

Article

Temporal and Spatial Analysis of Integrated Energy and Environment Efficiency in China Based on a Green GDP Index

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Abstract: China is experiencing a high speed economic development which may exert great pressure on the environment and energy systems. To measure the environmental and energy performance during the economic development process, this paper selected 30 provinces, cities or autonomous regions as the decision making unit (DMU), and proposed a Green GDP index (GGI) in view of energy intensity and pollution intensity using the generalized Data Envelopment Analysis (DEA) method, and the developing trends of integrated energy and environment efficiency of DMUs from 2006 to 2010 are also demonstrated by the Malmquist index. Results show that the integrated energy and environment efficiency varies for each DMU. GGI were both 1 in Beijing and Shanghai. GGI values for the developed cities in Eastern China, such as Guangdong, Fujian, Zhejiang, Tianjin, Jiangsu, and Hainan, ranked high, while those in the Northeast and Middle China remained relatively low. Moreover, there is a positive relationship between the GGI and *per capita* GDP with a correlation coefficient of 0.75. Increases in GGI are also observed in the results, representing great achievements are acquired in energy conservation and emission reduction. However, the GGIs do not converge to the green frontier across the provinces.

Keywords: integrated energy and environment efficiency; green GDP index; data envelopment analysis; Malmquist index

1. Introduction

Nowadays, constrained by the development stage, resource endowment, technical capabilities, and development mechanisms, China is experiencing a scale-driven development characterized by high pollution, extensive energy consumption and low efficiency, which leads to inefficient natural resource utilization and energy use in the production process, as well as high volumes of pollution emissions. To cope with these resource and environmental challenges, we should pay much attention to strategies for optimizing the use of resources and environment in a more efficient way. Thus, evaluating the energy and environmental efficiency is the first step and a key issue for energy conservation and environmental protection.

Different methods have been employed in evaluating the resource and environmental performance in China, such as ecological footprint method [1–3], energy analysis [4], exergy evaluation [5,6] and input-output modeling [7]. Among the wide spectrum of energy and environmental modeling techniques, Data Envelopment Analysis (DEA), a relatively new non-parametric approach for efficiency evaluation, has attracted much attention [8]. Measuring performance for various inputs was first proposed by Farrell [9] in his pioneering work. The production technique of the most efficient decision making unit (DMU) was regarded as the efficient frontier, and the technical efficiency of the other DMUs were evaluated through the calculation of their distance to the efficiency frontier. Farrell also put forward two alternatives for evaluation. One is the building of non-parametric piecewise linear convex frontier while the other one is based on the stochastic frontier production function, e.g., Cobb-Douglas Production Function. The former one has been developed afterwards into a non-parametric mathematical programming method, *i.e.*, conventional DEA. Later on, more efforts have been made in this research field by Burley, Banker *et al.*, Färe *et al.*, Lovell and Coelli [10–14].

DEA has been accepted as a major tool for benchmarking energy sectors in many studies. Mousavi-Avval *et al.* described the energy use pattern for canola production in the Golestan province of Iran and analyzed the degrees of technical and scale efficiency of producers using DEA [15]. Shi *et al.* considered both undesirable outputs and minimization of energy consumption in measuring Chinese industrial energy efficiency and investigates the maximum energy-saving potential in 28 administrative regions in China [16]. Ramanathan studied the energy efficiencies of transport modes in India [17].

Modeling environmental performance, which mainly includes environmental performance measurement and estimation of environmental regulation impacts, is another popular application area of DEA. Many researches have been conducted which focused on the environmental performance of firms, e.g., Färe *et al.* evaluated the environmental performances of 30 paper mills in the USA by using DEA [18]. Tyteca adapted three different DEA models to assess 48 power plants in the USA and observed an important discrepancy in the result rankings [19]. An eco-efficiency analysis for regional industrial systems in China was also conducted by developing DEA-based models [20]. Sueyoshi *et al.*

proposed a new DEA approach to evaluate the operational, environmental and unified performance of coal-fired power plants that are currently operating under the US Clean Air Act [21]. Recently, DEA has been more and more used in environmental efficiency comparison in regional and national level, Zhou *et al.* studied the total carbon emission performance of top 18 emitters in the World over time in a time series using Malmquist index analysis [22]. Similarly, Guo *et al.* used DEA to evaluate the carbon emission performance of 29 Chinese provincial administrative regions by computing potential carbon emission reductions for energy conservation technology and energy structural adjustment [23]. Hall and Kerr established a green index to evaluate the environmental quality of 50 states in the US and developed an environmental protection index (EPI) to quantify and compare the environmental performance across different countries and evaluate governments' efforts in environmental protection [24]. Bian and Yang evaluated the aggregated resource and environment efficiency with a new Shannon-DEA model [25]. As DEA method could avoid the derivation of weight coefficients, normative judgments and subjective valuations, it is an effective approach to construct an encompassing of environmental efficiency indicators.

This paper aims to assess the integrated energy and environment efficiencies of 30 provinces in China as DMUs based on the proposed Green GDP Index (GGI). The rest of the paper is organized as follows. In the second part, we describe the establishment of the GGI. Then, the GGIs of DMUs and regional disparities of energy and environment efficiency are addressed in detail. Based on the panel data, the Malmquist index is also employed to analyze the temporal changes of DMUs from 2006 to 2009 and to decide whether the GGIs are convergent.

2. Green GDP Index

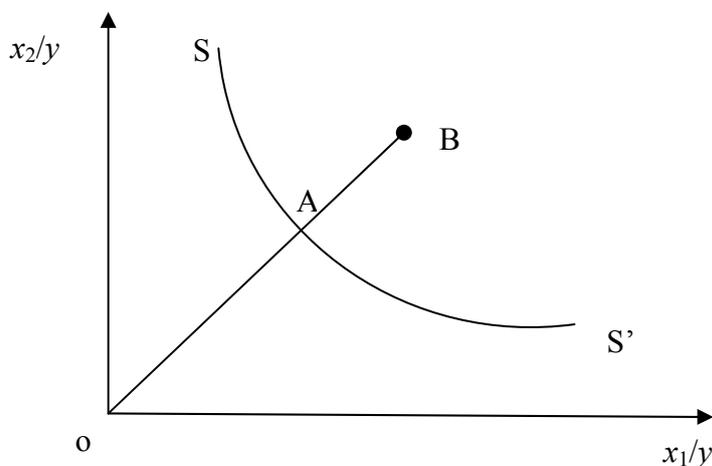
2.1. DEA Model

As shown in Figure 1, x_1 and x_2 stand for the quantity of energy consumption and environmental pollution, respectively. The term y is the GDP of the study area while SS' is the minimal combination of energy consumption and environment pollution *per* GDP [14]. In other words, SS' represents for the lowest energy intensity and emission intensity similar to the efficient frontier, which we can define as the "green frontier". If the combination of energy consumption and environment pollution per GDP of a specific area is on the right side of SS' , such as the point B, it means the degree of green economic growth is at a relatively low level. Compared with the green frontier, the energy consumed and pollution emitted per GDP of this area has increased from point A to point B.

To assess the green degree of the economy in a specific area, we define OA/OB as the Green GDP Index (GGI), which is a comprehensive index that could determine the level of energy consumption and environmental pollution in the process of GDP generation. The implication of "green" refers to the consideration of both pollution emissions and energy-consumption issues.

The value range of GGI is between 0 and 1. If the production efficiency is right on the green frontier, the GGI value of the concerned area (province) is 1. The farther the production efficiency from the green frontier, the lower the GGI is. Therefore, GGI is a useful indicator for evaluating the energy conservation and environment performance of multi-scale systems.

Figure 1. Green Frontier and GGI. x_1/y : Energy consumption/GDP, x_2/y : Environmental pollution/GDP.



The efficiency frontier is estimated from the panel data. Suppose there are k areas; n_1 kinds of energy are consumed while n_2 kinds of pollution are emitted in the production process, and n was set as $n_1 + n_2$. We define the output Y as GDP, and suppose matrix $X(n,k)$ stands for energy consumption and pollution of each area. Thereby, GGI can be calculated by solving the linear programming problem as below:

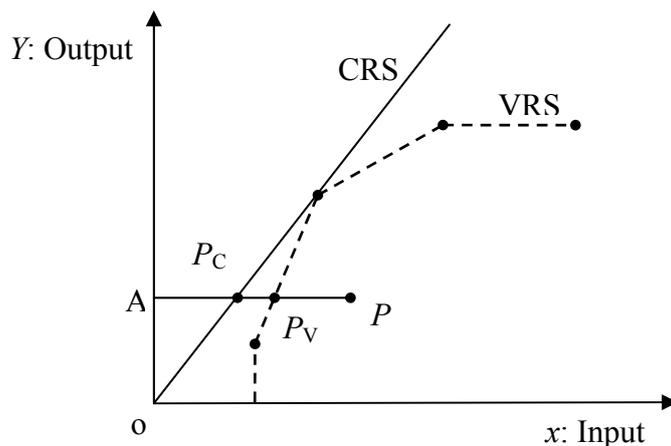
$$\begin{aligned}
 & \min_{\theta, \lambda} \theta, \\
 & \text{st } Y\lambda \geq y_i \\
 & \quad X\lambda \leq \theta x_i \\
 & \quad \lambda \geq 0
 \end{aligned} \tag{1}$$

where θ is the GGI value, λ is the k dimensional vector, $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_k)$.

The result of this linear programming problem is the GGI of the i th area, the GGI of every area could be obtained by calculating this linear programming problem k times. Note that the Equation 1 is based on the assumption that energy consumption and environment pollution is of constant returns to scale. So we can generalize this assumption and modify the GGI of variable returns to scale. Figure 2 depicts the influence of different assumptions on the calculation of GGI.

As shown in Figure 2, the solid line (CRS) and dotted line (VRS) represent the green frontiers of constant returns to scale and variable returns to scale, respectively [14]. Based on different assumptions, the green frontiers are totally different, although the sample data are the same. Taking point P for example, P_V , P_C and A are the horizontal intersection points of point P with CPS, VRS and the Y coordinate. Thus, the GGI value of P is AP_C/AP under the condition of constant returns to scale while it becomes AP_V/AP when the assumption is variable returns to scale. Then, $SE (GGI_C / GGI_V = AP_C / AP_V)$ is specified to evaluate the scale effect that influence the GGI, *i.e.*, the influence on the GGI when the economic scale is under the condition of variable returns to scale of energy consumption and environmental pollution. We can thereby deconstruct the GGI into pure green index and scale effect, *i.e.*, $GGI_C = GGI_V \times SE$.

Figure 2. Scale effect on GGI.



In order to calculate the green index under the condition of variable returns to scale, Equation 2 should be supplemented with a constraint as below [14]:

$$\begin{aligned}
 & \min_{\theta, \lambda} \theta, \\
 & \text{st } Y\lambda \geq y_i \\
 & \quad X\lambda \leq \theta x_i \\
 & \quad \sum_{j=1}^k \lambda_j = 1 \\
 & \quad \lambda \geq 0
 \end{aligned} \tag{2}$$

The GGI of the *i*th area can then be calculated in the context of variable returns to scale by solving the programming problem (Equation 2).

2.2. Malmquist Index

Except for the DEA in measuring GGI, the linear programming method based on the panel data could also be used. In this paper, the Malmquist index, which has been widely used in measuring total factor productivity, is introduced to analyze the change of GGI for each DMU and decompose it into two parts [14], *i.e.*, the change of green frontier and relative change of GGI, as shown in Equation 3:

$$m(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d^t(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)} \times \frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^{t+1}(x_t, y_t)} \right]^{\frac{1}{2}} \tag{3}$$

$$\begin{aligned}
 & d^t(x_t, y_t) = \min_{\theta, \lambda} \theta, \\
 & \text{st } Y_t \lambda \geq y_{it} \\
 & \quad X_t \lambda \leq \theta x_{it} \\
 & \quad \lambda \geq 0
 \end{aligned} \tag{4}$$

$$\begin{aligned}
 & d^{t+1}(x_t, y_t) = \min_{\theta, \lambda} \theta, \\
 & \text{st } Y_{t+1} \lambda \geq y_{it} \\
 & \quad X_{t+1} \lambda \leq \theta x_{it} \\
 & \quad \lambda \geq 0
 \end{aligned} \tag{5}$$

$$\begin{aligned}
 d^t(x_{t+1}, y_{t+1}) &= \min_{\theta, \lambda} \theta \quad , \\
 \text{st } Y_t \lambda &\geq y_{i,t+1} \\
 X_t \lambda &\leq \theta x_{i,t+1} \\
 \lambda &\geq 0
 \end{aligned} \tag{6}$$

$$\begin{aligned}
 d^{t+1}(x_{t+1}, y_{t+1}) &= \min_{\theta, \lambda} \theta \quad , \\
 \text{st } Y_{t+1} \lambda &\geq y_{i,t+1} \\
 X_{t+1} \lambda &\leq \theta x_{i,t+1} \\
 \lambda &\geq 0
 \end{aligned} \tag{7}$$

Based on the value of m calculated through Equations 3–7, we could observe the changes of GGI in the i th area during the period of $t - t + 1$. When $m > 1$, it means an improvement in GGI and a decrease in energy and pollution intensity, while if $m < 1$, GGI is declining, and the situation of energy consumption and pollution emissions is worsened.

The value of GGI can be decomposed into two parts: $\left[\frac{d^t(x_t, y_t)}{d^{t+1}(x_t, y_t)} \times \frac{d^t(x_{t+1}, y_{t+1})}{d^{t+1}(x_{t+1}, y_{t+1})} \right]^{\frac{1}{2}}$ which represents the changes of green frontier and can be used to evaluate the changes of GGI; and $\frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)}$ which symbolizes the relative changes of green index of the area. This decomposition process can be demonstrated as below:

$$m = \left[\frac{d^t(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)} \times \frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^{t+1}(x_t, y_t)} \right]^{\frac{1}{2}} = \left[\frac{d^t(x_t, y_t)}{d^{t+1}(x_t, y_t)} \times \frac{d^t(x_{t+1}, y_{t+1})}{d^{t+1}(x_{t+1}, y_{t+1})} \right]^{\frac{1}{2}} \times \frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)} \tag{8}$$

2.3. Data Sources

This paper examines 30 provinces, autonomous regions and municipalities in China, excluding Tibet, Hong Kong, Marco and Taiwan due to lack of data. Aiming to measure the integrated energy and environmental efficiency of 30 provinces in China, we choose the energy consumption and environmental emissions as input variables and GDP generated in each region as output variables, with reference to [17]. The total energy consumed is used as the energy input for the additivity of different kinds of energy sources. On account of the data incompleteness of solid wastes emission, the other five kinds of environmental emissions, *i.e.*, SO₂ emissions, soot emissions, dust emissions, COD emissions and ammonia nitrogen emissions) in the China Environment Statistical Database, are selected as environment indicators. Energy consumption and environment pollution data is obtained from the China Energy Statistical Yearbook (2005–2010) [26] and China Environment Statistical Yearbook (2005–2010) [27]. Note that we only use industrial emission data in this study to calculate GGI. As the proportion of household energy consumption in total energy consumption is less than 11%, we choose to account the total energy consumption as the unique input variable. Also the GDP values used in this paper are normalized based on the 2005 constant price.

3. Results and Discussion

3.1. Regional Discrepancies

The GGI values in 2009 are calculated and listed in Table 1.

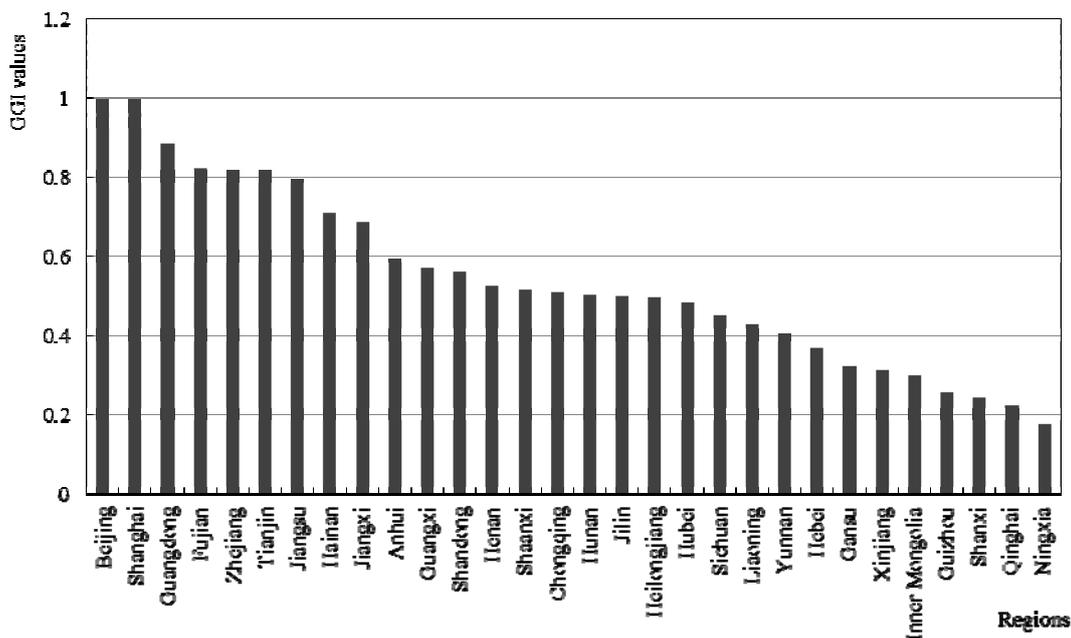
Table 1. GGI values of regions (DMUs) in China (2009).

Regions (DMUs)	GGI _C	GGI _V	SE	Stage	Regions (DMUs)	GGI _C	GGI _V	SE	Stage
Beijing	1	1	1	constant	Hunan	0.504	0.506	0.996	decreasing
Shanghai	1	1	1	constant	Jilin	0.501	0.522	0.958	increasing
Guangdong	0.885	1	0.885	decreasing	Heilongjiang	0.498	0.506	0.984	increasing
Fujian	0.825	0.841	0.981	decreasing	Hubei	0.485	0.486	0.998	decreasing
Zhejiang	0.818	0.892	0.917	decreasing	Sichuan	0.453	0.463	0.98	decreasing
Tianjin	0.817	1	0.817	increasing	Liaoning	0.43	0.446	0.964	increasing
Jiangsu	0.796	0.892	0.892	decreasing	Yunnan	0.406	0.431	0.941	decreasing
Hainan	0.713	1	0.713	increasing	Hebei	0.37	0.391	0.947	decreasing
Jiangxi	0.689	0.716	0.962	increasing	Gansu	0.325	0.379	0.857	increasing
Anhui	0.596	0.605	0.985	increasing	Xinjiang	0.314	0.348	0.9	increasing
Guangxi	0.573	0.595	0.963	increasing	Inner Mongolia	0.302	0.31	0.975	increasing
Shandong	0.564	0.641	0.881	decreasing	Guizhou	0.258	0.584	0.441	increasing
Henan	0.529	0.566	0.935	decreasing	Shanxi	0.247	0.257	0.958	increasing
Shaanxi	0.517	0.536	0.965	increasing	Qinghai	0.226	0.525	0.43	increasing
Chongqing	0.513	0.539	0.951	increasing	Ningxia	0.175	0.364	0.481	increasing
Average	0.544	0.611	0.889						

If we ignore the scale effect and assume that the energy consumption and environmental pollution are under the condition of constant returns to scale, the corresponding GGI values are calculated and shown as GGI_C in Table 1, Figure 3 illustrates the discrepancy of GGI amongst different areas in 2009.

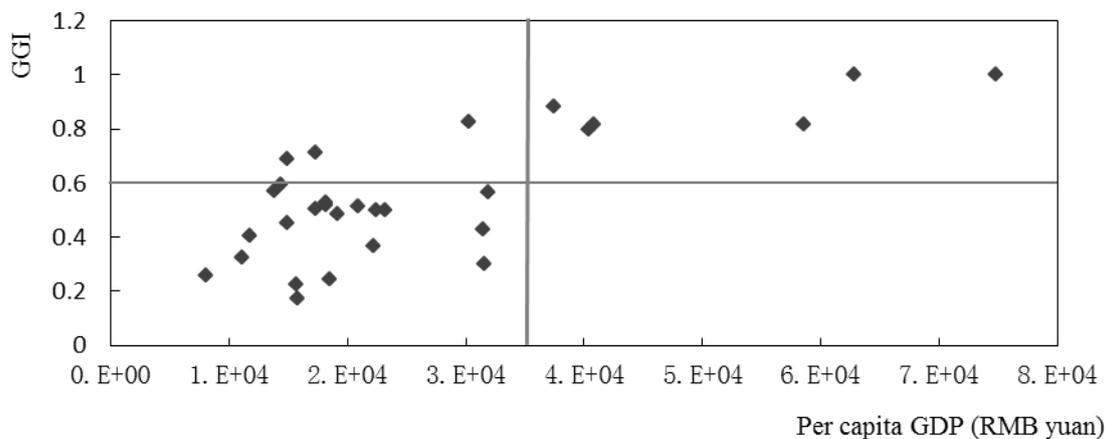
The integrated energy and environmental efficiency varies from region to region. Energy consumed and pollutants emitted associated with GDP growth were the lowest in Beijing and Shanghai, *i.e.*, the integrated energy and environmental efficiency was the highest and right on the green frontier with a GGI value of 1. GGI values of the developed eastern regions, like Guangdong, Fujian, Zhejiang, Tianjin, Jiangsu and Hainan, were relatively higher than those of the northeastern and middle regions. Ningxia, Qinghai, Shanxi, Guizhou and Inner Mongolia, whose energy and environmental efficiencies were far from the green frontier with GGI values all below 0.3, were under the heaviest energy and environmental pressures.

Figure 3. Ranking of GGI of regions (DMUs) in China (2009).



GGI discrepancies among provinces of China demonstrate the variations of economic growth mode. In general, the higher the GGI of a specific region, the larger proportion of agriculture and service industry it has. In other words, its dependence of economic growth on the energy input and environmental degradation is relatively low. On the contrary, in the regions of low GGIs, the economic growth is fueled by industry, especially heavy industry, and characterized as high energy consumption and pollution as well as low efficiency. It is obvious that the industrial structure of a region largely depends on the level of economic development. In Figure 4, there is a significant positive correlation between the GGI values and *per capita* GDP with the correlation coefficient of 0.75.

Figure 4. GDP per capita and GGI values in 2009.

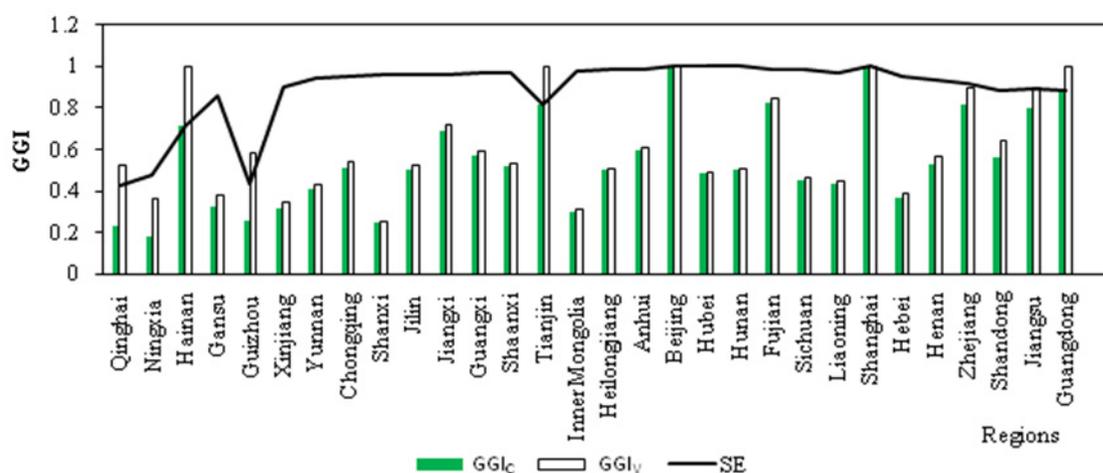


The GGI values are nearly above 0.6 in the regions whose *per capita* GDPs have reached 0.35 million yuan while the values are below 0.6 in regions whose *per capita* GDP is below 0.35 million yuan. Two reasons could be used to interpret the positive correlation between the GGI values and *per capita* GDP: (1) in the developed regions with high economic level, the development of

Tertiary Industry is relatively faster; (2) more investment and efforts have been made for environmental protection and control in the developed regions. In addition, because of the special industrial structure, GGI values of Fujian, Hainan and Jiangxi are relatively high, with values of 0.825, 0.713 and 0.689, respectively, although their GDP *per capita* are below 0.35 million yuan. Even though the economic growth of Fujian and Jiangxi is attributed to industrial development, the light industry is in the leading position in their industrial structure and the development of heavy industry is lagging far behind. The dominant industries of Hainan are the agricultural and tourism industries, the proportions of the first industry and the third industry are respectively 28% and 45% while that of the second industry is only 27%.

The analysis above is based on the assumption of constant returns to scale of energy consumption and environmental pollution. When the assumption is converted into variable returns to scale, GGI of DMUs will change accordingly, as shown in Figure 5, especially those regions with low GDP like Qinghai, Ningxia, Hainan, Gansu, Guizhou, and regions with high GDP like Guangdong, Jiangsu, Shandong, Zhejiang, Henan, Hebei, Liaoning. Hainan, Tianjin, Beijing, Shanghai and Guangdong, will be on the new green frontier.

Figure 5. Scale effect of GGI.



According to $GGI_C = GGI_V \times SE$, we can decompose the green index into pure green index (GGI_V) and scale effect (SE). From Figure 5 and Table 1, we can find that regions of the top 17 in the GDP ranking are all in the period of increasing returns to scale of energy consumption and environment pollution while the last 13 regions are in the period of decreasing returns to scale, *i.e.*, the current economic developing mode of China is unsustainable. If we keep on expanding in this way, the energy consumption control and environment pollution mitigation associated with GDP growth will be in a dilemma, and will ultimately exceed the carrying capacity. Thus, to realize the sustainable development of China, it is inevitable to change the traditional developing mode, adjust economic structure and improving input-output efficiency and as a result change the current green frontier.

3.2. GGI Trends

China has set up goals to slash its energy consumption per GDP by 20 percent and discharges of main pollutants by 10 percent. To ensure the realization of these targets, a series of policies and measures have been established. To validate the effects of these measures on improving energy and environment efficiency and promoting GDP developing in an environmental friendly way, we used the panel data of 30 provinces, municipalities and autonomous regions and established the Malmquist index through the calculation of linear programming model. We can directly get the GGI trends which could be used as the comprehensive indicators in evaluating effects of energy saving and consumption reduction by the Malmquist index: $\left[\frac{d^t(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)} \times \frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^{t+1}(x_t, y_t)} \right]^{\frac{1}{2}}$ as is shown in Table 2.

As seen in Table 2, from 2006 to 2009, the GGI of each region has increased to different degrees, except for Qinghai that had a slight decrease in 2006, which means that energy and environment efficiency of each region has largely been promoted against the background of the energy saving and consumption reduction strategy. The green index of Beijing had the largest growth, which may attribute to the efforts made to host the Olympic Games in 2008. Energy intensity of Beijing has declined by 17.4%, 5 percentage points higher than the national average. The rate of improvement of energy and environment efficiency has largely slowed down after the Olympic Games and was below the level of Shanghai.

Table 2. GGI of regions (DMUs) in China (2006–2009).

Year DMUs	2006	2007	2008	2009	Average
Beijing	1.491	1.194	1.355	1.072	1.268
Tianjin	1.116	1.073	1.126	1.057	1.093
Hebei	1.032	1.042	1.068	1.053	1.049
Shanxi	1.02	1.047	1.08	1.062	1.052
Inner Mongolia	1.026	1.047	1.068	1.074	1.053
Liaoning	1.037	1.042	1.054	1.053	1.047
Jilin	1.035	1.046	1.053	1.063	1.049
Heilongjiang	1.034	1.043	1.05	1.059	1.047
Shanghai	1.106	1.247	1.153	1.143	1.161
Jiangsu	1.036	1.044	1.062	1.054	1.049
Zhejiang	1.037	1.044	1.058	1.057	1.049
Anhui	1.031	1.043	1.047	1.057	1.044
Fujian	1.041	1.098	1.076	1.037	1.062
Jiangxi	1.033	1.044	1.063	1.047	1.047
Shandong	1.036	1.048	1.069	1.055	1.052
Henan	1.031	1.043	1.054	1.064	1.048
Hubei	1.033	1.042	1.072	1.061	1.052
Hunan	1.035	1.046	1.072	1.053	1.051
Guangdong	1.03	1.033	1.045	1.043	1.038
Jiangxi	1.026	1.034	1.041	1.046	1.037

Table 2. *Cont.*

Hainan	1.011	1.008	1.027	1.028	1.019
Chongqing	1.035	1.046	1.052	1.058	1.048
Sichuan	1.033	1.046	1.042	1.062	1.046
Guizhou	1.031	1.042	1.068	1.041	1.046
Yunnan	1.015	1.041	1.05	1.048	1.039
Shaanxi	1.035	1.048	1.063	1.047	1.048
Gansu	1.027	1.043	1.053	1.073	1.049
Qinghai	0.994	1.031	1.043	1.069	1.034
Ningxia	1.01	1.037	1.073	1.064	1.046
Xinjiang	1.011	1.032	1.032	1.015	1.022
Average	1.046	1.055	1.071	1.057	1.057

As for the national level, the average GGI value has increased by 4.6%, 5.5%, 7.1% and 5.7% in 2006, 2007, 2008, 2009, respectively, indicating the great achievements obtained in the aspect of energy conservation and pollution control. In Table 3, it can be shown that the energy intensity declined from 1.24 tce/10,000 yuan in 2006 to 1.08 tce/yuan in 2009, with a cumulative decline of 12.9%. Major environmental pollutants, such as SO₂, soot, dust, COD and ammonia nitrogen, have decreased by 16.51%, 30.09%, 35.23%, 18.8% and 35.53%, respectively. Energy intensity has declined by 12.9% from 2006 to 2009 and basically completed the “energy saving” task; while the total emission of SO₂ and COD have declined by 16.5% and 18.8% and over fulfilled the “emission reduction” objectives.

Table 3. Changes of inputs and outputs from 2006–2009.

Year	GDP (1 billion yuan)	Energy Intensity (tce/10,000 yuan)	SO ₂ (10,000 ton)	Soot (10,000 ton)	Dust (10,000 ton)	COD (10,000 ton)	Ammonia Nitrogen (10,000 ton)
2006	20,838.10	1.24	2234.8	864.5	808.4	541.5	42.5
2007	23,789.28	1.18	2140	771.1	698.7	511.1	34.1
2008	26,081.29	1.12	1991.4	670.7	584.9	457.6	29.7
2009	28,457.20	1.08	1865.9	604.4	523.6	439.7	27.4
Average	24,791.47	1.155	2058.025	727.675	653.9	487.475	33.425
Change rate	36.56%	12.90%	16.51%	30.09%	35.23%	18.80%	35.53%

Data sources: China Energy Statistical Year book (2010) and China Environment Statistical Yearbook (2010).

The change of green index can be divided into that of green frontier $\left[\frac{d^t(x_t, y_t)}{d^{t+1}(x_t, y_t)} \times \frac{d^t(x_{t+1}, y_{t+1})}{d^{t+1}(x_{t+1}, y_{t+1})} \right]^{\frac{1}{2}}$ and relative green index $\frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)}$, and the latter could be further decomposed to pure green index (GGI_V) and scale effect (SE) changes. The decomposition result is demonstrated in Table 4, where the changes of green index and relative green index are calculated as follows:

$$CCGI = CGF \times CRGI \tag{9}$$

$$CRGI = GGI_V \times CSE \tag{10}$$

where $CCGI$, CGF , $CRGI$, CSE are the changes of GGI, green frontier, relative Green Index and pure green index change and scale effect, respectively.

Table 4. Decomposition of annual changes in green indices of each region (2006–2009).

Region	Change in Relative Green Index	Change in Green Frontier	Change in Pure Green Index	Change in Scale Effect	Change in Green Index
Beijing	1	1.268	1	1	1.268
Tianjin	1.011	1.081	1.051	0.962	1.093
Hebei	0.981	1.069	0.994	0.987	1.049
Shanxi	0.984	1.069	0.991	0.993	1.052
Inner Mongolia	0.985	1.069	0.987	0.998	1.053
Liaoning	0.979	1.069	0.988	0.991	1.047
Jilin	0.981	1.069	0.987	0.995	1.049
Heilongjiang	0.979	1.069	0.981	0.998	1.047
Shanghai	1	1.161	1	1	1.161
Jiangsu	0.981	1.069	1.009	0.972	1.049
Zhejiang	0.981	1.069	1.002	0.979	1.049
Anhui	0.977	1.069	0.979	0.998	1.044
Fujian	0.994	1.069	0.998	0.995	1.062
Jiangxi	0.979	1.069	0.985	0.994	1.047
Shandong	0.984	1.069	1.011	0.973	1.052
Henan	0.98	1.069	0.996	0.984	1.048
Hubei	0.984	1.069	0.984	1	1.052
Hunan	0.984	1.069	0.984	0.999	1.051
Guangdong	0.971	1.069	1	0.971	1.038
Guangxi	0.97	1.069	0.975	0.995	1.037
Hainan	0.953	1.069	1	0.953	1.019
Chongqing	0.98	1.069	0.987	0.993	1.048
Sichuan	0.978	1.069	0.983	0.995	1.046
Guizhou	0.978	1.069	1.035	0.945	1.046
Yunnan	0.972	1.069	0.981	0.991	1.039
Shaanxi	0.981	1.069	0.985	0.996	1.048
Gansu	0.981	1.069	1.005	0.976	1.049
Qinghai	0.967	1.069	1.016	0.952	1.034
Ningxia	0.978	1.069	1.029	0.95	1.046
Xinjiang	0.956	1.069	0.973	0.983	1.022
Average	0.980	1.079	0.996	0.984	1.057

The decomposition results in Table 4 indicate that among all provinces, municipalities and autonomous regions, Beijing and Shanghai are always on the green frontier. Their relative green index remain unchanged; Tianjin is the only city whose green index is greater than 1, implying that this area is getting closer to the green frontier. The green index of the remaining 27 areas are all less than 1, which illustrates they are moving away from the green frontier to different degrees. On the whole, the average green index of all the regions from 2006 to 2008 is 0.98 and indicates that the GGI has not converged to the green frontier, showing a certain degree of divergent trends. However, from another

perspective, there are no notable changes on the relative green index of each region. The change of green frontier made the green index of all regions promoted in different degrees, even Hainan province, which has the biggest drop in relative green index. This indicates that energy consumption intensity and the extent of environmental pollution during regional economic growth has declined, while integrated energy and environment efficiency is dramatically improved.

A comparison between the results of this paper with some previous studies on China's energy and environmental efficiency is presented in Table 5. Although the objectives are quite different with various focuses on energy, environmental or resource aspects, the efficiencies are very close to 50%.

Table 5. Comparisons of different DEA studies on China.

Object	Studying Period	Production Efficiency	References
Integrated energy and environmental efficiency of China	2009	54.4	This paper
Industrial energy efficiency of Chinese industrial system	2006	47.67	[16]
Resource efficiency of Chinese industrial system	2004	49.8	[20]
Environmental efficiency of Chinese industrial system	2004	55.53	[20]
Resource efficiency of China	2006	42.15	[25]

4. Conclusions

Among the wide spectrum of energy and environmental evaluation methods, DEA is regarded as an effective way to construct a GGI to evaluate the energy and environmental performance. Since the identification of the relationships between the inputs and the outputs is not required, DEA needs less information compared to the traditional optimization methods. Meanwhile, different inputs and outputs with various dimensions can be combined to calculate the optimized efficiency. It could also avoid the derivation of weight coefficients, normative judgments and subjective valuations. Generally, it is considered as an effective tool for evaluating the performances of complex social-economic systems.

In this paper, DEA is employed by selecting 30 provinces, municipalities and autonomous regions except for Tibet, Hong Kong, Marco and Taiwan, as DMUs. Empirical results are listed below:

- (1) The integrated energy and environment efficiencies of these regions vary greatly. Beijing and Shanghai have the lowest energy consumptions and environment pollutions during the GDP growth process, with a green index of 1. The green indexes of the developed eastern regions like Guangdong, Fujian, Zhejiang, Tianjin, Jiangsu and Hainan are in the top ranking, while those of the northeastern and middle regions relatively fall behind. There are severe energy and environment problems in the northwest and south areas such as Ningxia, Qinghai, Shanxi, Guizhou and Inner Mongolia, which are far from the green frontier, with GGIs all being below 0.3.
- (2) The provincial differences between GGIs reflect the specific development modes, which depend on the varying level of development of each area. There is an obvious positive

correlation between the green index and *per capita* GDP, with the correlation coefficient being 0.75. Almost all the green indexes are above 0.6 in the regions with *per capita* GDP of more than 0.35 million yuan, while the green indexes are below 0.6 in the regions whose *per capita* GDP are below 0.35 million yuan, indicating that dependence of economic growth on energy consumption and environmental pollution will gradually decrease.

- (3) Increases of different degree in GGIs of all DMUs are found from 2006 to 2008, which represent the great achievements of the Energy Conservation & Emission Reduction movement in China. However, GGIs of these provinces have not converged to the green frontier, showing a more or less divergent trend.

It can be seen that the energy and environmental efficiency is lower for the central and west China, and the gap between these regions and east coast regions is still increasing. With heavy industries continuously moving from the east to the central and west regions, environmental and energy issues could become more serious. Thus, policy makers should pay much attention on this phenomenon and intensify the energy saving and emission reduction efforts rather than continue the traditional unsustainable production modes seen in the western area.

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References

1. Chen, B.; Chen, G.Q. Ecological footprint accounting based on emergy—A case study of the Chinese society. *Ecol. Model* **2006**, *198*, 101–114.
2. Chen, B.; Chen, G.Q.; Yang, Z.F.; Jiang, M.M. Ecological footprint accounting for energy and resource in China. *Energy Policy* **2007**, *35*, 1599–1609.
3. Chen, B.; Chen, G.Q. Modified ecological footprint accounting and analysis based on embodied exergy—a case study of the Chinese society 1981–2001. *Ecol. Econ.* **2007**, *61*, 355–376.
4. Zhang, L.X.; Chen, B.; Yang, Z.F.; Chen, G.Q.; Jiang, M.M.; Liu, G.Y. Comparison of typical mega cities in China using emergy synthesis. *Commun. Nonlinear Sci. Numer. Simul.* **2009**, *14*, 2827–2836.
5. Chen, B.; Chen, G.Q. Resource analysis of the Chinese society 1980–2002 based on exergy—Part 2: Renewable energy sources and forest. *Energy Policy* **2007**, *35*, 2051–2064.
6. Chen, B.; Chen, G.Q. Resource analysis of the Chinese society 1980–2002 based on energy—Part 5: Resource structure and intensity. *Energy Policy* **2007**, *35*, 2087–2095.
7. Chen, Z.M.; Chen, G.Q.; Zhou, J.B.; Jiang, M.M.; Chen, B. Ecological input–output modeling for embodied resources and emissions in Chinese economy 2005. *Commun. Nonlinear Sci. Numer. Simul.* **2010**, *15*, 1942–1965.

8. Zhou, P.; Ang, B.W.; Poh, K.L. A survey of data envelopment analysis in energy and environmental studies. *Eur. J. Oper. Res.* **2008**, *189*, 1–18.
9. Farrell, M.J. The Measurement of productive efficiency. *J. R. Stat. Soc. A Stat. Part 3* **1957**, *20*, 253–290.
10. Burley, H. Productive efficiency in U.S. manufacturing: A linear programming approach. *Rev. Econ. Stat.* **1980**, *11*, 619–622.
11. Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **1984**, *30*, 1078–1092.
12. Färe, R.; Grosskopf, S.; Norris, M.; Zhang, Z. Productivity Growth, Technical progress, and efficiency changes in industrialised countries. *Am. Econ. Rev.* **1994**, *84*, 66–83.
13. Lovell, C.A.K. Linear programming approaches to the measurement and analysis of productive efficiency. *Top* **1994**, *2*, 175–248.
14. Coelli, T.J. A multi-stage methodology for the solution of orientated DEA models. *Oper. Res. Lett.* **1998**, *23*, 143–149.
15. Mousavi-Avval, S.H.; Rafiee, S.; Jafari, A.; Mohammadi, A. Improving energy use efficiency of canola production using data envelopment analysis (DEA) approach. *Energy* **2011**, *36*, 2765–2772.
16. Shi, G.M.; Bi, J.; Wang, J.N. Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. *Energy Policy* **2010**, *38*, 6172–6179.
17. Ramanathan, R. A holistic approach to compare energy efficiencies of different transport modes. *Energy Policy* **2000**, *28*, 743–747.
18. Färe, R.; Grosskopf, S.; Lovell, C.A.K.; Pasurka, C. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. *Rev. Econ. Statist.* **1989**, *71*, 90–98.
19. Tyteca, D. Linear programming models for the measurement of environmental performance of firms-concepts and empirical results. *J. Prod. Anal.* **1997**, *8*, 183–197.
20. Zhang, B.; Bi, J.; Fan, Z.Y.; Yuan, Z. W.; Ge, J.J. Eco-efficiency analysis of industrial system in China: A data envelopment analysis approach. *Ecol. Econ.* **2008**, *68*, 306–316.
21. Sueyoshi, T.; Goto, M.; Ueno, T. Performance analysis of US coal-fired power plants by measuring three DEA efficiencies. *Energy Policy* **2010**, *38*, 1675–1688.
22. Zhou, P.; Ang, B.W.; Han, J.Y. Total factor carbon emission performance: a Malmquist index analysis. *Energy Econ.* **2010**, *32*, 194–201.
23. Guo, X.D.; Zhu, L.; Fan, Y.; Xie, B.C. Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA. *Energy Policy* **2011**, *39*, 2352–2360.
24. Hall, B.; Kerr, M.L. *1991–1992 Green Index: A State-by-State Guide to the Nation's Environmental Health*; Island Press: Washington, DC, USA, 1991.
25. Bian, Y.W.; Yang, F. Resource and environment efficiency analysis of provinces in China: A DEA approach based on Shannon's entropy. *Energy Policy* **2010**, *38*, 1909–1917.
26. *China Energy Statistical Yearbook 2010*; China Statistics Press: Beijing, China, 2010.
27. *China Environment Statistical Yearbook 2010*; China Statistics Press: Beijing, China, 2010.