Ecological Indicators 36 (2014) 665–671

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Short Communication

Using eco-efficiency as an indicator for sustainable urban development: A case study of Chinese provincial capital cities

Ke Yin[a], Rusong Wang[a,*], Qingxian An[b], Liang Yao[a], Jing Liang[c]

[a] State Key Laboratory of Urban and Regional Ecology, Research Centre for Eco-environmental Sciences, Chinese Academy of Sciences, Beijing 100085, China
[b] Department of Management, University of Science and Technology of China, Hefei 230026, China
[c] Hunan Environmental Monitoring Center, Changsha 411100, China

ARTICLE INFO

Article history:
Received 17 February 2013
Received in revised form 21 July 2013
Accepted 4 September 2013

Keywords:
Data envelopment analysis
Undesirable output
Desirable output

ABSTRACT

Urbanisation in China has resulted in an increased consumption of resources, energy and materials and led to negative environmental effects. All of these factors have motivated the widely discussed topic of urban sustainable development in China. The core of this discussion is how to quantitatively measure urban sustainable development. This research uses eco-efficiency as an indicator to measure urban sustainable development. A data envelopment analysis model was applied to eco-efficiency analysis using environmental pollution as an undesirable output, and a super-efficiency model was modified for ranking. Using real datum for 30 Chinese provincial capital cities, an empirical study was employed to describe their eco-efficiency. The results show that: almost half of the cities are fairly eco-efficient. The inefficient cities are mainly located in the southwest and northwest of China, which are the undeveloped economic zones, while some of the eco-efficient cities have more environmental pollution and consume more land, energy and water. When ranking cities using a modified model, it was found that Haikou, Fuzhou and Beijing were the top three most eco-efficient cities, while Yinchuan, Lanzhou, Guiyang were the bottom three. When exploring the driving force of eco-efficiency, this paper proposes changing the GDP-oriented growth model and appraisal system, continuously transforming and upgrading the industrial structure and stopping the migration of heavy industry from east to west, south to north and city to countryside.

1. Introduction

Since 1978, China has experienced rapid and unprecedented urbanisation, which was created by world history's largest flow of rural–urban migration (Zhang and Song, 2003). The urbanisation rate ranged from 17.92% in 1978 to 49.95% in 2010, and the average growth rate was 0.97% (National Bureau of Statistical of China, 2011). Meanwhile, many problems have arisen, such as traffic congestion, social disorder, a reduction in biodiversity and water quality deterioration. All of these issues serve as bottlenecks restricting urban sustainable development. The question then becomes how to develop a city in sustainable way.

The development of composite indicators is considered to be a unique approach for evaluating sustainable development (Singh et al., 2012). At present, hundreds of indicators and indices have been suggested for measuring sustainable development. Despite criticisms of data quality, comparability, objective function and necessary resources, most authors assume that a set of well-defined and harmonised indicators is the only way to make sustainability tangible (Reed et al., 2006). Among these indicators, eco-efficiency has been proposed as a route to promote a transformation towards sustainability (Mickwitz et al., 2006).

Eco-efficiency was first proposed in academia by Schaltegger and Sturnin in 1992 (Willard, 2002) and the concept then gained in popularity and spread throughout the business world (Jollands et al., 2004). To date, the applications of eco-efficiency have included products (Cerutti et al., 2013; Quariguasi-Frota-Neto and Bloemhof-Ruwaard, 2012), enterprises (Fernández-Viñé et al., 2013; Hahn et al., 2010) and industry sections (Oggioni et al., 2011; Wang et al., 2011). It was recently extended to a regional scale (Kielenniva et al., 2012; Yu et al., 2013) in an attempt to develop the potential of individual regions.

The WBCSD (World Business Council for Sustainable Development), OECD (Organisation for Economic Cooperation and Development), EEA (European Environmental Agency), UNCAD (United Nations Conference on Trade and Development) and Industry Canada have presented different definitions of eco-efficiency (Lv and Yang, 2006). Despite the range of interpretations, Hinterberger et al. (2000) notes that all definitions have a theme in common: "All concepts call for a more efficient use of natural resources". Beyond this basis, the details of eco-efficiency can be understood in a number of ways. Generally, efficiency is a multi-dimensional concept, as the units used to measure as input and output are different.

* Corresponding author. Tel.: +86 10 6294 3807.
E-mail address: wangrs@rcees.ac.cn (R. Wang).

1470-160X/$ – see front matter © 2013 Published by Elsevier Ltd.
http://dx.doi.org/10.1016/j.ecolind.2013.09.003

In the term ‘eco-efficiency’, the prefix ‘eco’ represents both ecological and economic performance. Thus, eco-efficiency is the ratio between the change in value and change in ecological impact (Schaltegger and Burritt, 2000): eco-efficiency = economic output/ecological impact. Any measure of eco-efficiency requires financial information to calculate the numerator and ecological information to calculate the denominator. The indicators of GDP, quantity of products/services produced, net sales and value added are the general economic indicators for the denominator. For the numerator, WBCSD uses energy consumption, material consumption, water consumption, greenhouse gas (GHG) emissions and ozone layer damage and material emissions as five general indicators and acidification gas emissions and total waste as two supplemental indicators.

As a ratio model, the eco-efficiency ratio can only be obtained if the numerator and the denominator could be integrated into one score. Regarding the economic dimension, integration is easy because there is a common benchmark – money. However, for the ecological dimension, the ecological impacts are extensive, complex and measured using different units. Thus, various ecological impacts must be weighted before integration. The essential question is then how this weight should be chosen or determined.

Composite indices can be constructed with or without weights depending on their application (Singh et al., 2012). According to the weighting system, the current method for eco-efficiency can be classified into three categories. The first class is the single-ratio model of ‘economic output/environmental impact’, which has been widely accepted and aggregates different environmental emissions into one score using life cycle analysis. The single-ratio model is easy to understand and communicate and is mainly used for the eco-efficiency analysis of product (Cerutti et al., 2013) and technology (Burchart-Korol et al., 2013). The second class substitutes the numerator with other composite indicators representing the ecological performance of the system, such as emergy indicators (Li et al., 2011), ecological footprint indicators (Cerutti et al., 2013) and material flow analysis indicators (Seppälä et al., 2005). The third class uses models to calculate eco-efficiency; some of the key methods of aggregation employed are principal components analysis (Jollands et al., 2004), factor analysis (Singh et al., 2012) and positive matrix factorisation (Wu et al., 2012). Recently, the data envelopment analysis (DEA) model has played an important role for eco-efficiency analysis, based on its specific advantages (Wu, 2006). It is now widely applied on different scales (Picazo-Tadeo et al., 2011; Oggioni et al., 2011; Iribarren et al., 2011), especially for systems with multiple inputs and outputs in different dimensions.

When reviewing the DEA model for eco-efficiency analysis, we found that many decision-making units (DMUs) are fairly eco-efficient, raising the question of which DMU is best. We proposed a modified super-efficiency analysis model based on the use of environmental pollution as an undesired output to solve this problem. In Section 2, a DEA model is selected for city eco-efficiency analysis, and a modified super-efficiency model is established for ranking. Section 3 presents the data collection and disposal processes for Chinese provincial capital cities. This paper then analyses the results of eco-efficiency in Section 4. The driving force and mechanism of eco-efficiency and the advantages and disadvantages of the methodology are described in Section 5. Finally, several proposals for making a city more sustainable are given in Section 6.

2. Method

2.1. The DEA model for eco-efficiency assessment

Eco-efficiency is usually measured by comparing environmental performance indicators. DEA has good potential to support such comparisons, as no explicit weights are needed to aggregate the indicators (Dyckhoff and Allen, 2001). In general, the outputs of the DMUs are neither “good” nor “bad”. However, from an ecological perspective, environmental pollutants are not desirable for a city. A commonly used method to address undesirable outputs (Dyckhoff and Allen, 2001; Korhonen and Luptacik, 2004; Zhang et al., 2008) is to treat them as inputs, so that the DMU simultaneously reduces the inputs and undesirable outputs to increase eco-efficiency. Based on this vision, this paper adopted the DEA model for eco-efficiency analysis.

Assume there are n homogeneous decision-making units, each consuming m inputs and producing p outputs. The outputs corresponding to indices 1,2,. . .,k are desirable, and the outputs corresponding to indices $k+1,k+2,\ldots,p$ are undesirable. The goal is to maximise the desirable outputs while excluding undesirable outputs. In the model, $X \in \Re_{+}^{m\times n}$ and $Y \in \Re_{+}^{s\times n}$ are the matrices which consisting of non-negative elements and containing the observed input and output measures for the DMUs. The matrix Y was decomposed into two parts, $Y = \begin{pmatrix} Y^g \\ Y^b \end{pmatrix}$, where a $k \times n$ matrix Y^g stands for “good” outputs and a $(p-k)\times n$ matrix Y^b stands for “bad” outputs. The model further assumes that there are no duplicated units in the data set. We denote the vector of inputs consumed by DMU$_j$ by x_j (the jth column of X) and the quantity of input i consumed by DMU$_j$ by x_{ij}. A similar notation is used for outputs. Occasionally, the vector y_j was decomposed 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, respectively.

Based on the basic model (Charnes et al., 1978), taking the undesirable outputs as inputs, this formulation leads to the following expressions:

$$
\begin{aligned}
&\max = \frac{\sum_{r=1}^{k} u_r y_{rj_0}}{\sum_{i}^{m} v_i x_{ij_0} + \sum_{r=k+1}^{s} u_r y_{rj_0}} \\
&s.t. \frac{\sum_{r=1}^{k} u_r y_{rj}}{\sum_{i}^{m} v_i x_{ij} + \sum_{r=k+1}^{s} u_r y_{rj}} \le 1, \\
&j = 1, 2, \ldots, n; \quad u \ge 0, \quad v \ge 0, \\
&i = 1, 2, \ldots, m; \quad r = 1, 2, \ldots, s.
\end{aligned}
$$

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

$$
\begin{aligned}
&\min[\theta - \varepsilon E^T(s^g + s^b + s^-)] \\
&s.t. \sum_{j=1}^{n} \lambda_j X_j + s^- = \theta X_{j_0}, \\
&\sum_{j=1}^{n} \lambda_j Y_j^g - s^g = Y_{j_0}^g, \quad \text{Model-1} \\
&\sum_{j=1}^{n} \lambda_j y_j^g + s^b = \theta y_{j_0}^b, \\
&\lambda \ge 0, s^g \ge 0, s^b \ge 0, s^- \ge 0, \\
&\varepsilon \succ 0, j = 1, 2, \ldots, n,
\end{aligned}
$$

The vectors s^- and s^b correspond to excesses in inputs and bad outputs, respectively, while s^g expresses a shortage of good outputs. Let an optimal solution of the above programme be $(\theta^*, s^{g^*}, s^{b^*}, s^{-^*})$. Next, we can demonstrate that the DMU (x_0, y_0^g, y_0^b) is efficient in the presence of undesirable output if and only if $\theta^* = 1$, i.e., $s^{g^*} = 0$, $s^{b^*} = 0$, $s^{-^*} = 0$. If the DMU is inefficient, i.e., $\theta^* \prec 1$, it can be improved and become efficient by deleting the excesses in inputs