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Green Development Performance in China: A Metafrontier Non-Radial Approach

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Abstract: This paper proposes a green development growth index (GDGI) for measuring the changes in sustainable development over time. This index considers a wide range of pollutants, and allows for the incorporation of group heterogeneity and non-radial slack in the conventional green development index. The GDGI is calculated based on a non-radial directional distance function derived by several data envelopment analysis (DEA) models, and was decomposed into an efficiency change (EC) index, a best-practice gap change (BPC) index and a technology gap change (TGC) index. The proposed indices are employed to measure green development performance in 30 provinces in China from 2000 to 2012. The empirical results show that China has a low level of green development, with a 2.58% increase per year driven by an innovation effect. China's green development is mainly led by the eastern region, and the technology gaps between the eastern region and the other two regions (the central and western regions) have become wider over the years. The group innovative provinces have set a target for resource utilization of non-innovative provinces in order to catch-up with the corresponding groups, while the metafrontier innovative provinces provide targets for the technology levels of other provinces to improve their green development performance.

Keywords: green development performance; non-radial directional distance function; metafrontier analysis; China

1. Introduction

Based on the concept of sustainable development, green growth has attracted increasing attention by the international community. The formal definition of green growth was introduced by the Organization for Economic Cooperation and Development (OECD): "green growth means fostering economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies" [1]. Achieving green growth is an important target for the Chinese government, and it is an effective strategy to follow given increasing energy demand/supply restraints, huge environmental costs and backward energy use technologies [2]. In this paper, we adopted recently developed techniques to measure green development performance based on four main environmental pollutants in 30 provinces of China over the period 2000–2012. The approach adopted allows for the incorporation of heterogeneity across provinces and non-radial slack in the conventional green development index.

China's economic growth is usually described as "unstable, unbalanced, uncoordinated and ultimately unsustainable" [3]. According to Ho and Jorgenson [4], China's total environmental damage accounted for approximately 2%–8% of total GDP in 1997. Faced with increasingly serious environmental costs, green development has become a priority for the Chinese government. Recently, green development became one of China's development philosophies in the 13th Five-Year Plan (13th FYP, corresponding the period 2016–2020).

Measuring the green development performance of China has become an important topic attracting attention from both academia and government policy-makers. Traditionally, the growth of total factor productivity (TFP) has been used as a signal of development performance. However, conventional TFP studies are seriously misleading and do not provide a reliable indicator of green development performance because they neglect both the energy inputs required for economic growth and their environmental impacts [3,5]. Taking environmental pollutants as undesirable outputs (bads), Chung *et al.* [6] presented the directional distance function (DDF). The rationale is that it strives to increase the "goods" while simultaneously decreasing the "bads" under the framework of data envelope analysis (DEA). Under their framework, Zhang and Choi [7] and Zhang *et al.* [8] proposed the total-factor CO_2 emission performance index (TCPI) and the metafrontier non-radial Malmquist CO_2 emission performance index (MNMCPI) for changes in TCPI over the years.

Our measure of green development performance is the extended form of TCPI and MNMCPI. In our opinion, green development is a comprehensive concept, and more pollutants should be considered. Thus, we adopt four main pollutants, including waste water, sulphur dioxide emission, solid wastes and CO_2 emissions rather than only one pollutant to measure its performance. Furthermore, we evaluate green development performance considering the heterogeneities across China's provinces under the framework of metafrontier analysis. Based on this augmented methodology, the parameters efficiency change, best-practice gap change and technology gap change present us with rich information about China's green development performance.

The rest of the paper is organized as follows. Section 2 is the literature review. Section 3 is the methodology of the study. Section 4 describes the data. Section 5 provides the results and discussion. Section 6 concludes this paper.

2. Literature

Economic theory measuring a "sustainable"/"green" economic growth model was developed more than half a century ago. As early as 1957, Solow [9] argued that sustainable economic growth only depends on technological progress in the long term. In other words, a rising contribution of total factor productivity (TFP) to economic growth is the only way to achieve sustainable growth [3]. Many studies analyze the sustainability of China's economic growth based on TFP via growth accounting [5,10–12] or non-parametric methods [13]. In essence, these studies are based on the framework of productivity improvement.

However, the conventional TFP studies ignore the environmental costs of economic growth (such as CO_2 emissions). It is widely accepted that China's economic growth is accompanied by huge environmental costs. In this sense, these studies may overestimate the true contribution of TFP to output growth, and thereby may lead to a wrong result about China's green development. Furthermore, this bias might direct our attention to less efficient use of environmental friendly abatement technologies or send wrong signals to policy-makers [5]. Thus, green development has been introduced, which is derived from the integration of productivity improvement and environmental protection, and it is a strategy for enhancing productivity and environmental performance for overall socio-economic development [1,14,15]. Obviously, measuring green development performance should take undesirable outputs into consideration.

Considering undesirable outputs, a number of studies evaluate green development performance via DEA models [14,16,17]. Zhang and Choi [7] introduced TCPI and MNMCPI to measure the CO_2 emission performance. These two indices are based on the non-radial DDF model, and incorporate the metafrontier approach. Further, a bootstrapping approach is conducted to introduce statistical inferences into these indices [8]. As an application, Zhang, Zhou and Kung [8] found that the total-factor carbon emission performance of the Chinese transportation industry as a whole decreased by 32.8% over the period 2002–2010, and this reduction was primarily caused by technological decline.

Yu-Ying Lin *et al.* [18] measures green (environmental) productivity in 70 countries over the period 1981–2007 by combining the directional distance function (DDF) model and the metafrontier analysis.

The Malmquist-Luenberger productivity index (MLPI), which is introduced by Chung, Färe and Grosskopf [6] and calculated by using the estimated DDF scores, is widely used to measure productivity change or green TFP because it incorporates undesirable output production [3], though it has an inconsistency problem [19]. Chen and Golley [3] used MLPI to evaluate the changing patterns of "green" TFP growth of 38 Chinese industrial sectors during the period 1980–2010. Song, *et al.* [20] used a non-radial DEA model with a slacks-based measure to evaluate the green development of Chinese transportation sectors across provinces in 2003–2012. The empirical result indicated that performance was poor and the average environmental efficiency was 0.45.

Acknowledging the shortcomings of the "discriminating power problem" and "technical regress" associated with the conventional DEA models in measuring green development performance, Li and Lin [21] proposed the SS-ML index, which improves the estimation method for DEA models with the combination of super-efficiency and the sequential DEA method, to measure the green productivity growth of Chinese industrial sectors under the constraints of energy consumption and CO_2 emissions. Combining the SS-ML index and the meta-frontier analysis, Li and Lin [22] found that eastern China has the highest level of green development, followed by western China and central China.

Due to data limitations, studies on green development at the micro-level are rare. Li *et al.* [23] adopted an improved DEA model to measure the green development performance of the 24 Chinese electric power supply companies of the State Power Grid (SGCC). Wei *et al.* [24] assessed the abatement potential of energy and associated CO_2 emissions from coal-fired power enterprises in China's Zhejiang province.

Nevertheless, the existing literature aiming at evaluating green development performance focuses primarily on CO_2 emissions or SO_2 emissions [25], and rarely considers other environmental pollutants. Therefore, they may not give an overall prospect of green development. This paper argues that measuring green development should include the main environmental pollutants, and the non-radial DDF model is a suitable method as it can accurately determine the efficiency when non-zero slacks exist. Zhou *et al.* [26] and Zhang, Zhou and Kung [8] applied this method. However, their research only takes CO_2 emissions as the environmental pollutant. This paper improves their method so as to incorporate more environmental pollutants, and presents a new index to evaluate the green development performance of China.

3. Methodology

3.1. Non-Radial Directional Distance Function

It is well known that desirable and undesirable outputs are jointly produced during the production process. Generally speaking, the production process strives to increase the desirable outputs while simultaneously decreasing the undesirable ones under a given input set and technology. In other words, considering the desirable outputs while ignoring the undesirable outputs to evaluate green development is misleading. Färe *et al.* [27] examined environmental technology that incorporated weak disposability of outputs and null-jointness. This framework is very useful to investigate environmental performance. Assume that $x = (x_1, x_2, \cdots, x_N) \in \mathbb{R}_N^+$, $y = (y_1, y_2, \cdots, y_M) \in \mathbb{R}_M^+$ and $b = (b_1, b_2, \cdots, b_J) \in \mathbb{R}_J^+$ the vectors of inputs, desirable outputs and undesirable outputs respectively. Then, the production process can be described as using inputs x to produce desirable outputs y while also emitting undesirable environmental pollutants b. This production technology can also be conceptually defined as $T = \{(x, y, b)$: x can produce $(y, b)\}$. Mathematically, the technology set T is usually assumed to be a closed, bounded, and convexity set. Additionally, it must satisfy the following properties [21,27,28]:

(1) If $(x, y, b) \in T$, and $b = 0$, then $y = 0$;

(2) If $(x, y, b) \in T$, and $x' > x$, then $T(x) \subseteq T(x')$;

(3) If $(x, y, b) \in T$, and $y' < y$, then $(x, y', b) \in P(x)$;
(4) If $(x, y, b) \in T$, and $0 \leqslant \theta \leqslant 1$, then $(\theta y, \theta b) \in P(x)$.

The production technology T has been well-defined conceptually to reflect green development as it considers both the desirable and undesirable outputs, and the abatement of undesirable outputs is not free but costly in terms of a proportional reduction in desirable outputs. However, it cannot be applied in empirical analysis directly.

In fact, the directional distance function (DDF) method introduced by Chung, Färe and Grosskopf [6] is a suitable framework to measure the above production technology T and its properties. Originally, the DDF is defined as follows:

$$\vec{D}_o(x, y, b; g) = \sup\{\beta : (y, b) + g \times \beta \in T\} \tag{1}$$

where $g = (g_y - g_b) \in \mathbb{R}_M^+ \times \mathbb{R}_J^+$ is a direction vector and it implies that the desirable outputs and the undesirable outputs can increase and decrease simultaneously. As the DDF reflects the essence of green development, it is widely used in empirical studies to evaluate environmental performance. Examples of such studies include Picazo-Tadeo *et al.* [29], Färe *et al.* [27], Watanabe and Tanaka [30], Macpherson *et al.* [31], Yuan *et al*. [32], Li and Lin [21] and Li and Lin [22].

However, Equation (1) has a rigid assumption that the expansion of desirable outputs and the reduction of the undesirable outputs are at the same rate. In this sense, it is a radical efficiency measure, and when there are non-zero slacks it may overestimate the environmental performance. Another limitation of Equation (1) is that it cannot evaluate the performance of a given input [33]. In order to overcome these limitations, Zhou, Ang and Wang [26] presented a non-radial directional distance function (NDDF) in order to model green performance considering both the desirable and undesirable outputs. Zhou, Ang and Wang [26] believed that NDDF relaxes the assumption of the proportional adjustments of inputs and (desirable and undesirable) outputs, and has higher discriminating power than DDF. It can be defined as follows [26]:

$$N\vec{D}(x, y, b; g) = \sup\{\mathrm{w}^T\beta : (x, y, b) + g \times diag(\beta) \in T\} \tag{2}$$

where $\beta = (\beta_x, \beta_y, \beta_b)^T \geqslant 0$ is a vector of scaling factors which measure the distance of the real inputs/outputs from the optimal state; $\mathrm{w}^T = (w_x, w_y, w_b)$ denotes the weights of the inputs/outputs; $g = (g_x, g_y, g_b)$ is a directional vector, while *diag* implies the diagonal matrices. One of the advantages of NDDF is that $\mathrm{w}^T = (w_x, w_y, w_b)$ and $g = (g_x, g_y, g_b)$ can be set in different ways according to the research goals. Furthermore, Model (2) is related to Fukuyama and Weber [34] (FW hereafter) with the difference that FW did not consider bad outputs. However, as Pastor and Aparicio [35] pointed out, the directional slacks-based measure of FW is a weighted additive-type measure in the sense that it maximizes a specific weighted sum of slacks. In fact, Model (2) is mathematically equivalent to a weighted additive-type model. Similar to DDF, NDDF also cannot be employed in empirical analysis directly.

Most studies use the piecewise convex combinations (DEA-type) of the observed data to characterize the production technology and the related distance function. As a nonparametric method, DEA constructs the best-practice frontier using linear programming. This paper applies DEA to calculate the NDDF to evaluate the green development performance of China. Specifically, each province is regarded as a DMU, and it uses capital stock (K), labor force (L), and energy (E) to generate the desirable output—gross regional product (Y). Meanwhile, we assume the production process generates four undesirable environmental pollutants as byproducts, which include waste water (W), sulphur dioxide emission (S), solid wastes (D) and carbon dioxide emissions (C). To accurately measure the green development performance, it is appropriate to assume the non-energy inputs are fixed in the NDDF model, as capital stock (K) and labor force (L) do not emit pollutants directly [8]. In other words, the weight vector and the directional vector are set as

$\mathrm{w}^T = (0, 0, \frac{1}{3}, \frac{1}{3}, \frac{1}{12}, \frac{1}{12}, \frac{1}{12}, \frac{1}{12})$ and $g = (0, 0, -E, Y, -W, -S, -D, -C)$, respectively. The assumption of weight vector $\left(0, 0, \frac{1}{3}, \frac{1}{3}, \frac{1}{12}, \frac{1}{12}, \frac{1}{12}, \frac{1}{12}\right)$ is similar to Wang *et al.* [36], Zhang, Zhou and Kung [8] and Lin and Du [37], and it means that energy reduction, desirable output expansion and pollutants reduction are assigned the same importance, namely 1/3. For pollutants, the Chinese government introduced a series of regulations and measures to control the main pollutants in 2006. In other words, it is difficult to present the accurate weight for the different pollutants. Thus, we give the weight $\frac{1}{12}\left(= \frac{1}{3} \times \frac{1}{4}\right)$ to the pollutants. This setup also assigns the same importance to reduction of waste water (W), sulphur dioxide emission (S), solid wastes (D) and carbon dioxide emissions (C) (Note that different choices of the weight vector might lead to different performance scores. We thank a reviewer for pointing out this.). Although it is a naive choice, it is a common one and has been widely used in previous studies. Furthermore, as the effects of capital and labor are eliminated, it places emphasis on the effective consumption of energy inputs. Based on the above analysis, the value of NDDF of a specific DMU (a province in China) can be calculated by solving the following linear programming,

$$\begin{aligned}
&\overrightarrow{ND}(K, L, E, Y, W, S, D, C; g) = \max\left\{\frac{1}{3}\beta_E + \frac{1}{3}\beta_Y + \frac{1}{12}\beta_W + \frac{1}{12}\beta_S + \frac{1}{12}\beta_D + \frac{1}{12}\beta_C\right\} \\
&s.t. \quad \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}K_{it} \leqslant K \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}L_{it} \leqslant L \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}E_{it} \leqslant E - \beta_E g_E \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}Y_{it} \geqslant Y + \beta_Y g_Y \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}W_{it} = W - \beta_W g_W \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}S_{it} = S - \beta_S g_S \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}D_{it} = D - \beta_D g_D \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}C_{it} = C - \beta_C g_C \\
&\qquad \lambda_{it} \geqslant 0 \ (i = 1, 2, \cdots, N; t = 1, 2, \cdots, T) \\
&\qquad \beta_j \geqslant 0 \ (j = E, Y, W, S, D, C)
\end{aligned} \tag{3}$$

It is worth noting that we employ the global DEA method, which uses the whole sample to construct the best-practice frontier. That implies a single global frontier is used as a benchmark technology for all DMUs over the whole period. Thus, the estimate values can be compared over time.

Suppose that $\beta^* = \left(0, 0, \beta_E^*, \beta_Y^*, \beta_W^*, \beta_S^*, \beta_D^*, \beta_C^*\right)^T \geqslant 0$ are the optimal solutions to Equation (3), which implies that, under the best-practice scenario, the energy input, desirable output and undesirable environmental pollutants will be $E_{it} - \beta_{E,it}^* \times E_{it}$, $Y_{it} + \beta_{Y,it}^* \times Y_{it}$ and $U_{it} - \beta_{U,it}^* \times U_{it} (U = W, S, D, C)$. Obviously, $\beta^* = 0$ means that the DMU on the best-practice frontier. Following Zhou, Ang and

Wang [26], Zhang *et al.* [38] and Lin and Du [37], the green development performance index (GDPI) can be defined as follows:

$$
\begin{aligned}
GDPI_{it} &= \frac{1}{2}\left[\frac{\left(E_{it}-\beta^{*}_{E,it}\times E_{it}\right)/\left(Y_{it}-\beta^{*}_{Y,it}\times Y_{it}\right)}{E_{it}/Y_{it}}\right]+ \\
&\frac{1}{2}\left[\frac{1}{4}\sum_{J=W,S,D,C}\frac{\left(J_{it}-\beta^{*}_{J,it}\times J_{it}\right)/\left(Y_{it}-\beta^{*}_{Y,it}\times Y_{it}\right)}{J_{it}/Y_{it}}\right]
\end{aligned}
\tag{4}
$$

It should be noted that the values of GDPI lie between zero and unity, and the higher the GDPI, the better the green development performance.

3.2. Green Development Growth Index and Its Decomposition

In the above section, we define an index, *i.e.*, GDPI to measure green development performance. However, it assumes all provinces have the same level of technology, or it does not account for the technology heterogeneities across provinces. In fact, the different regions may have various technical conditions or technical constraints. For example, the eastern provinces have a relatively high level of economic development, and have advanced technologies to combat undesirable environmental pollutants. Furthermore, the GDPI index is a static index, or it cannot measure the change of green development over years. In order to investigate the changes in GDPI over time while also considering the region heterogeneity, we first combine the GDPI with a meta-frontier analysis.

Suppose N DMUs (provinces of China in this study, N = 30) can be divided into h (h = 3, including the eastern, central and western China, respectively) independent groups, and each group includes N_h (h = 1, 2, 3) DMUs and uses different production technologies. Thus, we can define three benchmark technology sets: a contemporaneous benchmark technology, an intertemporal benchmark technology and a global benchmark technology [7,39,40].

For a given group h, the contemporaneous benchmark technology (denoted as T_h^C) can be reflected in the following linear programming,

$$
\begin{aligned}
&\overrightarrow{ND}_h^{C}(K,L,E,Y,W,S,D,C;g) = \max\left\{\frac{1}{3}\beta_E+\frac{1}{3}\beta_Y+\frac{1}{12}\beta_W+\frac{1}{12}\beta_S+\frac{1}{12}\beta_D+\frac{1}{12}\beta_C\right\} \\
&s.t.\quad \sum_{i=1}^{N_h}\lambda_{it}K_{it}\leqslant K \\
&\qquad \sum_{i=1}^{N_h}\lambda_{it}L_{it}\leqslant L \\
&\qquad \sum_{i=1}^{N_h}\lambda_{it}E_{it}\leqslant E-\beta_E g_E \\
&\qquad \sum_{i=1}^{N_h}\lambda_{it}Y_{it}\geqslant Y+\beta_Y g_Y \\
&\qquad \sum_{i=1}^{N_h}\lambda_{it}W_{it}= W-\beta_W g_W \\
&\qquad \sum_{i=1}^{N_h}\lambda_{it}S_{it}= S-\beta_S g_S \\
&\qquad \sum_{i=1}^{N_h}\lambda_{it}D_{it}= D-\beta_D g_D \\
&\qquad \sum_{i=1}^{N_h}\lambda_{it}C_{it}= C-\beta_C g_C \\
&\qquad \lambda_{it}\geqslant 0\ (i=1,2,\cdots,N_h;t=1,2,\cdots,T;h=1,2,3) \\
&\qquad \beta_j\geqslant 0\ (j=E,Y,W,S,D,C)
\end{aligned}
\tag{5}
$$

Essentially, T_h^C constructs the best-practice frontier based on the observations for the specific group h only for that time period t. Based on $\hat{\beta}_j (j = E, Y, W, S, D, C)$ calculated by Equation (5), the GDPI given by Equation (4) can be denoted as $GDPI_h^C$.

An intertemporal benchmark technology for a given group h is defined as $T_h^I = T_h^1 \cup T_h^2 \cup \cdots \cup T_h^T$. Obviously, the intertemporal benchmark technology develops a single best-practice frontier for a given group h over the whole period. Because we have h (= 3) independent groups, there are h (= 3) distinct intertemporal technologies. Based on T_h^I, the result of GDPI can be denoted as $GDPI_h^I$ and can be calculated by Equation (6) and Equation (4).

$$\begin{aligned}
&\overrightarrow{ND}_h^I(K, L, E, Y, W, S, D, C; g) = \max\left\{\frac{1}{3}\beta_E + \frac{1}{3}\beta_Y + \frac{1}{12}\beta_W + \frac{1}{12}\beta_S + \frac{1}{12}\beta_D + \frac{1}{12}\beta_C\right\} \\
&s.t. \quad \sum_{t=1}^{T}\sum_{i=1}^{N_h} \lambda_{it} K_{it} \leqslant K \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N_h} \lambda_{it} L_{it} \leqslant L \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N_h} \lambda_{it} E_{it} \leqslant E - \beta_E g_E \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N_h} \lambda_{it} Y_{it} \geqslant Y + \beta_Y g_Y \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N_h} \lambda_{it} W_{it} = W - \beta_W g_W \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N_h} \lambda_{it} S_{it} = S - \beta_S g_S \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N_h} \lambda_{it} D_{it} = D - \beta_D g_D \\
&\qquad \sum_{t=1}^{T}\sum_{i=1}^{N_h} \lambda_{it} C_{it} = C - \beta_C g_C \\
&\qquad \lambda_{it} \geqslant 0 \; (i = 1, 2, \cdots, N_h; t = 1, 2, \cdots, T; h = 1, 2, 3) \\
&\qquad \beta_j \geqslant 0 \; (j = E, Y, W, S, D, C)
\end{aligned} \tag{6}$$

Finally, a global benchmark technology can be defined as $T^G = \text{Convex}\left\{T_1^I \cup \cdots \cup T_h^I\right\}$. T^G is the convex envelope of all the contemporaneous technologies. It can be inferred that T^G constructs only one best-practice frontier based on the whole observation (including observations for all groups over the entire time period) [41]. Obviously, T^G can be reflected in Equation (3), and the corresponding GDPI is denoted as $GDPI_h^I$.

Similar to a global Malmquist productivity index introduced by Pastor and Lovell [42], a new index, namely the green development growth index (GDGI), is introduced to measure the changes in GDPI over time,

$$\begin{aligned}
GDGI_{i,t}^{t+1} &= \frac{GDPI^G(K_{i,t+1}, L_{i,t+1}, E_{i,t+1}, Y_{i,t+1}, W_{i,t+1}, S_{i,t+1}, D_{i,t+1}, C_{i,t+1})}{GDPI^G(K_{i,t}, L_{i,t}, E_{i,t}, Y_{i,t}, W_{i,t}, S_{i,t} D_{i,t}, C_{i,t})} \\
&\triangleq \frac{GDPI^G(\cdot^{t+1})}{GDPI^G(\cdot^{t})}
\end{aligned} \tag{7}$$

Since $GDPI_h^I$ is calculated by a global DEA method (Equation 3), in other words there is only one global benchmark technology, and its scores can be compared over the years [43], so there is no need to resort to the geometric mean convention when defining the global index [41,42].

As developed by Oh [40] and Zhang and Choi [7], the GDGI can be decomposed into different components as follows:

$$\begin{aligned} GDGI_{i,t}^{t+1} &= \left[\frac{GDPI^C(\cdot^{t+1})}{GDPI^C(\cdot^{t})}\right] \times \left[\frac{GDPI^I(\cdot^{t+1})/GDPI^C(\cdot^{t+1})}{GDPI^I(\cdot^{t})/GDPI^C(\cdot^{t})}\right] \times \left[\frac{GDPI^G(\cdot^{t+1})/GDPI^I(\cdot^{t+1})}{GDPI^G(\cdot^{t})/GDPI^I(\cdot^{t})}\right] \\ &\triangleq \frac{TE^{t+1}}{TE^{t}} \times \frac{BPR^{t+1}}{BPR^{t}} \times \frac{TGR^{t+1}}{TGR^{t}} \\ &\triangleq EC \times BPC \times TGC \end{aligned} \tag{8}$$

In Equation (8), the green development performance at time period s (= t, $t + 1$) based on the contemporaneous benchmark technology (T_h^C) is measured by $GDPI^C(\cdot^S)$ and abbreviated as TE^S. So, the EC term in Equation (8) measures how close a DMU for a specific group moves toward the contemporaneous benchmark technology at time period $t + 1$ compared to time period t, which indicates a "catch-up" effect. EC > (or <) 1 implies that a DMU moves close to (or far away from) the best-practice frontier at time period $t + 1$ compared to time period t. $BPR = GDPI^I/GDPI^C$ measures the best-practice gap ratio between a contemporaneous benchmark technology and an intertemporal benchmark technology, and it changes over time measured by BPC in Equation (8). BPC > (or <) 1 means the contemporaneous technology frontier shifts toward (or far away from) the intertemporal technology frontier, and is also considered to reflect the innovation effect [7]. $TGR = GDPI^G/GDPI^I$ is the technology gap ratio between an intertemporal benchmark technology and a global benchmark technology, and it changes over time measured by TGC in Equation (8). TGC > (or <) 1 indicates a decrease (increase) in the technology gap between the intertemporal technology for a specific group and the global technology. Thus, TGC reflects the technology leadership effect for a given group.

4. Data

As stated in Section 3, data on the inputs, desirable output and undesirable environmental pollutants are collected to evaluate the green development performance across 30 Chinese provinces from 2000 to 2012. Tibet is excluded because of data unavailability. The variables and data sources are discussed as follows:

(1) Inputs: include capital stock (K), labor force (L) and energy consumption (E). The data on capital stock (constant 2000 prices) and labor force can be found in Li and Lin [22]. The data on capital stock is estimated by the perpetual inventory approach, and each province has different depreciation rates of gross fixed capital formation [44]. Energy consumption is measured by 10^4 tons of standard coal equivalent (10^4 tce), and the data is obtained from the *China Energy Statistical Yearbook* [45].

(2) Desirable output: it is measured by the gross regional product (GRP) at 100 million Yuan (Y). It has been converted into 2000 prices with GRP deflators. Data are collected from the *China Energy Statistical Yearbook* [45].

(3) Undesirable environmental pollutants: include waste water (W), sulphur dioxide emission (S), solid wastes (D) and carbon dioxide (CO_2) emissions (C). According to the *China Statistical Yearbook* and *China Statistical Yearbook of Environment*, the China's environmental protection puts more emphasis on the status quo and the recovery of three wastes (waste water, waste gas and industrial residue). Correspondingly, the main environmental indicators of this study are waste water (W), sulphur dioxide emissions (S), carbon dioxide emissions (C) and solid wastes (D). Here, sulphur dioxide emissions (S) and carbon dioxide emissions (C) are two main types of waste gas and are closely related to air quality. In *China Statistical Yearbook*, the solid wastes (D) is the main form of industrial residue. From the perspective of statistical indicators released by the Chinese government, using only one pollutant to measure the performance of green development is not comprehensive. The data on waste water (W), sulphur dioxide emissions (S) and solid wastes (D) are collected from the *China Statistical Yearbook* [46]. Carbon dioxide is emitted from fossil

fuel usage, and it can be estimated by using the fuel-based carbon calculation model introduced by IPCC (2006) [47]. This paper uses eight fuel types (including coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas) to estimate CO_2 emissions, while their consumption levels are collected from the *China Energy Statistical Yearbook* [45].

Table 1 shows the descriptive statistics for the input and output variables. Among all the variables, the maximum values are much larger than the minimum values, indicating that there are huge heterogeneities across provinces in China. Furthermore, Table 2 indicates the average share of outputs for each province of the country. Overall, the eastern region has a high share of desirable output and a relatively low share of undesirable environmental pollutants, while the central and the western regions are found to have the opposite results. Taking Beijing for example; its GRP accounts for about 3.088% of the whole country, but its waste water, sulphur dioxide emissions, solid wastes and CO_2 emissions only account for about 0.557%, 0.494%, 0.698% and 1.428%, respectively. For the western provinces such as Yunnan, Gansu and Qinghai, their shares of undesirable environmental pollutants are higher than their shares of desirable outputs. In other words, the environment cost of economic growth in eastern provinces is lower than that of the western provinces.

Table 1. Descriptive statistics of variables (N = 390).

Variable (Unit)	Mean	Std.dev	Minimum	Maximum
Capital stock (100 million RMB)	20,067.44	17,952.33	1390.72	108,951.70
Labor (ten thousand workers)	2321.64	1540.87	239.47	6242.54
Energy consumption (10^4 tce)	9570.24	7005.88	479.95	38,899.00
Gross Regional Product (100 million RMB)	7211.28	6938.54	263.68	42,865.93
Waste water (10^4 ton)	75,186.57	63,500.79	3453.00	296,318.00
Sulphur dioxide emission (10^4 ton)	62.74	39.23	1.93	171.50
Solid wastes (10^4 ton)	5725.87	5876.08	75.00	45,576.00
CO_2 emissions (10^4 ton)	26,934.84	21,364.15	445.25	122,379.40

Table 2. The average share of outputs for each province to the whole country (2000–2012) (unit: %).

Province	GRP	W	S	D	C
(E) Beijing	3.088	0.557	0.494	0.698	1.428
(E) Fujian	3.739	5.132	1.806	2.775	1.919
(E) Guangdong	11.313	8.022	5.454	2.115	5.311
(E) Guangxi	2.062	5.846	4.166	2.619	1.518
(E) Hainan	0.501	0.304	0.127	0.105	0.371
(E) Hebei	4.809	5.116	6.271	11.798	7.495
(E) Jiangsu	9.144	11.463	5.898	3.796	6.150
(E) Liaoning	4.715	4.038	4.513	8.248	6.604
(E) Shandong	8.849	6.704	8.059	6.540	9.269
(E) Shanghai	4.617	2.321	1.590	1.160	2.832
(E) Tianjin	2.048	0.948	1.136	0.686	1.690
(E) Zhejiang	6.305	8.076	3.657	1.753	4.014
(C) Anhui	2.808	2.984	2.401	3.612	2.964
(C) Heilongjiang	2.958	2.006	1.894	2.405	3.378
(C) Henan	5.012	5.638	5.988	4.693	5.544
(C) Hubei	3.444	4.253	2.954	2.694	3.416
(C) Hunan	3.471	4.706	3.520	2.547	2.760
(C) Inner Mongolia	2.162	1.228	5.653	5.859	5.027
(C) Jilin	1.991	1.685	1.469	1.751	2.436
(C) Jiangxi	2.012	2.631	2.422	4.429	1.595
(C)Shanxi	1.904	1.679	5.736	8.296	7.158
(W) Chongqing	1.655	3.046	3.247	1.188	1.315

Table 2. *Cont.*

Province	GRP	W	S	D	C
(W) Gansu	0.980	0.817	2.276	1.794	1.731
(W) Guizhou	0.986	0.735	3.811	3.103	2.415
(W) Ningxia	0.287	0.730	1.508	0.738	1.108
(W) Qinghai	0.271	0.286	0.487	1.494	0.352
(W) Shaanxi	1.924	1.753	3.814	2.796	2.758
(W) Sichuan	3.959	4.774	5.221	4.631	2.919
(W) Xinjiang	1.216	0.939	2.154	1.451	2.327
(W) Yunnan	1.770	1.581	2.274	4.226	2.197
Eastern China	61.191	57.211	43.698	50.396	58.526
Central China	25.761	26.374	33.628	30.973	26.812
Western China	13.048	16.415	22.674	18.631	14.662

Note: E—the eastern China; C—the central China; W—the western China.

In order to further describe the green development of China, the 30 provinces of China are categorized into three groups based on geographical closeness and regional development strategies, namely eastern China, central China and western China [22]. The average values and growth rates for the variables in the three groups for the entire period are presented in Table 3. It can be seen that the eastern provinces use much more inputs than the central and western provinces, and its average GRP is also much higher. Also, heterogeneities across groups can be found among undesirable environmental pollutants. For example, the average values of sulphur dioxide emissions, solid wastes and CO_2 emissions for the eastern provinces are much higher than those for the western provinces, but they are very close to those for the central provinces. However, the average value of waste water for the eastern provinces is about 1.64 times larger than that of the central provinces. These differences in patterns of outputs/inputs across groups imply that different regions have varied production technologies, and it provides justification for developing a metafrontier to measure and decompose green growth using the GDGI index.

Table 3. Average values and growth rates for variables in three groups (2010–2012).

Group	Num	K	L	E	Y	W	S	D	C
Eastern	156	28,701.88 (14.56%)	2536.28 (2.92%)	12,057.56 (9.19%)	11,031.55 (12.19%)	110,009.60 (1.69%)	67.72 (0.27%)	6054.16 (11.57%)	32,726.45 (10.48%)
Central	117	17,641.95 (16.72%)	2602.41 (1.45%)	9880.52 (9.75%)	6192.39 (12.62%)	67,196.26 (1.92%)	67.00 (4.34%)	6925.58 (11.87%)	30,775.59 (9.32%)
Western	117	10,980.35 (14.30%)	1754.68 (1.67%)	5943.55 (10.66%)	3136.46 (12.05%)	36,746.17 (1.87%)	51.85 (6.18%)	4088.44 (19.31%)	15,371.94 (11.84%)

Note: The growth rates in parentheses.

5. Results and Discussion

5.1. Staticistal Analysis: the Green Development Performance Index under the Global Benchmark Technology

We use R3.2 to solve the Equations (3) and (4), and the estimation results of GDPI under the global benchmark technology across China's 30 provinces during the period 2000–2012 are reported in Table 4. The average score of GDPI in China during the sample period is only 0.398, and Table 4 shows that only 85 of the 390 estimated scores are found to be higher than 0.5, indicating that China is at a low level of green development. It is worth noting that during the first 10 years (2000–2009), there are 58 estimated scores higher than 0.5. However, during the past three years (2010–2012), there are 27 scores. Obviously, the average proportion of the development during 2010–2012 per year is higher than during 2000–2009 (27/90 > 58/300). This result indicates that green development performance has made significant progress in recent years. Additionally, only a few scores of the GDPI are equal to unity, and most of the unity scores correspond to developed provinces, such as Beijing, Tianjin and Guangdong. Except for the year 2005, Guangdong has unity scores of GDPI during 2000–2012, indicating its high performance in green development.

Table 4. Estimation results of green development performance index (GDPI) in China.

Province	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Beijing	0.351	0.388	0.434	0.464	0.493	0.533	0.601	0.711	0.836	0.903	1.000	1.000	1.000
Tianjin	0.294	0.308	0.334	0.366	0.382	0.382	0.412	0.461	0.537	0.582	0.610	0.714	1.000
Hebei	0.236	0.261	0.238	0.238	0.231	0.235	0.249	0.265	0.288	0.314	0.330	0.246	0.250
Shanxi	0.189	0.172	0.165	0.175	0.176	0.183	0.176	0.196	0.212	0.224	0.228	0.228	0.232
Inner Mongolia	0.238	0.242	0.231	0.235	0.235	0.239	0.249	0.257	0.264	0.189	0.213	0.206	0.252
Liaoning	0.221	0.246	0.275	0.292	0.292	0.300	0.320	0.340	0.339	0.363	0.384	0.367	0.381
Jilin	0.277	0.299	0.298	0.302	0.310	0.327	0.346	0.298	0.295	0.317	0.334	0.342	0.375
Heilongjiang	0.288	0.321	0.349	0.350	0.364	0.373	0.391	0.425	0.446	0.473	0.486	0.494	0.484
Shanghai	0.394	0.411	0.436	0.469	0.518	0.538	0.583	0.667	0.737	0.793	1.000	0.913	1.000
Jiangsu	0.477	0.497	0.514	0.515	0.486	0.444	0.460	0.493	0.528	0.557	0.571	0.577	0.607
Zhejiang	0.499	0.530	0.493	0.491	0.490	0.491	0.501	0.526	0.556	0.581	0.602	0.624	0.661
Anhui	0.298	0.310	0.328	0.345	0.361	0.372	0.357	0.371	0.387	0.402	0.427	0.442	0.461
Fujian	0.580	0.637	0.561	0.536	0.524	0.497	0.517	0.534	0.552	0.555	0.576	0.597	0.622
Jiangxi	0.371	0.417	0.378	0.377	0.378	0.385	0.358	0.369	0.396	0.412	0.423	0.428	0.451
Shandong	0.371	0.429	0.363	0.360	0.353	0.331	0.341	0.354	0.373	0.387	0.390	0.394	0.405
Henan	0.324	0.338	0.340	0.336	0.311	0.313	0.323	0.340	0.306	0.302	0.311	0.320	0.350
Hubei	0.285	0.322	0.323	0.316	0.308	0.318	0.331	0.354	0.325	0.343	0.351	0.352	0.363
Hunan	0.435	0.408	0.393	0.375	0.354	0.321	0.344	0.363	0.391	0.410	0.426	0.426	0.455
Guangdong	1.000	1.000	0.955	1.000	1.000	0.924	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Guangxi	0.367	0.393	0.386	0.369	0.345	0.340	0.353	0.360	0.381	0.339	0.343	0.356	0.371
Hainan	0.532	1.000	0.504	0.504	0.520	0.543	0.522	0.512	0.516	0.547	0.579	0.519	0.544
Chongqing	0.303	0.287	0.325	0.333	0.321	0.281	0.289	0.302	0.317	0.290	0.310	0.329	0.365
Sichuan	0.409	0.466	0.498	0.530	0.630	0.632	0.732	1.000	0.601	0.717	0.879	1.000	1.000
Guizhou	0.178	0.191	0.186	0.176	0.172	0.198	0.198	0.212	0.226	0.230	0.239	0.241	0.245
Yunnan	0.300	0.321	0.306	0.300	0.286	0.284	0.290	0.306	0.332	0.249	0.262	0.262	0.277
Shaanxi	0.314	0.304	0.299	0.299	0.293	0.285	0.300	0.311	0.336	0.274	0.284	0.298	0.313
Gansu	0.207	0.226	0.229	0.228	0.241	0.238	0.252	0.271	0.280	0.297	0.219	0.299	0.230
Qinghai	0.206	0.218	0.246	0.229	0.220	0.204	0.204	0.211	0.205	0.214	0.226	0.210	0.212
Ningxia	0.169	0.210	0.187	0.149	0.156	0.136	0.139	0.132	0.131	0.129	0.130	0.127	0.139
Xinjiang	0.261	0.269	0.273	0.278	0.271	0.266	0.263	0.264	0.268	0.255	0.243	0.215	0.191

Compared to the scores of GDPI in 2000, the scores of GDPI in 26 provinces increased in 2012. Four provinces, namely Yunnan, Shaanxi, Ningxia and Xinjiang, decreased. These four provinces are in western China, indicating its low level of green development. An important finding is that the GDPIs of eight provinces in 2009 are lower than the level in 2008. The possible reason is that large-scale economic stimulus plan adopted by the government to address the global crisis worsened the performance.

Figure 1 plots the trends of the average scores of the GDPI in the three regions (the eastern, central and western China). It can be found that the scores of GDPI in all regions show upward trends, with the average scores of 0.525, 0.330 and 0.297 in eastern, central and western China respectively. Furthermore, eastern China not only has the highest GDPI, but also shows the fastest growth rate. Specifically, its average score across provinces increases from 0.443 in 2000 to 0.653 in 2012, an increase of 47.321%. Figure 1 also indicates that the scores of GDPI in western China are lower than in central China, and both have slower growth rates than eastern China. Thus, the green development performance gap between eastern China and the other two regions becomes widened. In this sense, enhancing the green development performance in central and western China is crucial to China's sustainable development.

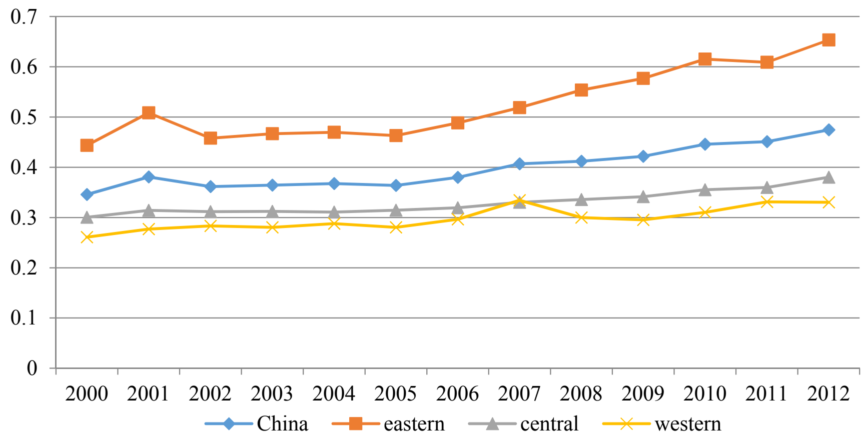


Figure 1. The average green development performance index (GDPI) in 2000–2012.

For individual provinces, the GDPI scores show a huge difference. Among the 30 provinces, only eight provinces show a relatively strong performance, with the average scores higher than 0.5 (Figure 2). Guangdong shows the best performance, and its average scores is 0.991; while Ningxia shows the lowest score (0.149). Corresponding to Figure 1, Figure 2 also indicates that the eastern provinces performed better than the central and western provinces.

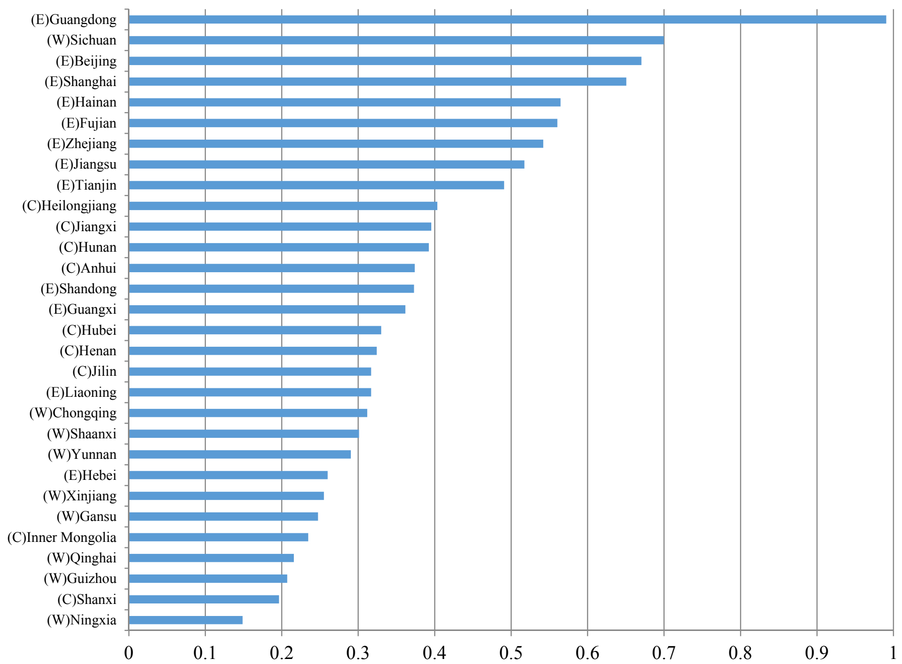


Figure 2. The average green development performance index (GDPI) across provinces. (Note: E—the eastern China; C—the central China; W—the western China.)

5.2. The Green Development Growth Index

To assess the changes in green development performance in China, the green development growth index (GDGI) is calculated based on Equations (7) and (8). Table 5 shows the average results of GDGI and its decomposition during the period 2000–2012. Recall that GDGI values greater (less) than unity indicate improvement (deterioration) in green development performances. Thus, Table 5 indicates that the growth rate of green development performance in the study sample is 2.58% per year, and it is mainly driven by the innovation effect (BPC). Furthermore, heterogeneities across groups/regions can be confirmed in green development. The average annual growth rate in green development of the eastern region is higher than those of the central and the western regions. Innovation effect (BPC) is the main contributor to green development for all three regions. Additionally, "catch-up" and technical leadership effects cannot be found in China.

Table 5. Average values of GDGI and its decomposition in 2000–2012.

Group	GDGI	EC	BPC	TGC
Eastern	1.0375	0.9868	1.0535	1.0000
Central	1.0214	0.9995	1.0322	0.9992
Western	1.0146	0.9897	1.0570	0.9902
China	1.0258	0.9915	1.0482	0.9968

We examine the cumulative GDPI and its decomposition by setting the values in year 2000 equal to 1, and the results are shown in Table 6. It can be seen that for China, the green development performance increased by 35.12% in 2012 compared with the year 2000. It further indicates that the innovation effect increased by 73.76% during the period 2000–2012. In other words, the innovation effect is the main contributor to green development in China. This conclusion is applicable to all three regions.

Table 6. The cumulative values of GDGI and its decomposition in 2000–2012.

Group	GDGI	EC	BPC	TGC
Eastern	1.5357	0.8517	1.8451	1.0000
Central	1.2862	0.9918	1.4393	0.9800
Western	1.1828	0.8654	1.8634	0.8742
China	1.3512	0.9011	1.7376	0.9588

Figure 3 shows the changes in green development performance and the decomposed sources in China and the three regions. For the period 2001–2002 and 2004–2005, the values of GDGI for China is less than unity, indicating a decrease in green development performance. After 2005, the GDGI of China shows values higher than unity. In other words, China's green development performance has shown improvement since 2005. This result implies that the policy of "energy-saving and emission-reduction" since 2006 does matter for China's green development. The eastern region shows larger fluctuations in GDGI than the central and western regions. For example, due to the economic crisis, the GDGI of the eastern region during the period 2010–2011 sharply declined from 1.059 to 0.984. Interestingly, the GDGI of the western region during the same period increased to 1.045. The decomposed results show that the main reason is that the value of BPC increased to the highest point (1.306), which implies that the contemporaneous technology frontier of the western region significantly shifted toward an intertemporal technology frontier. In terms of EC index, the values of EC in China during 2005–2012 are less than unity, implying there is no "catch-up" effect. Because *TE* measures the efficiency given the technology level, these results imply the poor performance of allocative efficiency. It also reflects the dilemma and hysteresis of reform in factor markets. In 2010–2011, the values of EC for the western region sharply declined to 0.831, indicating efficiency deterioration under the constraint of maintaining economic growth through huge investment. The values of BPC show opposite trends to EC. It seems that the "innovation effect" is driven by the "poor" performance of the intertemporal technology frontier rather than the "better" performance of the contemporaneous technology frontier. The values of TGC for the eastern region are always unity, indicating that the technology in the eastern region is of the highest level in China. Since 2006, the values of TGC for the central and western regions are less than unity, indicating a decrease in the technology leadership effect, or the technology gaps becoming wider rather than narrower.

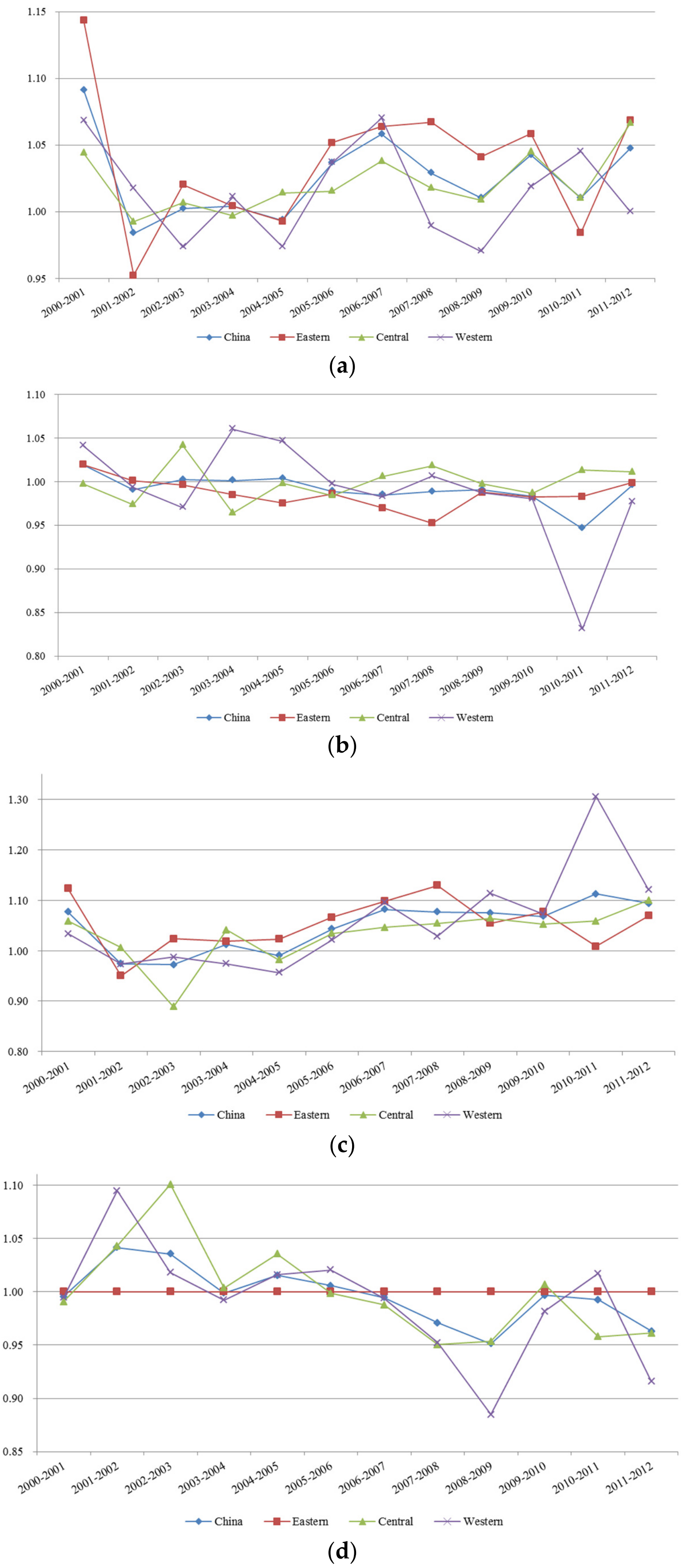
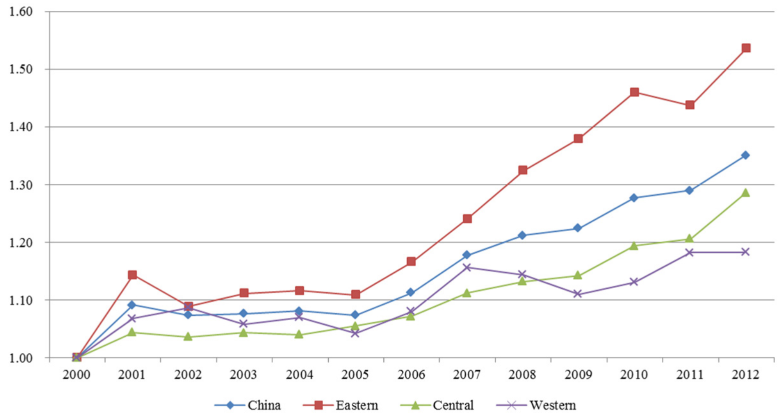
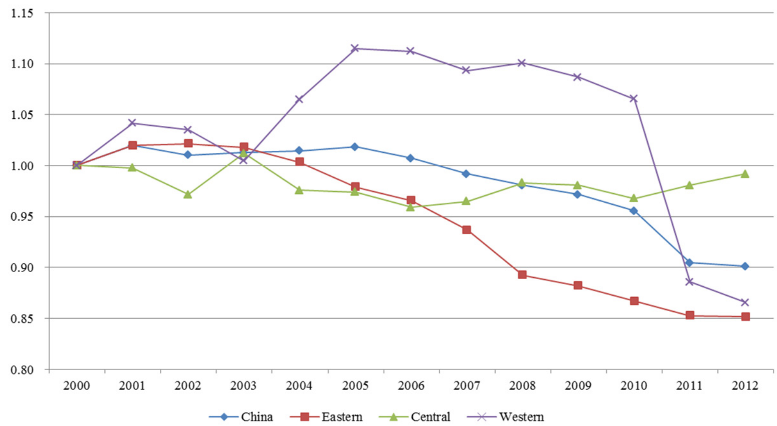


Figure 3. Trends in the green development growth index (GDGI) and its decomposition. (**a**) green development growth index (GDGI); (**b**) efficiency change (EC); (**c**) best-practice gap change (BPC); (**d**) technology gap change (TGC) index.

Figure 4 shows the cumulative changes in green development performance and the decomposed sources based on the GDPI. The GDPI shows values larger than unity, indicating an increase in green development performance. It is found that the sample provinces as a whole show an increase in green development performance by approximately 35.12% from 2000 to 2012. Among the three regions, the eastern region shows the highest GDPI (53.57%), followed by the central region and the western region (28.62% and 18.28%, respectively). This finding indicates that all the regions experienced green development performance gains. For efficiency changes (EC), Figure 4b indicates that the eastern region and the western region show upward trends during the period 2001–2004 and 2000–2010, respectively. However, all three regions experienced efficiency loss over the whole period (2000–2012), which implies there has been a deterioration in efficiency in recent years. Regarding the innovation effect (BPC) in Figure 4c, all the regions show increasing trends in 2000–2012. The eastern and western regions have a similar growth rate at 84.51% and 86.34%, respectively, while the central region increased by 43.94%. Figure 4d further confirms that the technology in the eastern region is of the highest level in China.



(**a**)



(**b**)

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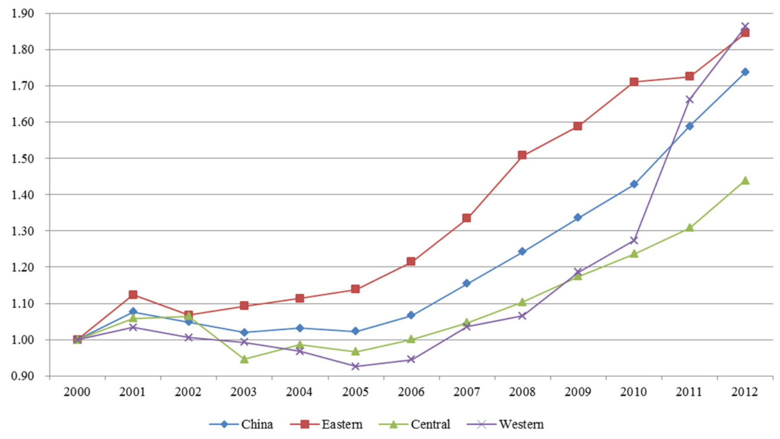

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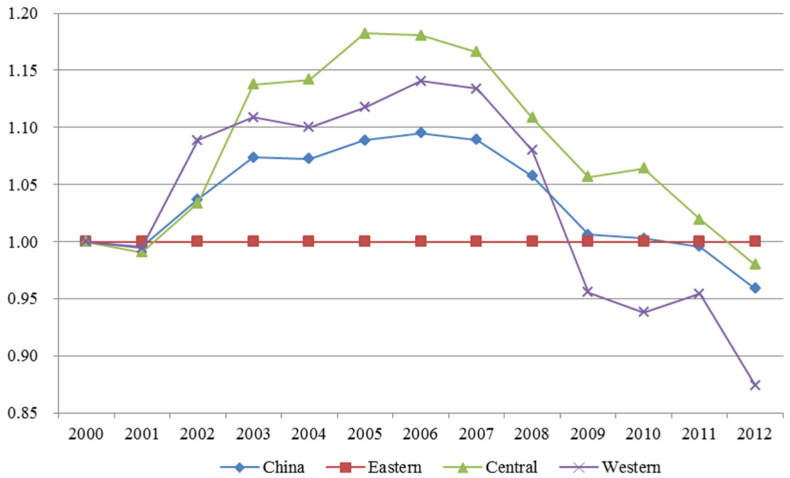

(**d**)

Figure 4. Trends of cumulative GDGI and its decomposition (2000–2012). (**a**) green development growth index (GDGI); (**b**) efficiency change (EC); (**c**) best-practice gap change (BPC); (**d**) technology gap change (TGC) index.

Table 7 shows the empirical results for the average GDGI for the 2000–2012 period and its decomposition for each province. Although most provinces have larger GDGI than unity, three provinces (Yunnan, Ningxia and Xinjiang) are observed to have GDGI lower than unity. Tianjin has the highest GDGI (average = 11.1%), indicating an 11.1% increase in green development performance. For EC, seven provinces show "catch-up" effects (their values of EC are larger than unity), whereas 12 provinces show no "catch-up effects". The BPCs of all provinces are larger than unity, implying there are innovation effects. The TGC of all eastern provinces and two other provinces (Guangxi and Qinghai) are at unity, implying high level of technology.

Table 7. Average green development growth (GDGI), efficiency change (EC), best practice gap change (BPC), and technical gap ratio change (TGC) of provinces in 2000–2012.

Province	GDGI	EC	BPC	TGC
Beijing	1.093	1.000	1.093	1.000
Tianjin	1.111	1.033	1.084	1.000
Hebei	1.010	0.967	1.046	1.000
Shanxi	1.019	0.988	1.058	0.978
Inner Mongolia	1.012	1.000	1.024	1.034

Table 7. *Cont.*

Province	GDGI	EC	BPC	TGC
Liaoning	1.047	1.004	1.044	1.000
Jilin	1.027	1.002	1.042	0.990
Heilongjiang	1.045	1.000	1.039	1.015
Shanghai	1.083	1.000	1.083	1.000
Jiangsu	1.021	0.987	1.035	1.000
Zhejiang	1.024	0.989	1.037	1.000
Anhui	1.037	1.005	1.036	0.998
Fujian	1.007	0.964	1.050	1.000
Jiangxi	1.018	1.000	1.021	1.002
Shandong	1.010	0.969	1.042	1.000
Henan	1.008	0.990	1.027	0.995
Hubei	1.022	1.011	1.040	0.976
Hunan	1.005	1.000	1.002	1.005
Guangdong	1.001	1.000	1.001	1.000
Guangxi	1.002	0.973	1.031	1.000
Hainan	1.039	0.956	1.098	1.000
Chongqing	1.018	1.000	1.045	0.975
Sichuan	1.096	1.000	1.063	1.039
Guizhou	1.028	1.032	1.086	0.979
Yunnan	0.998	0.973	1.053	0.982
Shaanxi	1.002	1.000	1.047	0.960
Gansu	1.021	1.008	1.063	0.982
Qinghai	1.004	0.939	1.080	1.000
Ningxia	0.990	0.956	1.053	0.988
Xinjiang	0.975	1.000	1.022	1.006

5.3. Innovative Provinces

Although TGC indicates technology leadership, it cannot present information on which provinces are leading the way. In other words, it cannot specify which provinces serve the role of innovators. Because we have three benchmark technology sets, there are two ways to define innovators: group and metafrontier innovative provinces. The former refers to the outstanding provinces within a given group, while the latter refers to the innovative provinces from an integrated perspective. According to Zhang and Choi [7] and Li and Lin [21], three conditions are used for determining group innovative provinces,

$$BPC > 1 \tag{9}$$

$$GDPI_h^{C,t}(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, W^{t+1}, S^{t+1}, D^{t+1}, C^{t+1}) > 1 \tag{10}$$

$$GDPI_h^{C,t+1}(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, W^{t+1}, S^{t+1}, D^{t+1}, C^{t+1}) = 1 \tag{11}$$

Equation (9) suggests that the contemporaneous technology frontier should shift toward the intertemporal technology frontier, or the group innovators should have an innovation effect. Equation (10) implies that for group innovators, the technology in period t cannot produce the required quantity of outputs in period t + 1. Equation (11) specifies that the innovators must be located on the best practice frontier.

Because the metafrontier innovative provinces is based on global benchmark technology, we add two additional conditions to choose metafrontier innovative provinces,

$$TGC > 1 \tag{12}$$

$$GDPI^G(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, W^{t+1}, S^{t+1}, D^{t+1}, C^{t+1}) = 1 \tag{13}$$

Equation (12) means that a metafrontier innovative province should be among the technologically leading provinces. Equation (13) suggests that a metafrontier innovative province should be located along the global technology frontier.

Table 8 shows the innovative provinces for every period. In the eastern group, Guangdong is found to be an innovator six times. The province is also shown to perform the highest in green development (Figure 2). Heilongjiang is an important innovator in the central group, and it is registered as an innovator six times. For the western group, Sichuan is found to be an innovator four times. Guangdong is a metafrontier innovator twice, Beijing and Tianjin are metafrontier innovators once. The group innovative provinces set targets for non-innovative ones to catch-up with the corresponding groups, while the metafrontier innovative provinces can be regarded as targets of other provinces to improve their green development performance.

Table 8. Group and metafrontier innovators.

Year	Group Innovator			Metafrontier Innovator
	Eastern	Central	Western	
2000–2001	Hainan	Inner Mongolia, Jiangxi	Xinjiang	-
2001–2002	-	Heilongjiang	-	-
2002–2003	Guangdong	-	-	-
2003–2004	Guangdong	Heilongjiang	-	Guangdong
2004–2005	-	Heilongjiang	-	-
2005–2006	Guangdong	-	-	-
2006–2007	-	-	Sichuan	-
2007–2008	-	Heilongjiang, Hunan	-	-
2008–2009	Guangdong	Heilongjiang	Sichuan	Guangdong
2009–2010	Beijing, Shanghai	Hunan	-	Beijing
2010–2011	Guangdong	-	Sichuan, Xinjiang	-
2011–2012	Tianjin, Shanghai, Guangdong	Inner Mongolia, Jiangxi, Heilongjiang, Anhui, Hubei, Hunan	Chongqing, Sichuan, Shaanxi, Xinjiang	Tianjin

6. Conclusions

Although many studies measure the green development performance of China, most of them only consider one environmentally harmful by-product, for example CO_2 emissions. In theory, green development is quite encompassing and other major pollutants need to be considered in the case of China. This paper uses four main pollutants, namely waste water, sulphur dioxide emission, solid wastes and CO_2 emissions, to measure green development performance. In terms of methodology, the green development performance index (GDPI) is presented, which is based on the total-factor production efficiency framework, and considers non-radial slacks. In order to incorporate *ex ante* group heterogeneities, the above GDPI is combined with the metafrontier analysis. With this augmented methodology, the green development growth index (GDGI) is decomposed into EC, BPC and TGC indices. All the above indices can be calculated by solving several non-radial DEA-type models.

The proposed approach is employed to analyze the changes in green development performance of 30 provinces in China during the period 2000–2012. The main results are: (1) the average score of GDPI in China during the sample period is 0.398, indicating a low level of green development, but it has improved in recent years; (2) mainly driven by BPC, China's green development performance improves by 2.58% each year; (3) green development is mainly led by the eastern region. It should be noted that this result is relative. In other words, it only implies that the eastern region's performance is better than the central and the western regions. In fact, the average score of GDPI for the eastern region is 0.525, implying a low level of green development.

There are some limitations for this study. Methodologically, the paper adopts geographical closeness as a criterion for grouping provinces. In theory, heterogeneity is main reflected by production technology. In this regard, an in-depth analysis of the heterogeneity is more effective in reflecting different characteristics of provinces in China. Furthermore, in our case, it needs to be recomputed when a new time period is added to the data set. In this sense, biennial technology rather than global technology may be more suitable [48]. Additionally, we do not provide statistical inferences on green development performance. By doing this, the bootstrapping method should be used to perform the statistical inference. Finally, a regression analysis on the determinants of green development performance may be an interesting empirical extension.

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