Short Communication

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

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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.

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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-Viñe 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.

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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 $1, 2, \dots, k$ are desirable, and the outputs corresponding to indices $k+1, k+2, \dots, p$ are undesirable. The goal is to maximise the desirable outputs while excluding undesirable outputs. In the model, $X \in \mathbb{R}_+^{m \times n}$ and $Y \in \mathbb{R}_+^{s \times n}$ 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 *j*th 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:

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

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:

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

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., $\theta^* < 1$, it can be improved and become efficient by deleting the excesses in inputs

and outputs and augmenting the shortfalls in good outputs by the following projection:

$$\begin{aligned}x_0 - s^{-*} &\Rightarrow x_0, \\ y_0^g + s^{g*} &\Rightarrow y_0^g, \\ y_0^b + s^{b*} &\Rightarrow y_0^b.\end{aligned}$$

2.2. The modified super-efficiency model

However, the DEA models mentioned above can only determine whether the DMUs are DEA-efficient or DEA-inefficient. They cannot distinguish the efficiencies of the DEA-efficient DMUs. The question then becomes which DMU performs best. What is the rank of all the DMUs?

Andersen and Petersen proposed the super-efficiency data envelopment analysis (SE-DEA) model in 1993 (Andersen and Petersen, 1993). In this model, the efficiency value is no longer restricted to a scope of 0–1. That is, the efficiency value will most likely be greater than 1. Therefore, the DEA-efficient and DEA-inefficient DMUs are ranked according to their super-efficiency values, and the benchmark can be selected. The basic model is as follows:

$$\begin{aligned}\min \theta \\ \text{s.t.} \\ \theta X_{iK} &\geq \sum_{j \in J-K} \lambda_j X_{ij}, i = 1, \dots, m; \\ Y_{rK} &\leq \sum_{j \in J-K} \lambda_j Y_{rj}, r = 1, \dots, s; \\ \lambda_j &\geq 0, j \in J-K.\end{aligned}$$

We also treat the undesirable outputs as inputs, a concept that leads to the following (CCR):

$$\begin{aligned}\max h_{j_0} &= \frac{\sum_{r=1}^k u_r y_{rj_0} - u_0}{\sum_{i=1}^m v_i x_{ij_0} + \sum_{s=k+1}^p u_s y_{sj_0}} \\ \text{s.t.} \\ \frac{\sum_{r=1}^k u_r y_{rj} - u_0}{\sum_{i=1}^m v_i x_{ij} + \sum_{s=k+1}^p u_s y_{sj}} &\leq 1, j \neq j_0. \\ u_r, v_i &\geq \varepsilon, i = 1, 2, \dots, m, r = 1, 2, \dots, p, \varepsilon > 0.\end{aligned}$$

Introducing flabby variables and the concept of Archimedes, the model can be transformed into linear programming.

$$\begin{aligned}\max h_{j_0} &= u_g^T y_{j_0}^g \\ \text{s.t.} \\ v^T x_{j_0} + u_b^T y_{j_0}^b &= 1, \text{ Model-2} \\ u_g^T y^g - u_g^T y^b - v^T x &\leq 0, g \neq j_0. \\ u_g, u_b, v &\geq \varepsilon 1, \varepsilon > 0.\end{aligned}$$

3. Case study

3.1. The DMUs

As of the end of 2010, China had 34 provincial administrative regions, including four municipalities directly under the Central Government (Beijing, Tianjin, Shanghai and Chongqing), two special administrative regions (HongKong and Macao), 23 provinces (including Taiwan) and five autonomous regions (Inner Mongolia, Guangxi, Tibet, Ningxia and Sinkiang).

The provincial capital cities were selected for our research. The capital cities are always the political, economic and cultural centres of the province. The most important party and government offices and institutions and the headquarters of large enterprises and financial centres are located in these cities, and they feature better transportation, education, scientific research and medical conditions. Finally, the implementation of many policies, laws and regulations is prioritised in provincial capital cities. To some extent, the provincial capital cities represent the highest development level in the province. Due to the lack of available data for Taiwan, HongKong, Macao and Tibet, the DMUs comprise the other 30 provincial capital cities (Table 1).

3.2. The indicators

A city is a typical social–economic–natural complex ecological system (Wang et al., 2004) with multiple inputs and outputs. Eco-efficiency can also be understood as a wider concept including socio-cultural aspects (Sorvari et al., 2009). There are few suitable indicators that can be quantitatively measured in the social dimension for eco-efficiency analysis. However, the numbers of employed person can represent a city's stability (Topa, 2001), prosperous and vitality. Whether it should be used as an input or output depends on the purpose of the research; this paper uses it as an input to measure its contribution to the desirable outputs.

In the economy–natural dimension, we input material, energy and products produced (i.e., value), while waste and emissions (i.e., other undesirable outputs) are unavoidable (Zhang et al., 2008). Therefore, there are two essential classes of inputs from nature into the economy: the supply of resources (i.e., energy, money, water) and nature's function as sink for the discharge of residuals and pollutants. For the resource class, indicators were selected based on material flow accounts. Direct material input (DMI) was selected for the calculation of the regional (Mickwitz et al., 2006) eco-efficiency analysis. Two main categories of DMI were finally selected in our research: total water consumption and comprehensive energy consumption. In addition, the construction land area (which represents land utilisation) and total investment in fixed assets (which describes the capital investment) were selected as input indicators. For the environment impact, environmental pressure indicators were chosen. Based on Chinese environmental, economic and energy statistics systems and data availability, seven main indicators were selected: total waste water emissions, chemical oxygen demand (COD) emissions, SO₂ emissions, soot emissions, industrial dust emissions, solid waste emissions, and the GHG emissions.

For the output, the gross domestic production (GDP) is usually used. This research uses GDP to represent the values of products and services. Table 2 shows the inputs and outputs mentioned above.

3.3. Data collection

This research is based on data from 2009. All the data were collected from the 2010 China City Statistical Yearbook (which presents data for 2009), the 2010 China Mining Yearbook, the 2010 Provincial Statistical Yearbook, the 2010 City Statistical Yearbook, the 2009 Environment Quality Bulletin of each city and the 2009 National Economy and Social Development Statistical Bulletin of each city. The emission of GHG (i.e. CO₂) for each city are obtained based on the final energy consumption of six industrial sections (i.e., farming, forestry, animal husbandry, fishery and water conservancy; industry; construction; transport, storage and post; wholesale and retail trade and hotels and restaurants;

Table 1
Results of eco-efficiency and super-efficiency analyses.

Area	DMUs	Eco-efficiency (Model 1, θ)	Super-efficiency (Model 2, score)	Ranking
North	Beijing	1.000	4.8504	3
	Tianjin	1.000	1.1140	11
	Shijiazhuang	1.000	1.1435	10
	Taiyuan	0.767	0.7667	24
	Hohhot	1.000	1.3046	6
Northeast	Shenyang	1.000	1.1105	12
	Changchun	0.999	0.9990	14
	Harbin	1.000	1.1602	8
East	Shanghai	1.000	1.1459	9
	Nanjing	0.776	0.7761	22
	Hangzhou	1.000	1.1041	13
	Hefei	0.925	0.9246	19
	Fuzhou	1.000	5.3193	2
	Nanchang	0.931	0.9308	18
	Jinan	1.000	1.1706	7
Central South	Zhengzhou	0.970	0.9704	15
	Wuhan	0.804	0.8043	21
	Changsha	1.000	1.9127	5
	Guangzhou	1.000	2.1911	4
	Nanning	0.734	0.7340	25
	Haikou	1.000	7.8700	1
Southwest	Chongqing	0.769	0.7689	23
	Chengdu	0.948	0.9483	16
	Guiyang	0.518	0.5182	30
	Kunming	0.734	0.7340	26
Northwest	Xi'an	0.934	0.9338	17
	Lanzhou	0.597	0.5971	29
	Xining	0.726	0.7258	27
	Yinchun	0.600	0.5996	28
	Urumchi	0.813	0.8130	20

residential consumption) according to 2010 Chinese energy statistics.

4. Results

4.1. Eco-efficiency analysis of the city

According to model-1 (CCR), under the assumption of a constant return to scale, we apply the undesirable outputs (pollutants) as inputs. As shown in Table 1, the results indicate that almost half of the cities are eco-efficient, including Beijing, Tianjin, Shijiazhuang, Hohhot, Shenyang, Harbin, Shanghai, Hangzhou, Fuzhou, Jinan, Changsha, Guangzhou and Haikou.

When examining the spatial distribution of eco-efficiency, we found that the provincial capital cities in the northwest and southwest are less efficient than those in other districts. According to

the Chinese economic zone division, these districts belong to the economically undeveloped region. This trend can be attributed to multiple causes. Historical explanations include a lack of education, less advanced technology and ineffective administration, among many others. Additionally, the industrial structure is unreasonable, as the economic foundation is traditional industry, which has low economic benefits and serious pollution. Furthermore, with rapid economic development, the eastern region has entered a new period of industry reformation and promotion. The industries with high energy consumption, high material consumption, high contamination and emission have been all but forbidden in developed cities and were forced to move to rural areas, migrating from east to west, south to north, and developed areas to undeveloped regions. As a result, relatively undeveloped cities consume more resources, materials and water while discharging pollution, which undoubtedly leads to relatively poor eco-efficiency.

Table 2
Summary of input and output indicators.

Category	Variable	Units	Obs.	Mean	Std. dev.	Min	Max
Input	Total water consumption	10 thousand tons	30	58,977.87	67,044.41	10,225.00	341,389.00
	Comprehensive energy consumption	10 thousand of SEC	30	3671.33	2342.41	367.16	10,938.77
	Construction land area	Square kilometres	30	395.77	312.48	49.00	1350.00
	Total investment in fixed assets	Billion yuan	30	224.30	151.27	27.70	531.79
	Numbers of employed person	10 thousand person	30	244.05	214.55	55.13	1012.67
Undesirable output	Waste water emission	10 thousand tons	30	47,527.54	51,946.94	10,563.87	230,500.00
	COD emission	10 thousand tons	30	8.20	6.05	1.47	24.34
	CO ₂ emission	10 thousand tons	30	7938.82	5152.65	843.75	23,844.05
	SO ₂ emission	10 thousand tons	30	10.11	10.28	0.06	58.62
	Soot emission	10 thousand tons	30	3.00	2.29	0.01	10.87
	Industrial dust emission	10 thousand tons	30	2.86	6.61	0.01	36.00
	Solid waste emission	10 thousand tons	30	889.99	715.19	4.30	2552.00
Desirable output	Gross domestic production	Billion yuan	30	376.04	340.39	48.96	1504.65

Table 3
Optimisation results.

DMUs	Water consumption	Energy consumption	Construction land area	Wastewater	COD	CO ₂	SO ₂	Soot	Industrial dust	Solid waste
Total reduction	39,011.36	9226.94	768.86	218,019.05	58.23	20,356.67	61.99	23.66	20.84	5890.36
Total original quantity	1,769,336.00	110,139.85	11,873.00	1,425,826.10	245.96	238,164.51	303.28	90.01	85.91	26,699.62
%	2.20	8.38	6.48	15.29	23.67	8.55	20.44	26.28	24.25	22.06

4.2. Ranking of the cities

Table 1 show that 13 eco-efficient cities occupy more than 40% of the total DMUs. Thus, a fundamental challenge is distinguishing between the eco-efficient cities.

To solve this problem, we rank the cities according to the modified super-efficiency model (model-2). In the results, Haikou, Fuzhou and Beijing are the top three eco-efficient cities and Yinchuan, Lanzhou and Guiyang are the bottom three. Cities with higher GDP are not necessary more eco-efficient, as is the case for Shanghai, Tianjin and Nanjing. Further analysis reveals Haikou as the city with the highest eco-efficiency ranking. This ranking is attributed to the Haikou's leading industry being eco-tourism, which contributes only low levels of pollution; the scarcity of heavily polluting industries; and its focus on developing its real estate, culture, sports and exhibition industries. Beijing has the second highest eco-efficiency rating. Beijing underwent a drastic reformation before the 2008 Olympic games: various heavily polluting industries were forced to move, and the Shougang Steel Manufacturer Group relocated to Caofeidian in Hebei province. Now, new and high-tech industries as well as high-end service and financial industries are the predominant contributors to Beijing's economy, allowing for improved economic performance but little environmental pollution.

Yinchuan, Lanzhou and Guiyang are located in undeveloped regions and are ranked in the given order in the eco-efficiency analysis. Moreover, it should be noted that Nanjing is less eco-efficient and lower ranking than Hangzhou, although both sites are in the same developed region. This difference may be because Hangzhou is a tourism city, while Nanjing is a city with heavy industry. In 2012, Nanjing's government decided to shut down 173 heavily polluting enterprises, almost the total number opened in the last five years, which demonstrates its commitment to industry reformation and promotion.

4.3. Optimisation of the city

According to model-1, we can obtain more details by optimising the DMUs. The results of the model are shown in Table 3. Overall, provincial capital cities could reduce water consumption by 2.20%, energy consumption by 8.38%, construction land area by 6.48%, total investment in fixed assets by 8.85%, waste water emission by 15.29%, COD emission by 23.67%, CO₂ emission by 8.55%, SO₂ emission by 20.44%, soot emission by 26.28%, industrial dust emission by 24.25% and solid waste by 22.06%. This finding implies that there is still a large room for reduction if the correct management policy, technology and financial support are provided based on the unique attributes of each city.

5. Discussion

Based on the use of environmental pollutants as undesirable outputs in the DEA model, we have assessed the eco-efficiency of Chinese provincial cities, and the results are in accord with the cities' economic development level. Nearly 40% of the cities are eco-efficient, and the inefficient cities are mostly located in the southwest and northwest, which are the undeveloped areas in

China. The higher the GDP of a city is, the higher its eco-efficiency but the higher its environmental pollutant emission (Fig. 1). We could therefore not judge whether eco-efficient cities are more sustainable. A possible explanation is that we chose GDP as the only "desirable output", but GDP has been severely criticised as not adequately capturing human welfare and progress (van den Bergh, 2009). Additionally, GDP has been criticised for its failure to appropriately address the degradation and depletion of natural capital, gross income inequalities and economic activity that is purely defensive in nature, such as expenditures needed to clean up toxic waste. Furthermore, GDP ignores a large number of economically valuable inputs and outputs that are not bought and sold in the marketplace, such as the wide range of ecosystem services (Talberth and Bohara, 2006). That is, only some of nature's value is incorporated in the GDP (Boyd, 2007). Therefore, the green GDP could be used in future regional-scale eco-efficiency measurements.

Our research also compared the DEA model and the ratio model for city eco-efficiency analysis. Ratio indicators are very straightforward and communicative (the higher the ratio, the better the performance), but when multiple inputs or outputs are used, aggregation into a single numerator or denominator must be conducted using appropriate methods and reasonably assigned aggregation weights. The DEA can overcome this matter; it does not require weights or the aggregation of different inputs or outputs (Lauwers, 2009).

Although eco-efficiency can measure a city's sustainability, the question of how to improve eco-efficiency remains. In general, a city's eco-efficiency will be enhanced whenever there is a greater economic return for a given amount of environmental impact, less environmental impact for a given amount of economic return or both more economic return and less environmental impact (Hahn et al., 2010). There is also a rebound effect whenever improvements in eco-efficiency are associated with greater environmental impact (Fet, 2003). The desired outcome is a strong improvement in a city's eco-efficiency, characterised by an increase in economic return and a simultaneous decrease in environmental impact. We should therefore determine the driving force of eco-efficiency, explore the mechanism of the city (especially its industry structure, as industry is an indispensable motor for economic growth in modern society, is inevitable in developing countries, and fulfils most of human needs through goods and services) and manage the city such that sustainable development is strengthened by choosing the best management systems, technologies and industry structures.

Furthermore, it is worth mentioning that our research has analysed 30 provincial cities, but there are also other cities in China with good economic, social and environmental performances, such as Shenzhen, Suzhou and Wuxi. In the future, we must classify cities in more detail to define them using the same DMUs. The results will be more precise, and the city eco-efficiency will be distinguished more exactly. For a specific city, there is a need for time-series dynamic analysis, which would provide a better history review and help support decision-making.

Finally, there is no standard definition of eco-efficiency or corresponding decision-making tool (Côté et al., 2006; Erkkö et al., 2005; Fernández-Viñe et al., 2010). Eco-efficiency is a popular topic in academic circles, but the decision-makers in the government,

Fig. 1. Relationship between eco-efficiency and COD emissions in 30 provincial capital cities.

various organisations and enterprises and the public know little about this concept, much less than its application. We need a series of programmes to increase the awareness and application of this concept (Willson and Côté, 2009).

6. Conclusion

This paper mainly addresses eco-efficiency analysis by using environmental pollution as an undesirable output and combining it with a DEA model to assess eco-efficiency. Furthermore, a super-efficiency model was established to rank the DMUs. Using the real data for 30 Chinese provincial capital cities, an empirical study was employed to measure the cities' levels of sustainable development. A possible extension of this research is to investigate the undesirable output allocation mechanism, which would provide deeper insights into the causes of eco-efficiency and further insights into policy-making to encourage city-level sustainable development.

Based on an empirical study, we judge the DEA model to be suitable for city eco-efficiency analysis. The results demonstrate that the eco-efficiency of a city is in line with its economic development level, and almost half of the cities were eco-efficient, illustrating that the continuous cleaner production, circular economy, energy conservation and emission reduction movements have yielded dividends in China. However, cities with higher eco-efficiency also have higher pollution, and the inefficient cities are mainly located in the undeveloped areas, such as the southwest and northwest. The prevalence of these cities in undeveloped areas is mainly due to Chinese officeholders' practice of assessing and promoting economic growth rather than social and environmental performance. Additionally, an irrational industrial structure has led to this situation. The migration of heavy industry from east to west, south to north and city to country is another important factor.

Given this assessment, we propose the following. (1) The GDP-oriented growth model and appraisal system should be changed; we should consider the city as a social-economic-natural complex ecological system and prioritise the city's overall well-being. (2) We should establish a cooperation platform with developed countries and expand the financial, technological and human investments to reach the carbon reduction goal by 2020 (reduce carbon emission by 40–45%). (3) The government should continue to promote the transformation and upgrading of industrial structure, develop a low-carbon economy and expand the service sector presence in the national economy. (4) The heavy-industry migration should be stopped, as developed cities have numerous advantages over undeveloped areas in terms of capital, technology and management to address the mixture problem. Otherwise, China's beautiful countryside will no longer exist, depriving future generations.

Finally, our research has multiple limitations. Further work needs to be performed in this area. First, we should expand the input and output indicators, e.g., using the total material requirement (TMR) and hidden flow (HF), which can represent the overall

use and waste of a city from a material analysis standpoint. Second, future research regarding the DEA approach should aim at the integration of a non-linear preference structure, as increasing insights into the impacts of production progress are likely to lead to a non-linear impact model. Furthermore, we should explore the driving mechanism of eco-efficiency, combined with other methods (such as input-output analysis, the ecological footprint method and the emergy method). This would allow a city's sustainable development to be reflected more comprehensively and accurately. Apart from that, the most important thing is to spread the notion of eco-efficiency to the public, enterprises and the government. Only when the entire country understands the concept, then it can be accepted and put into practice.

Acknowledgements

This research was financially supported by the National Natural Science Foundation of China (71033005) and the Key Supporting Project of Ministry of Science and Technology of China (2012BAC13B04).

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