Brady et al., 1999; DeSimone and Popoff, 2000; Schaltegger and Synnestvedt, 2002; Bleischwitz, 2003; Reith and Guidry, 2003).

Eco-efficiency plays an important role in expressing how efficient the economic activity is with regard to nature's goods and services. According to the definition, eco-efficiency is measured as the ratio between the (added) value of what has been produced (income, high quality goods and services, jobs, GDP etc) and the (added) environmental impacts of the product or service:

$$\text{Eco}-\text{efficiency} = \frac{\text{Value of products or service (added)}}{\text{Environmental impacts (added)}}$$

Recently, a number of alternative measures or indicators have been suggested (Glauser and Muller, 1997; Metti, 1999; Schaltegger and Burritt, 2000), most of them being simple indicators such as "economic output per unit of waste" ratios that approach eco-efficiency from a very limited perspective (Kuosmanen and Kortelainen, 2005). On the other hand, most eco-efficiency indicators are focused on the firms or products levels. However, governments are also interested in applying eco-efficiency principles because these are considered to result in national long-term advantages in terms of international competitiveness, particularly in the Asian region (Hur et al., 2004; Seppälä et al., 2005). To date, there are few case studies of regional eco-efficiency (Basque Government, 2003; Seppälä et al., 2005; Mickwitz et al., 2006).

In view of the importance of eco-efficiency analysis and the insufficient researches in China, this study aims to select appropriate indicators and aggregation measurement, to illustrate possibilities for measuring regional eco-efficiency. Thus, the rest of the paper is organized as follows: Section 2 reviews previous researches on indicators and measurement of eco-efficiency analysis. Based on previous works, a set of regional eco-efficiency indicators and DEA model are developed for regional eco-efficiency analysis in Section 3. Section 4 illustrates DEA models with real data set of 30 provinces in China.[1] Section 5 provides discussions on the results and methodology of our research. Finally, overall conclusions and areas that require further work are presented (Section 6).

2. Eco-efficiency measurement framework

How exactly to determine the numerator and denominator of the "eco-efficiency equation", is currently subject to international research and development (Seppälä et al., 2005). Although, the equation is open to widely differing interpretations depending on which viewpoint is selected, it has become customary to define eco-efficiency as a combination of economic and environmental (ecological) values, expressed by the ratio of economic value/environmental impact or, environmental impact/economic value (Keffer and Shimp, 1999; Sturm et al., 2002).

There are still no standard indicators and measurement for economic and environmental values, as well as eco-efficiency (Reijnders, 1998). For the economic part of the eco-efficiency ratio, WBSCD takes quantity of goods or services and net sales as general indicators of product/service value, and value added as supplemental indicators (WBCSD, 2000). United

[1] Due to the lack of data, Tibet, Taiwan, Hongkong and Macao are not included in our research.

Nations Conference on Trade and Development (UNCTAD) suggests using value added indicators to represent performance indicators, such as Sales Revenue (UNCTD, 2003). At regional level, Seppälä et al. (2005) apply three economic indicators to represent the value of products and services in the Kymenlaakso region, that is, gross domestic product (GDP), value added of industries and output at basic prices.

In the process of arriving at eco-efficiency ratios, cost or values should be aggregated into one score. Huppes and Ishikawa (2005) conclude two main domains types of value and cost aggregation, cost-benefit analysis (CBA) and life cycle costing (LCC), both developed in the middle of the 20th century.

For the environmental part of the eco-efficiency ratio, ISO 14031 code on ''Environmental Performance Evaluation'' (ISO, 1998) has been widely applied to select the most relevant indicators (Fet, 2003). Other institutions and researchers also established environmental performance indicators (WBCSD, 2000; UNCTD, 2003). While referring to the regional environmental impact indicators, Mickwitz et al. (2006) apply physical input–output tables of Kymenlaakso's regional economy to produce indicators for natural resource consumption, such as total material requirement (TMR) or direct material input (DMI), which are also used as alternative environmental indicators. Seppälä et al. (2005) divide environmental impact indicators into three parts: pressure indicators (e.g., emissions of CO_2), impact category indicators (e.g., CO_2 equivalents in the case of climate change), and a total impact indicator (aggregating different impact category indicator results into a single value).

These environmental impact indicators also need to be aggregated into top-indicators. In the economic dimension the issue was the easiest, since there is a common unit — money, however, in the environmental dimension, the data and the indicators are extensive, complex, and measured on different scales. To build up an encompassing environmental impact score, a weighted sum of the various environmental impacts is usually used. The essential question is how the weights should be chosen or determined. Prior approaches to quantifying the eco-efficiency ratio either using an arbitrary equal weighting scheme or determining weights based on subjective valuations or judgments (Kuosmanen and Kortelainen, 2005). Huppes and Ishikawa (2005) introduce two basic dimensions, collective preferences (sociopolitical) and individual/private preferences, to help survey the field and clarify actual approaches.

However, in the derivation of weight coefficients, normative judgments and subjective valuations of weights can easily be incorporated into the model framework. Data envelopment analysis (DEA) (Farrell, 1957; Charnes et al., 1978) is considered to be a solution for aggregating different environmental pressures to construct an encompassing of eco-efficiency indicators. Data Envelopment Analysis (DEA), occasionally called frontier analysis, was first put forward by Charnes, Cooper and Rhodes in 1978 (Charnes et al., 1978). It is commonly used to evaluate the efficiency of a number of "units" such as a group of producers, banks, or hospitals characterized by multiple inputs and outputs. In fact, the DEA is suitable for evaluating almost any relatively homogeneous set of units, but nowadays it is also recognized as a decision aid in multi-criteria analyses of discrete alternatives (Srdjevic et al., 2005).

While applying DEA model for eco-efficiency analysis, it shows quite different combinations of ways to treat undesirable output (waste or emission) and model choice (Allen, 1999). Lovell et al. (1995) treat undesirable outputs (carbon and nitrogen emissions) as normal outputs after taking their reciprocals. Courcelle et al. (1998) assess the economic and environmental performance of a set of 23 municipal solid waste collection and storing programs. The ratio of the material sent to final disposal from the processing to total amount of material leaving the processing represents an undesirable output.

Alternative approach is using the original data of undesirable outputs. Färe et al. (1996) use "weak disposability assumption" to model the undesirable output, while comparing the environmental performance of US fossil-fuel-fired electric utilities. Others take the undesirable outputs as a classical DEA input (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005). Dyckhoff and Allen (2001) conclude the advantages and disadvantages of approaches of treating undesirable output in DEA model and introduce extended preference structures for ecologically motivated applications of DEA. Vencheh et al. (2005) develop a DEA-based model for efficiency evaluation incorporating undesirable inputs and undesirable outputs, simultaneously.

On the basis of above analysis, our research aims to develop and select appropriate indicators and DEA model for regional eco-efficiency analysis in China.

3. Methodology

3.1. *Input and output indicators*

In the physical economy, we input material and energy, and produce products (or value), while the wastes and emissions (or other undesirable outputs) are unavoidable. Therefore, there are two essential classes of inputs from the nature into the economy that may be distinguished: the supply of goods/resource (such as raw materials), and nature's function as the sink for the discharge of residuals and pollutants. If we only consider the environmental impacts of resource use, it can be defined as "resource efficiency" or "technology efficiency" (Korhonen and Luptacik, 2004). In contrast, if we only consider the environmental impacts of waste emissions, it can be defined as "environmental efficiency". However, in an integrated eco-efficiency analysis we should include the environmental impacts related to both resource use and pollution emissions (or for other undesirable outputs) (Dyckhoff and Allen, 2001).

Seppälä et al. (2005) figure out that regional eco-efficiency can be detected inside and outside the region. A basic eco-efficiency approach is limited to the economic performance inside the region and the environmental effects caused by the activities in the region. A broader approach also incorporates the consequences caused by activities outside the region that are related to the material and energy flows used by the activities within the region. In this study, only basic eco-efficiency approach was applied.

More detailed input factors should be specified in any proposed models. For the resource use part, indicators were selected based on material flow accounts. Direct material input (DMI) was selected for the calculation of the regional industrial system eco-efficiency, which consists of all materials (biomass, fossil fuels, minerals) extracted for use in a region and of all imported materials (Seppälä et al., 2005). Three main categories of DMI were finally selected in our research, that is, water resource input, raw mining resource input and energy input. For the environmental impact part, we chose environmental pressure indicators (e.g. SO_2 emission). Based on China environmental statistics system and data availability, we choose six main categories of environmental pressure indicators, namely, COD, Nitrogen, SO_2, soot, dust and solid waste.

For the economic value part, Seppälä et al. (2005) suggested three economic indicators to represent the value of products and services in regional eco-efficiency analysis, that is, gross domestic product (GDP), value added of industries and output at basic prices. In consideration that our research focuses on regional industrial system, value added of industries was selected to represent value of products and services.

All the data were collected from China Statistical Yearbook in 2005,[2] China Mining Yearbook in 2005, Provincial Statistical Yearbook in 2005, China Environmental Statistical Yearbook in 2005, and China Land & Resources Yearbook in 2005.

3.2. *The DEA model*

3.2.1. *The basic model*

Suppose we have a set of n decision making units, $j=1,\cdots,n$. For each unit, there are s outputs, $r=1,\cdots,s$ and m inputs, $i=1,\cdots,m$. Let y_{rj} (x_{ij}) be the rth(ith) known output (input) of unit j. Define $h_j=\frac{\sum_{r=1}^{s}u_r y_{rj}}{\sum_{i=1}^{m}v_r x_{rj}}$, where $u_r\geq 0, v_r\geq 0$ are unknown variables. The DEA relative efficiency measure h_{j0} for a target decision making unit j_0 can be determined by solving the following famous CCR (developed by Charnes, Cooper and Rhodes) model (Charnes et al., 1978).

$$
\begin{aligned}
&\max=\frac{\sum_{r=1}^{s}u_r y_{rj_0}}{\sum_{i=1}^{m}v_i x_{ij_0}}\\
&\text{s.t. } \frac{\sum_{r=1}^{s}u_r y_{rj}}{\sum_{i=1}^{m}v_i x_{ij}}\leq 1\\
&v\geq 0, u\geq 0\\
&j=1,2,\cdots,n
\end{aligned}
$$

Introducing flabby variable and the concept of Archimedes, the CCR model can be transformed to linear programming.

$$
\begin{aligned}
&\min\left[\theta-\varepsilon E^T(s^-+s^+)\right]\\
&\text{s.t. } X_{j_0}\cdot\theta=\sum_{j=1}^{n}\lambda_j\cdot X_j+s^-\\
&\sum_{j=1}^{n}\lambda_j\cdot Y_j-s^+=Y_{j_0} \qquad\qquad \text{Model}-1\\
&s^-\geq 0, s^+\geq 0, \lambda_j\geq 0, \theta\leq 0\\
&j=1,\cdots,n
\end{aligned}
$$

where $\lambda_1,\lambda_2\cdots\lambda_n$ are the power variables of decision making units (DMUs) and θ is the pending parameter variable. s^- and s^+ are the flabby variables (remnant variables). ε is a positive non-Archimedean infinitesimal smaller than any positive real number and is used to prevent the weights from being zero.

The input-oriented BCC (developed by Banker, Charnes and Cooper) model (Banker et al., 1984) is the dual of this linear program together with a constraint capturing returns to scale characteristics, and can be described as:

$$
\begin{aligned}
&\min\left[\theta-\varepsilon E^T(s^-+s^+)\right]\\
&\text{s.t. } X_{j_0}\cdot\theta=\sum_{j=1}^{n}\lambda_j\cdot X_j+s^-\\
&\sum_{j=1}^{n}\lambda_j\cdot Y_j-s^+=Y_{j_0} \qquad\qquad \text{Model}-2\\
&\sum_{j=1}^{n}\lambda_j=1\\
&s^-\geq 0, s^+\geq 0, \lambda_j\geq 0, \theta\leq 0\\
&j=1,\cdots,n
\end{aligned}
$$

where ε is the same as that in above model, θ and $\lambda_j\geq 0$ are dual variables, s^- and s^+ are slack variables, $\sum_{j=1}^{n}\lambda_j=1$ is the variable returns to scale constraint.

Denote the optimal solution of problem as (θ^*, λ_j^*, s^{-*}, s^{+*}). The unit j_0 is called weak DEA efficiency if $\theta^*=1$, and $s^{-*}\neq 0$ or $s^{+*}\neq 0$. The unit j_0 is called DEA efficiency if $\theta^*=1$, and $s^{-*}=0$, $s^{+*}=0$. Otherwise if $\theta<1$, it is labeled as inefficient when compared to the other units.

3.2.2. *The DEA model of eco-efficiency analysis*

Treating the undesirable outputs like classic inputs to be minimized in DEA model was already valued as a quite intuitive approach (Dyckhoff and Allen, 2001), we envision the undesirable outputs as inputs in our DEA model for eco-efficiency analysis.

Assume we have n homogeneous DMUs, each consuming m inputs and producing p outputs. The outputs corresponding to indices 1, 2,…, k are desirable and the outputs corresponding to indices $k+1$, $k+2$,…, s are undesirable outputs. We would like to produce desirable outputs as much as possible and not to produce undesirable outputs. Let $x\in\mathcal{R}_+^{m\times n}$ and $Y\in\mathcal{R}_+^{s\times n}$ be the matrices, consisting of non-negative elements, containing the observed input and output measures for the DMUs. We decompose matrix Y into two parts:

$$Y=\begin{pmatrix}Y^g\\ Y^b\end{pmatrix}$$

where a $k\times n$ matrix Y^g is standing for desirable outputs ("good") and a $(s-k)\times n$ matrix Y^b is standing for undesirable outputs ("bad") (Dyckhoff, 1994). We further assume that there are no duplicated units in the data set. We denote by x_j (the jth column of X) the vector of inputs consumed by DMU_j, and by x_{ij} the quantity of input i consumed by DMU_j. A similar notation is used for outputs. Occasionally, we decompose the vector y_j into two parts: $y_j=\begin{pmatrix}y_j^g\\ y_j^b\end{pmatrix}$, where the vectors y_j^g and y_j^b refer to the desirable and undesirable output-values of unit j.

We will carry out the considerations by using a CCR model but the results can be generalized to other DEA models as well. We will review some approaches and show that these seemingly different models lead to similar results (Korhonen and Luptacik, 2004).

[2] Yearbook in 2005 will present the data of 2004.

Envisioning the undesirable outputs as inputs, this idea leads to the following approach, which is called Model 3:

$$\max = \frac{\sum_{r=1}^{k} u_r y_{rj_0}}{\sum_{i}^{m} v_i x_{ij_0} + \sum_{r=k+1}^{s} u_r y_{rj_0}}$$

$$\text{s.t.} \frac{\sum_{r=1}^{k} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=k+1}^{s} u_r y_{rj}} \le 1 \qquad \text{Model} - 3$$

$$j = 1, 2, \cdots, n,\ u, v \ge 0$$
$$j = 1, 2, \cdots, m; r = 1, 2, \cdots, s.$$

Using a standard technique (Charnes et al., 1978, 1979) to transform the above fractional model into a linear mode, we will get the following primal-dual LP-model pair. Note that the original primal formulation in Charnes et al. (1978) is currently in the DEA literature called the dual and vice versa (Charnes et al., 1994). The input-oriented CCR primal model is as follows:

$$\min\left[\theta - \varepsilon E^T\left(s^b + s^g + s^-\right)\right]$$
$$\text{s.t. } X_{j_0} \cdot \theta = \sum_{j=1}^{n} \lambda_j \cdot X_j + s^-$$
$$\sum_{j=1}^{n} \lambda_j Y_j^g - s^g = Y_{j_0}^g \qquad \text{Model3} - 1$$
$$\sum_{j=1}^{n} \lambda_j Y_j^b + s^b = \theta y_{j_0}^b$$
$$\lambda, s^-, s^g, s^b \ge 0$$
$$\varepsilon > 0; j = 1, 2, \cdots, n$$

The corresponding input-oriented BCC model is as follows:

$$\min\left[\theta - \varepsilon E^T\left(s^b + s^g + s^-\right)\right]$$
$$\text{s.t. } x_{j_0} \cdot \theta = \sum_{j=1}^{n} \lambda_j \cdot X_j + s^-$$
$$\sum_{j=1}^{n} \lambda_j Y_j^g - s^g = Y_{j_0}^g$$
$$\sum_{j=1}^{n} \lambda_j Y_j^b + s^b = \theta y_{j_0}^b \qquad \text{Model3} - 2$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda, s^-, s^g, s^b \ge 0,$$
$$\varepsilon > 0; j = 1, 2, \cdots, n$$

The primal model (Model 3-1) corresponds to a standard input-oriented primal CCR model provided that undesirable outputs behave in the model like inputs. In this model, the DMU reduces simultaneously the inputs and undesirable outputs in order to increase eco-efficiency.

The vectors s^- and s^b correspond to excesses in inputs and bad outputs, respectively, while s^g expresses shortages in good outputs. Let an optimal solution of the above program be (θ^*, s^{-*}, s^{g*}, s^{b*}). Then we can demonstrate that the DMU (x_o, y_o^g, y_o^b) is efficient in the presence of undesirable output if and only if $\theta^*=1$, i.e., $s^{-*}=0$, $s^{g*}=0$, $s^{b*}=0$. If the DMU is inefficient, i.e., $\theta^*<1$, it can be improved and become efficient by deleting the excesses in inputs and bad outputs and augmenting the shortfalls in good outputs by the following projection.

$$x_0 \Leftarrow x_0 - s^{-*}$$
$$y_0^g \Leftarrow y_0^g + s^{g*}$$
$$y_0^b \Leftarrow y_0^b + s^{b*}$$

4. Results

In this section, we describe how we used our approach to evaluate the eco-efficiency of 30 provincial industrial systems in China.

4.1. *Input and output indicators*

The desirable output is value added of industry (100 million Yuan) with a minimum of 102.70 and a maximum of 7068.40 (Table 1). The material and energy are considered as inputs, including water resource input (min 3.00*100 million cu.m, max 182.60*100 million cu.m), raw mining resource input (min 321.54*10 thousand ton, max 322,693.00*10 thousand ton) and energy input (min 374.86 10 thousand tons of SCE, max 13,971.35*10 thousand tons of SCE). The undesirable outputs or the pollutants are COD [0.30, 69.30], nitrogen [0.10, 5.00], SO_2 [2.20, 154.40] soot [1.00, 87.70], dust [1.10, 72.60] and solid waste [112.00, 16765.00]. Both the inputs and undesirable outputs express the environmental impacts of industrial system.

4.2. *Resource efficiency and environmental efficiency*

First, we use Model-1 to measure the resource efficiency and environmental efficiency, respectively. The results given in Table 2 provide eco-efficiency performance indicators of 30 provinces. The column denoted by "Res. Eff." contains the resource efficiencies which are the results of Model-1 using water, raw mining resource and energy consumption as inputs and the value added of industry as an output. In this

Table 1 – Summary of input and output indicators

Category	Variable	Units	Obs.	Mean	Std. dev.	Min	Max
Input	Water resource	100 million cu.m	30	40.96	40.73	3.00	182.60
	Raw mining resource	10 thousand tons	30	56,090.47	77,648.67	321.54	322,693.00
	Energy	10 thousand tons of SCE	30	4463.09	3408.24	374.86	13,971.35
Undesirable output	COD discharge	10 thousand tons	30	16.98	15.09	0.30	69.30
	Nitrogen discharge	10 thousand tons	30	1.41	1.39	0.10	5.00
	Sulphur dioxide emission	10 thousand tons	30	63.05	40.06	2.20	154.40
	Soot emission	10 thousand tons	30	29.55	22.92	1.00	87.70
	Dust emission	10 thousand tons	30	30.17	21.75	1.10	72.60
	Industria l solid wastes produced	10 thousand tons	30	4000.60	3439.70	112.00	16,765.00
Desirable output	Value-ad ded of industry	100 million Yuan	30	1826.50	1890.40	102.70	7086.40

Table 2 – Results of resource efficiency and environmental efficiency analysis (CCR model)

No.	Area	DMUs	Res. Eff.	Envi. Eff.	θ
1	North	Beijing	0.9342	1.0000	1.0000
2		Tianjin	1.0000	1.0000	1.0000
3		Hebei	0.3566	0.2009	0.3566
4		Shanxi	0.3267	0.1128	0.3267
5		Neimengu	0.2730	0.0746	0.2887
6	Northeast	Liaoning	0.4630	0.3449	0.5352
7		Jilin	0.4215	0.4569	0.4574
8		Heilongjiang	0.4933	0.5453	0.5549
9	East	Shanghai	1.0000	1.0000	1.0000
10		Jiangsu	0.6847	0.6117	0.7249
11		Zhejiang	0.8505	0.5386	0.8509
12		Anhui	0.3450	0.2470	0.3538
13		Fujian	0.7448	0.5909	0.7791
14		Jiangxi	0.3473	0.1307	0.3473
15		Shandong	0.8362	0.4280	0.8362
16	South	Henan	0.3470	0.2109	0.3470
17		Hubei	0.3289	0.2752	0.3467
18		Hunan	0.3750	0.1692	0.3750
19		Guangdong	1.0000	0.6404	1.0000
20		Guangxi	0.3386	0.0667	0.3386
21		Hainan	0.3539	1.0000	1.0000
22	Southwest	Chongqing	0.3927	0.0918	0.3927
23		Sichuan	0.3504	0.1403	0.3504
24		Guizhou	0.2249	0.1702	0.2437
25		Yunnan	0.3812	0.2200	0.3985
26	Northwest	Shanxi	0.5191	0.1497	0.5362
27		Gansu	0.2679	0.1161	0.2768
28		Qinghai	0.3516	1.0000	1.0000
29		Ningxia	0.1679	0.0570	0.1679
30		Xinjiang	0.4646	0.1962	0.4766

simple CCR model, only three provinces perform efficiently, namely, Tianjing, Shanghai and Guangdong. Column denoted by "Envi. Eff." presents the environmental efficiency. The results are obtained solving Model-1 with value added of industry as the desirable output and with COD, nitrogen, SO_2, soot, dust and solid waste as inputs. In this simple CCR model, only five provinces perform efficiently, namely, Beijing, Tianjing, Shanghai, Hainan and Qinghai.

Using this approach, there are only two provinces that are eco-efficient in both resource and environmental categories, namely Tianjing, and Shanghai. Provinces such as Beijing, Hainan and Qinghai are environmentally efficient without showing ideal resource efficiency, however, Guangdong is resource efficient without environmental efficiency. These four provinces are only weakly eco-efficient. While examining the relationship between environmental efficiency and resource efficiency, provinces with higher resource efficiency often present higher environmental efficiency with an exception of Hainan and Qinghai (Fig. 2).

The above analysis presented environmental efficiency and resources efficiency, respectively. An integrated eco-efficiency analysis will improve our understanding of eco-efficiency of provincial industrial systems.

4.3. *Eco-efficiency of regional industrial system*

An alternative approach to evaluate eco-efficiency is to use Model 3-1 (CCR). Table 2 shows the results of DEA taking both pollutants and resources as inputs, under the assumption of constant returns to scale. As shown in Table 2, only six provinces are eco-efficient, including Beijing, Tianjing, Shanghai, Guangdong, Hainan and Qinghai. Most provinces have relatively low levels of eco-efficiency in the model. Eco-efficient DMUs are either environmentally efficient or have an ideal resource efficiency. Although Qinghai and Hainan have relatively low levels of resource efficiency, both of them are relatively eco-efficient.

While examining the spatial distribution of eco-efficiency, we use different colors to represent levels of eco-efficiency (Fig. 3). The results show that provinces in the East are more eco-efficient than both northern and southern provinces.

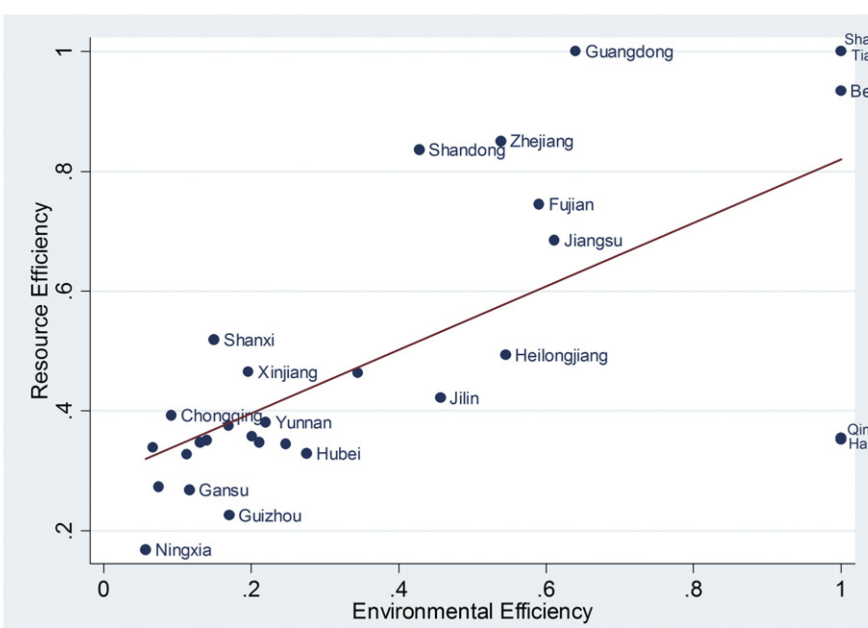

Fig. 2 – Relationship between environmental efficiency and resource efficiency.

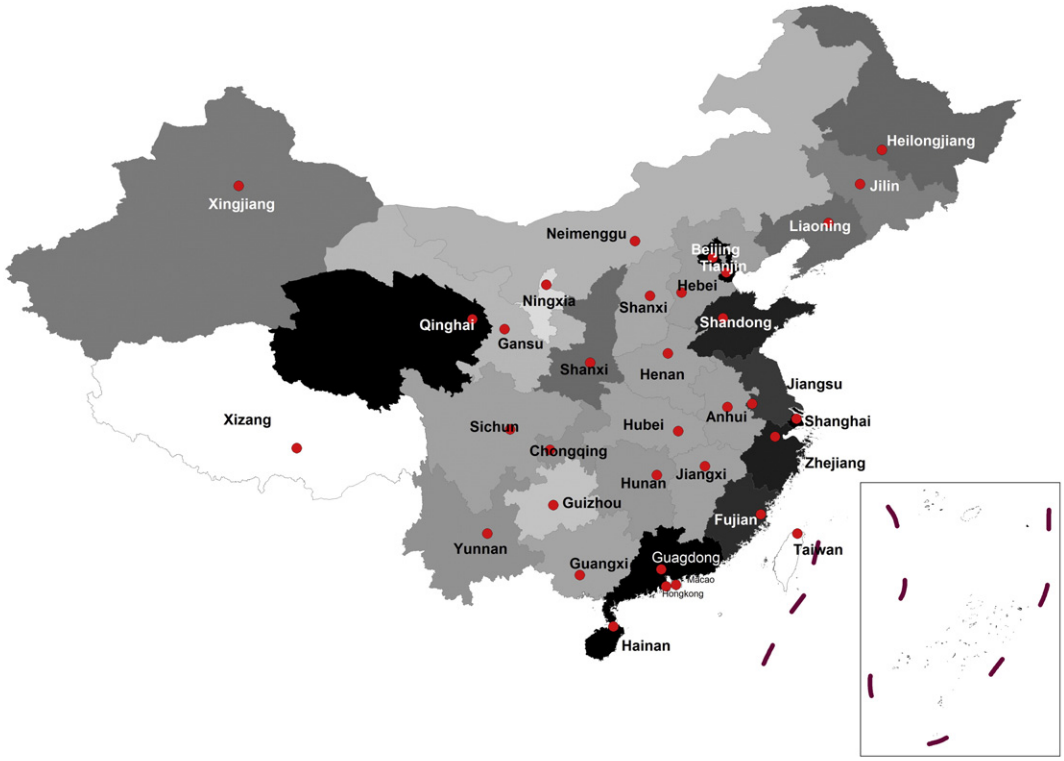

Fig. 3 – Eco-efficiencies of 30 provinces in China (A blacker color indicates a higher eco-efficiency).

Regional disparity of eco-efficiency presents a similar pattern of economic development in China. In relatively developed regions, provinces usually have more modern industries, advanced technology, higher management levels, and quality human resources, which undoubtedly will use resources more efficiently and discharge fewer pollutants.

Fig. 4 examined the relationship between eco-efficiency and economic development level. The results show that the provinces with higher GDP per capita also have higher eco-efficiencies with exception of a few provinces such as Hainan and Qinghai. Both Hainan and Qinghai are eco-efficient with relatively lower GDP per capita.

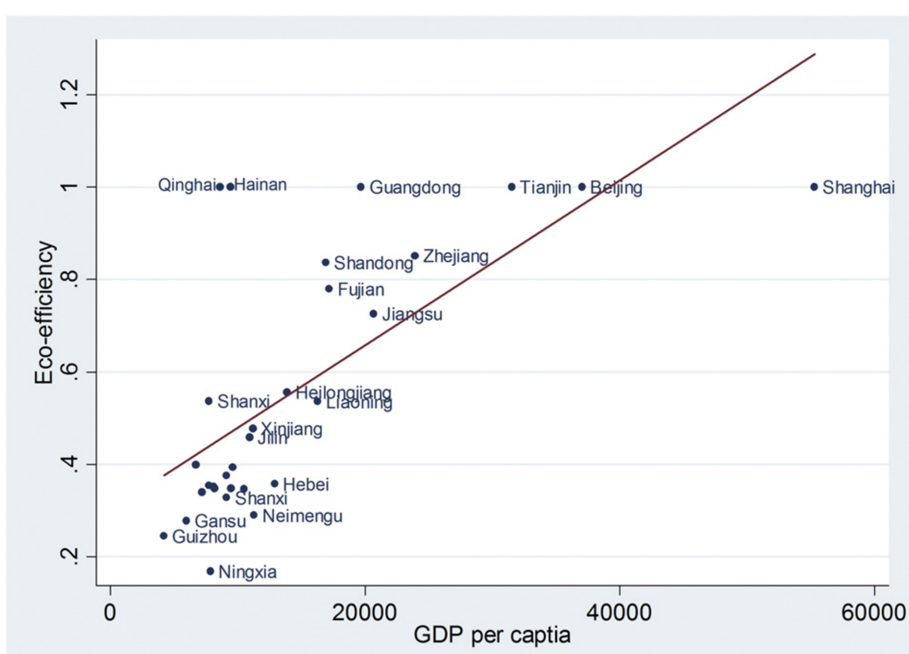

Fig. 4 – Relationship between eco-efficiency (model-3) and GDP per capita in 30 provinces of China.

Table 3 – The optimization results of eco-efficiency

DMUs	Water resource s^-	Raw material s^-	Energy s^-	COD s^-	Nitrogen s^-	SO_2 s^-	Soot s^-	Dust s^-	Solid waste s^-
Total	26.8	612,049.7	4013.4	119.5	9.7	235.2	214.1	271.4	27,386.8
Total of original indicators' value	1228.8	1,682,714.2	133,892.637	509.5	42.2	1891.5	886.4	905.1	120,018
%	2.2	36.4	3.0	23.5	23.1	12.4	24.2	30.0	22.8

4.4. *Eco-efficiency optimization*

The model 3-1 provides more details of optimizing DMUs according to the equation $\begin{matrix} x_0 \Leftarrow x_0 - s^{-*} \\ y_0^g \Leftarrow y_0^g + s^{g*} \\ y_0^b \Leftarrow y_0^b + s^{b*} \end{matrix}$. The results of the model are shown in Table 3. Totally, 2.2% of water, 36.4% of raw mining materials, 3.0% of energy, 23.5% of COD, 23.1% of Nitrogen, 12.4% of SO_2, 24.2% of Soot, 30.0% of Dust, and 22.8% of Solid waste should be reduced in China (Table 3). Thus, reducing raw material inputs and pollution emission is the most urgent task for China to promote eco-efficiency. Different provinces should have different strategies of optimizing eco-efficiency. Various policies should be developed for specific areas to achieve higher eco-efficiency and sustainable development.

5. Discussions

Our results provide eco-efficiency of regional industrial systems in China using DEA models, which are in line with the spatial distribution of development in China. The results show that only six provinces are eco-efficient, and most provinces are still at low level of eco-efficiency. Both central and local governments in China traditionally have preferences for GDP growth while neglecting environmental degradation and low efficiency resource utilization. Such a governance framework encouraged low eco-efficiency activities, causing crisis in both resource shortage and environmental risks. The DEA model thus could be used as a tool to reflect the order of eco-efficiency in a defined region and help governments at various levels to find the most optimized solutions in improving their eco-efficiencies. On the other hand, even high eco-efficiency areas such as Beijing and Shanghai are relatively inefficient compared to Japan, the United States and other developed counties (Zhu, 2005). Moreover, China is still maintaining its higher GDP growth rate, and its GDP will be quadrupled by 2020. In order to avoid further degradation of the environment and increasing demand of resource of the whole world, achieving "factor 4" or more is crucial for China's sustainable development in the next two decades.

Although increased eco-efficiency might provide a route towards sustainable development, eco-efficiency analysis is part of sustainable development measurement and the improvement of eco-efficiency does not guarantee sustainability (Mickwitz et al., 2006; Hukkinen, 2001). Eco-efficiency would increase even though the environmental impact increases as

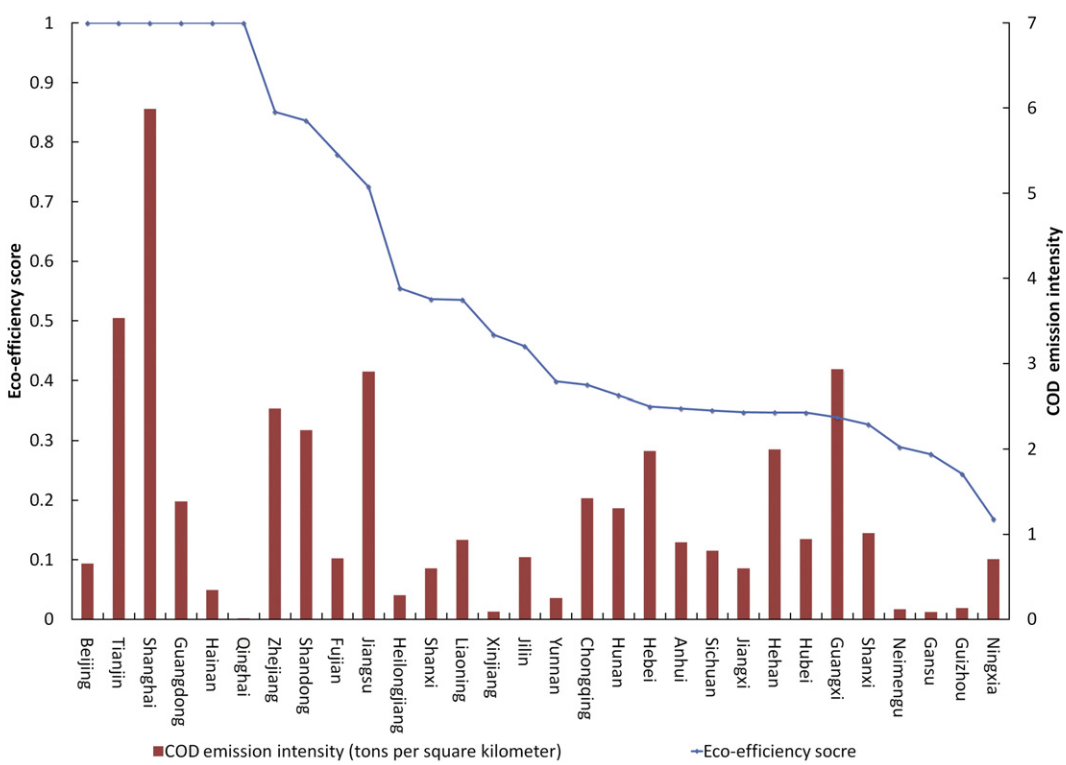

Fig. 5 – Relationship between eco-efficiency and COD emission intensity in 30 provinces of China.

long as the economic value increases faster. Even if the relative level of environmental pressure is lower compared to economic output, the absolute environmental pressure can still exceed the carrying capacity of the ecosystem.

In addition, eco-efficiency is a notion that is meaningful only in the context of the economic model of sustainable development. Although the WBCSD's statements indicate that production output should be kept "in line with the Earth's carrying capacity," there is nothing in the analytic representation of eco-efficiency that provides a clue to this (Ehrenfeld, 2005). Thus, rendering eco-efficiency only a partially useful concept while refer to sustainable development. We took COD emission intensity (tons per square kilometer) as proxy variables of "the environmental impact of production output while comparing to carrying capacity" and examined the relationship of emission intensity indicators and eco-efficiency. We found that provinces with high eco-efficiency score, such as Shanghai and Tianjing, also had high emission intensity (Fig. 5). Thus, we cannot make the judgment that Shanghai and Tianjing is more sustainable than other provinces in this paper.

This, however, does not render the concept of eco-efficiency and downplay our research. Measurement of eco-efficiency is critically important for finding a cost-effective way of reducing environmental pressures. In addition, policies targeted at efficiency improvements tend to be easier to adopt than policies that restrict the level of economic activity (Kuosmanen and Kortelainen, 2005), which is more welcome in a developing country like China.

Secondly, this research took the standard definition of eco-efficiency as "economic value added divided by environmental impacts". However, social aspects are an essential part of sustainable development and also clearly part of human needs. They are not yet embedded in the concept of eco-efficiency in practical applications, including our research. This is one of the reasons why the use of eco-efficiency has been harshly criticized by many scholars. At the regional level, the ignorance of social aspects will limit the concept of eco-efficiency with which ecological resources are used to provide economic welfare instead of to "meet human needs" (Mickwitz et al., 2006).

Thirdly, most researches choose resource use and pollution emission as environmental imparts indicators in eco-efficiency analysis, so as our research. However, evaluation of time-scale effects on the economic value and environment impact should be considered for regional eco-efficiency analysis. Life Cycle Assessment (LCA) is used for analyzing the life cycle environmental impact of product. At regional level it will be more complex and cumbersome.

Finally, this paper has adopted data envelopment analysis as a method for eco-efficiency analysis that can accommodate various desirable and undesirable effects of regional industrial system into a single efficiency index. In contrast to other methods presented in the eco-efficiency literature, DEA does not require any priori weights for various environmental pressures.

There are also some limitations of employing DEA methodology. First, the DEA measurement needs extensive data. Since it is based on relative efficiency assessment of comparable units in a general framework that lets the data speak for themselves, the data must be relatively accurate and reliable, and the sample size must be sufficiently large. Second, DEA identifies weights that maximize the efficiency score of the evaluated unit or activity in comparison with a group of similar units or activities. However, some activities may appear as efficient even though they perform well only on a single, relatively unimportant criterion (Kuosmanen and Kortelainen, 2005).

In our research, Qinghai and Hainan are low resource efficiency and considered to be weakly eco-efficient, but reveal high eco-efficiency in model-3. Thus, it is important to provide additional information concerning the relative importance of different environmental impacts imposing soft weight restrictions.

6. Conclusion

This paper addressed eco-efficiency analysis by taking various undesirable outputs into account and developed a DEA-based model. Using the real data of 30 provinces, an empirical study was employed to illustrate the eco-efficiency of regional industrial systems in China. A possible extension of this research was to investigate undesirable outputs allocation mechanism. This would gain deeper insights into the causes of eco-inefficiency, and gave further hints on policy-making of environmental protection in China.

The results also provided evidences and suggestions with respect to China's development. If rapid economic development continues, achieving "factor 4" or more is crucial for China's sustainable development in the next two decades. Circular economy could be adopted as one of the strategies to developing the economy while aiming at environmental protection, pollution prevention and sustainable development through "3 R (reduce, reuse and recycle)" approaches (Yuan et al., 2006) Distinguishing policies should be developed to different areas for higher eco-efficiency and sustainable development with regard to the region disparity of eco-efficiency. Central government should provide more technical and financial resources and assistance to less developed areas. Regional policies should be developed to encourage developed regions such as Shanghai to transfer advanced technologies to less developed regions. Moreover, resource-based regions usually do not have sufficient fund for environmental protection because a centrally control price system makes mining activities damaged by lower resource prices in China. Therefore, resource prices should be increased or eco-compensation[3] mechanism and policies should be established to help less developed areas financially. In addition, tighter regulation and implementation toward pollution control still play a critical role and should not be neglected anyway.

Traditionally, Chinese officeholders are assessed and promoted depending on economic growth other than social and environmental performance. It will inevitably lead local

[3] Eco-compensation is a type of institutional and financial arrangement developed in China recently to protect sustainable use of ecosystem services, and to adjust the distribution of costs and benefits between different actors, stakeholders and regions, mainly through economic measures.

governments to focus on GDP growth with less attention to environmental protection. A new promotion system with consideration of environmental performance such as eco-efficiency indicators will encourage local governments to take a more comprehensive development strategy to balance economic development and environment protection.

Finally, there are some limitations in our research as mentioned above. Further work remains to be done in this area. In order to make eco-efficiency become a useful indicator for sustainable development, it must be coupled with other indicators and tools, such as aforementioned carrying capacity indicators, social and cultural indicators, as well as LCA techniques for a time-scale analysis. Furthermore, future research regarding DEA approach should aim at the integration of non-linear preference structure, as increasing insights in the impacts of production progress are likely to lead to non-linear impact model. Apart from that, relative weight restrictions should be included into DEA model according to previous discussion. Finally, current procedure may be useful in comparing one nation or region to another, but again tells limited about the direction of progress toward the goal of sustainable development. Further empirical researches should extend the static and cross-sectional framework in this article toward dynamic eco-efficiency analysis. This approach might offer useful techniques for quantifying and explaining changes of eco-efficiency over time. In addition, integrated empirical researches combining of regional eco-efficiency and industrial eco-efficiency are also suggested. In this respect, tools such as input–output tables might offer useful techniques for quantifying and explaining the causes of eco-inefficiency.

Acknowledgements

This research is supported by China's Natural Sciences Foundation (40471057 and 40501027), Major Program of National Social Science Foundation of China (06&ZD026) and the Eleventh Five-year Key Technology R&D Program (2006BAC02A15).

REFERENCES

Allen, K., 1999. DEA in the ecological context: an overview. In: Westermann, G. (Ed.), Data Envelopment Analysis in the Service Sector. Gabler Edition Wissenschaft, Wiesbaden, pp. 203–235.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale efficiencies in data envelopment analysis. Manage Science 30, 1078–1092.

Basque Government, 2003. The environment in the Basque country. Environmental Framework Programme Series, vol. 21. Sociedad Püblica de Gestion Ambiental (IHOBE), Bilbao, Spain.

Bleischwitz, R., 2003. Cognitive and institutional perspectives of eco-efficiency. Ecological Economics 46, 453–467.

Brady, K., Henson, P., Fava, J., 1999. Sustainability, eco-efficiency, life cycle management and business strategy. Environmental Quality Management 8, 33–41.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring efficiency of decision making units. European Journal of Operational Research 2, 429–444.

Charnes, A., Cooper, W.W., Rhodes, E., 1979. Short communication: measuring efficiency of decision making units. European Journal of Operational Research 3 (4), 339.

Charnes, A., Cooper, W.W., Levin, A., Seiford, L., 1994. Data Envelopment Analysis: Theory, Methodology and Applications. Kluwer Academic Publishers, Boston.

Choucri, N., 1995. Globalisation of eco-efficiency: GSSD on the WWW. UNEP Industry and Environment.

Courcelle, C., Kestemont, M.P., Tyteca, D., 1998. Assessing the economic and environmental performance of municipal solid waste collection and sorting programmes. Waste Management and Research 16, 253–263.

Cramer, J., 1997. How can we substantially increase eco-efficiency? UNEP Industry and Environment 58–62 July–September.

DeSimone, L.D., Popoff, F., 2000. Eco-efficiency: The Business Link to Sustainable Development. MIT Press Development WBCFS, Cambridge, p. 47.

Dyckhoff, H., 1994. Betriebliche Produktion. Springer Verlag, Berlin, p. 65 (in German).

Dyckhoff, H., Allen, K., 2001. Measuring ecological efficiency with data envelopment analysis (DEA). European Journal of Operational Research 132, 312–325.

Ehrenfeld, J.R., 2005. Eco-efficiency: philosophy, theory, and tools. Journal of Industrial Ecology 9, 6–8.

Färe, R., Grosskopf, S., Tyteca, D., 1996. An activity analysis model of the environmental performance of firms application to fossil-fuel-fired electric utilities. Ecological Economics 18, 161–175.

Farrell, M.J., 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society, Series A 120, 253–281.

Fet, A.M., 2003. Eco-efficiency reporting exemplified by case studies. Clean Technology Environmental Policy 5, 232–239.

Freeman, M.A., R.H., H., A.V., K., 1973. The Economics of Environmental Policy. John Wiley & Sons, New York.

Glauser, M., Muller, P., 1997. Eco-efficiency: a prerequisite for future success. CHIMIA 51, 201–206.

Hukkinen, J., 2001. Eco-efficiency as abandonment of nature. Ecological Economics 38, 311–315.

Huppes, G., Ishikawa, M., 2005. A framework for quantified eco-efficiency analysis. Journal of Industrial Ecology 9, 25–41.

Hur, T., Kim, I., Yamamoto, R., 2004. Measurement of green productivity and its improvements. Journal of Cleaner Production 21, 673–683.

ISO, 1998. Environmental performance evaluation. ISO 14031, the International Standardisation Organisation.

Keffer, C., Shimp, D., 1999. Eco-efficiency Indicators and Reporting. World Business Council for Sustainable Development (WBCSD), London.

Korhonen, P.J., Luptacik, M., 2004. Eco-efficiency analysis of power plants: an extension of data envelopment analysis. European Journal of Operational Research 154, 437–446.

Kuosmanen, T., Kortelainen, M., 2005. Measuring eco-efficiency of production with data envelopment analysis. Journal of Industrial Ecology 9, 59–72.

Lovell, C.A.K., Pastor, J.T., Turner, J.A., 1995. Measuring macroeconomic performance in the OECD: a comparison of European and non-European countries. European Journal of Operational Research 87, 507–518.

McIntyre, R.J., J.R, T., 1974. Environmental divergence: air pollution in the USSR. Journal of Environmental Economics and Management 1, 109–120.

McIntyre, R.J., Thornton, J.R., 1978. On the environmental efficiency of economic systems. Soviet Studies 30, 173–192.

Metti, G., 1999. Global environmental factors and eco-efficiency. Beverage World 1999, pp. 82–83.

Mickwitz, P., Melanen, M., Rosenström, U., Seppälä, J., 2006. Regional eco-efficiency indicators: a participatory approach. Journal of Cleaner Production 14, 1603–1611.

Reijnders, L., 1998. The factor X debate: setting targets for eco-efficiency. Journal of Industrial Ecology 2, 13–22.
Reith, C.C., Guidry, M.J., 2003. Eco-efficiency analysis of an agricultural research complex. Journal of Environmental Management 68, 219.
Schaltegger, S., Sturm, A., 1990. Öologische Rationalität (German/in English: Environmental rationality). Die Unternehmung 4, 117–131.
Schaltegger, S., Burritt, R., 2000. Contemporary Environmental Accounting-Issues. Concepts and Practice. Greenleaf Publishing, Sheffield.
Schaltegger, S., Synnestvedt, T., 2002. The link between “green” and economic success: environmental management as the crucial trigger between environmental and economic performance. Journal of Environmental Management 65, 339–346.
Schmidheiny, S., 1992. Changing course: a global business perspective on development and the environment. MIT Press. Cambridge, MA.
Seppälä, J., Melanen, M., Mäenpää, I., Koskela, S., Tenhunen, J., Hiltunen, M.-R., 2005. How can the eco-efficiency of a region be measured and monitored? Journal of Industrial Ecology 9, 117–130.
Srdjevic, B., Medeiros, Y.D.P., Porto, R.L.L., 2005. Data envelopment analysis of reservoir system performance. Computers & Operations Research 32, 3209–3266.
Sturm, A., Müller, K., Upasena, S., 2002. Accounting framework and guidelines for eco-efficiency indicators: a manual for preparers and users. Release 1.1/November 2002. Prepared for the United Nations Conference on Trade and Development (UNCTAD)/Intergovernmental Working Group of Experts on International Standards of Accounting and Reporting (ISAR). Ellipson/UNCTAD-ISAR, Basel, Switzerland.
United Nations Conference On Trade And Development (UNCTD), 2003. Integrating Environmental and Financial Performance at the Enterprise Level: A Methodology for Standardizing Eco-efficiency Indicators. United Nations Publication. 29–30 pp.
Vencheh, A.H., Matin, R.K., Kajani, M.T., 2005. Undesirable factors in efficiency measurement. Applied Mathematics and Computation 163, 547–552.
World Business Council For Sustainable Development (WBCSD), 2000. Measuring Eco-efficiency: A Guide to Reporting Company Performance.
Yuan, Z.W., Bi, J., Moriguichi, Y., 2006. The circular economy: a new development strategy in China. Journal of Industrial Ecology 10, 2–5.
Zhu, D.J., 2005. Eco-efficiency and circular economy. Fudan Journal (Social Science) 2, 60–66.