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Climate Drives Environmental Efficiency Across Chinese Provinces

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Abstract

Balancing economic growth and environmental pollution is essential for the sustainable development of Mainland China. To address this issue, this study applied an improved data envelopment analysis model to evaluate the environmental efficiency of 29 provinces in Mainland China from 2006 to 2016. The study divided the 29 provinces into two groups: the subtropical and tropical zones and the temperate zone. The study then compared the differences in environmental efficiency between the two groups. The results indicate that the overall environmental efficiency of the provinces in Mainland China increased significantly from 2006 to 2016; however, there remained significant potential for improvement. In particular, the environmental efficiency is significantly lower in the temperate zone compared with the subtropical and tropical zones. As Mainland China's population is increasingly moving to coastal areas in the subtropical and tropical zones, each province should adopt targeted policy measures to improve its environmental efficiency based on its industrial and population conditions.

Keywords

DEA, meta-frontier, climate, environmental efficiency

Introduction

As its reform and opening up, China's economy has experienced 40 years of rapid economic growth. This growth is associated with an exponential increase in energy consumption. Due to constraints in resource endowments, China's energy structure is dominated by coal. Rapid economic growth has also created a series of problems such as environmental pollution and excessive contaminant emissions. There is an urgent need to improve energy and environmental efficiency, to sustain economic growth with less energy consumption, and to minimize the negative impact of economic growth on the environment.

Different methods have been used to study topics related to both energy and the environment. Edmonds and Reilly (1983) developed a long-term global energy–economic model to assess possible scenarios using alternative energy. Kamiuto (1994) presented a simple model for the global carbon cycle. These results indicated that there was a marked change in the rate of carbon dioxide emissions, with a turning point around 1875 due to deforestation and changing land use. Jebaraj and Iniyan (2006) reviewed different energy models including an energy planning model, forecasting model, and emission-reduction model. They argued that energy–economy models were useful for understanding the interaction between economic development and energy consumption. In addition, index decomposition analysis and decision analysis have been popular in studying energy and environmental issues (Ang & Zhang, 2000; Zhou, Ang, & Poh, 2006).

Compared with other methods, data envelopment analysis (DEA) has been applied to evaluate the relative efficiency of several decision-making units (DMUs) that transform multiple inputs into multiple outputs. DEA is a data-oriented method that has become very popular as

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a nonparametric approach because of its several advantages. For example, (a) it does not need to assume the relationships between inputs and outputs (Choi, Zhang, & Zhou, 2012; X. P. Zhang, Cheng, & Yuan, 2011) and (b) it provides a benchmark against which inefficient units can be compared (Adler, Friedman, & Sinuany-Stern, 2002; Camanho & Dyson, 1999).

As being applied by Färe, Grosskopf, and Logan (1983) to evaluate the energy efficiency, DEA has been constantly improved and modified to meet different situations.Hu and Wang (2006) adopted the constant-returns-scale DEA model to analyze the energy efficiency of 29 provinces in Mainland China from 1995 to 2002. The result indicated that energy efficiency improves with economic growths. Z. H. Wang, Zeng, and Wei (2012) applied the classical Banker–Charnes–Cooper model to evaluate the energy efficiency of the manufacturing industry in 30 provinces in Mainland China from 2005 to 2009. The result showed that energy efficiency of Mainland China has significant potential to improve, as there is a large amount of energy input redundancy, especially in the western provinces. Hu and Kao (2007) used a modified constant-returns-scale DEA model to identify an energy-saving target for Asia-Pacific Economic Cooperation economies. The disadvantage of these studies is that they consistently modeled energy consumption as one input within a production framework, without considering undesirable outputs such as carbon emissions. As such, these studies do not provide an unbiased energy efficiency evaluation, because if energy was placed into the production process, it would generate undesirable products (Wu, Fan, & Zhou, 2012).

To more accurately evaluate energy efficiency or the environmental efficiency of DMUs, some methods have been designed to incorporate undesirable outputs into the traditional model (Scheel, 2001). In general, these methods can be classified into three groups. The first group treats the undesirable outputs as classical DEA inputs (Cerutti, Bruun, Beccaro, & Bounous, 2011; Korhonen & Luptacik, 2004; Shi, Bi, & Wang, 2010; B. Zhang, Bi, Fan, Yuan, & Ge, 2008). The second group applies the same classical DEA model after transforming the undesirable output data (Lovell, Pastor, & Turner, 1995; Seiford & Zhu, 2002; K. Wang, Wei, & Zhang, 2012; Zhu & Chen, 1993). The third group models the undesirable output under the weak disposability assumption, implying that ending the production process is the only way to eliminate all undesirable outputs (Färe & Grosskopf, 2004; Färe, Grosskopf, & Tyteca, 1996).

Zhou, Ang, and Poh (2008) relaxed the assumption of constant returns to scale in other studies and presented the carbon emission performance of eight world regions under a different DEA technology. This approach acknowledged that the assumption that returns to scale are always constant does not always match the real production processes. H. Yang and Pollitt (2009) evaluated Chinese coal-fired power plants, simultaneously considering undesirable outputs and uncontrollable variables by proposing six DEA models.

To break the restriction that all input or output variables should change in the same proportion as efficiency targets, Q. Wang, Zhao, and Zhou (2013) adopted the multidirectional efficiency analysis approach to identify the improvement potential in each input or output when investigating Chinese regional energy and emissions efficiency. N. Zhang and Choi (2013) used two slacks-based measure efficiency indices to measure energy efficiency by incorporating three undesirable outputs in regional economies from 2001 to 2010. Tao and Zhang (2013) applied environmental DEA technology to measure the environmental efficiency of the electric power industry in the Yangtze River Delta from 2000 to 2010. Their study considered both a constant return of scale and variable return of scale. Based on the superefficiency DEA model, L. Yang, Ouyang, and Fang (2015) evaluated environmental efficiency of 30 provinces in Mainland China from 2000 to 2010.

DMUs often face different technology frontiers. As such, Hayami (1969) introduced the meta-production function to avoid biased evaluation. Following this seminal work, Q. Wang et al. (2013) and Du, Lu, and Yu (2014) evaluated energy efficiency and carbon emission efficiency, respectively, using a meta-frontier DEA approach. Yao, Zhou, Zhang, and Li (2015), Q. Wang, Su, Zhou, and Chiu (2016), and Q. Wang, Chiu, and Chiu (2017) used a meta-frontier nonradial directional distance function (DDF) to analyze energy efficiency and carbon emission performance. Q. Wang, Hang, Hu, and Chiu (2018) argued that when the traditional meta-frontier approach was used in nonradial DEA models, there were some unreasonable results. As such, they extended an alternative meta-frontier framework to evaluate the technological gaps for both radial and nonradial DEA models under a variable returns-to-scale assumption.

Most previous studies have grouped Mainland China provinces into three areas: eastern, central, and western areas. However, Mainland China is still in the process of rapid urbanization, which is essentially a spatial redistribution of population and industry. Worldwide, there is a growing trend of population concentration in coastal areas, especially metropolises (Tabuchi, 2014). In Mainland China, this population agglomeration is mainly taking the form of population migration from the temperate zone to the subtropical and tropical zones. The traditional classification method does not address this changing dynamic and the long-term effects of climate and geographic location on environmental efficiency.

This study evaluates the environmental efficiency of 29 provinces in Mainland China from 2006 to 2016, comparing the differences in environmental efficiency between the subtropical and tropical zones and the temperate zone. This study makes two main contributions to the field. First, we divided the 29 provinces into the subtropical and tropical zones and the temperate zone. With the rapid development of a new economic geography, many scholars have begun to realize that a region's geography and climate significantly impact its economic activities. Of the four provinces in China with the highest gross domestic product (GDP), Guangdong, Jiangsu, and Zhejiang all fall in the subtropical climate group. The only one that does not is Shandong province. Therefore, it was of both theoretical and practical significance to group the provinces according to climatic conditions and to compare the environmental efficiency of different places with different climatic conditions. This ultimately allows for the adoption of targeted energy-saving and emission-reduction strategies in the future.

Second, in terms of model selection, this study applied the DEA model constructed by Sun, Wang, and Li (2018), which improves upon the baseline traditional DDF model. This model allows us to estimate the improvement possible for each energy input and desirable and undesirable outputs. This provides a more accurate assessment of the environmental efficiency of the provinces and highlights targeted policy recommendations. Moreover, we can ensure that the technical efficiency based on the meta-frontier is no more than the technical efficiency based on the group-frontier, even in the nonradial DEA model.

The rest of this article is organized as follows. An improved DEA model proposed by Sun et al. (2018) is introduced in "Methods" section. The empirical research of the 29 provinces in Mainland China is described in "Results" section. Finally, the article presents the "Discussion" and "Implications for Conservation" sections.

Methods

This study adopted the model proposed by Sun et al. (2018) to evaluate the environmental efficiency of 29 provinces in Mainland China. The study then evaluated the potential for improvement based on the efficiency score. Each province consumes energy and nonenergy inputs to produce both desirable and undesirable outputs. The energy input is denoted as $X_e(j = 1, \ldots, J)$, the nonenergy input is denoted as $X_{ne}(k = 1, \ldots, K)$, the desirable output is denoted as $Y_d(p = 1, \ldots, P)$, and the undesirable output is denoted as $Y_{ud}(q = 1, \ldots, Q)$. This model has several advantages (Sun et al., 2018): (a) The model proposes a new index (technology gap ratio [TGR]), solving the problem that the meta-frontier does not envelop group-frontiers in the actual calculation process. (b) The model can decompose the total latent improvement capacity into management potential (MP) capacity and technology potential (TP) capacity. (c) The model can properly characterize convex technology, which exhibits the weak disposability of desirable and undesirable outputs.

Group-Frontier DEA Model

$$\vec{D}^{g}(X_e^j, X_{ne}^k, Y_d^p, Y_{ud}^q) = \sup\{w^T\theta : (X_e^j, X_{ne}^k, Y_d^p, Y_{ud}^q + \mathrm{diag}(\theta) * g \in T^g\} \tag{1}$$

where $\theta = (\theta_o^j, \theta_o^k, \theta_o^p, \theta_o^q)$ and $g = (-g_{X_e}, 0, g_{Y_d}, -g_{Y_{ud}})$.

The variable W^T stands for the weight of each dimension of the vector θ. For example, the weights of θ_o^j, θ_o^p, and θ_o^q are $\frac{1}{2J}$, $\frac{1}{2Q}$, and $\frac{1}{P}$, respectively.

Under the assumption of variable returns to scale, the efficiency of $\mathrm{DMU_o}$ is measured using the group-specific technology:

$$\begin{aligned}
&\min \theta_o^g = \frac{\frac{1}{2}\left[\left(1 - \frac{1}{J}\sum_{j=1}^{J}\theta_o^j\right) + \left(1 - \frac{1}{Q}\sum_{q=1}^{Q}\theta_o^q\right)\right]}{1 + \frac{1}{P}\sum_{p=1}^{P}\theta_o^p}\\
&\text{s.t.}\sum_{f=1}^{N^g}(\lambda_f^g + u_f^g)X_e^j \le X_{eo}^j - \theta_o^j X_{eo}^j, \quad j = 1, \ldots, J,\\
&\sum_{f=1}^{N^g}(\lambda_f^g + u_f^g)X_{ne}^k \le X_{neo}^k, \quad k = 1, \ldots, K,\\
&\sum_{f=1}^{N^g}\lambda_f^g Y_d^p \ge Y_{do}^p + \theta_o^p Y_{do}^p, \quad p = 1, \ldots, P,\\
&\sum_{f=1}^{N^g}\lambda_f^g Y_{ud}^q = Y_{udo}^q - \theta_o^q Y_{udo}^q, \quad q = 1, \ldots, Q,\\
&\sum_{f=1}^{N^g}(\lambda_f^g + u_f^g) = 1, \quad f = 1, \ldots, N^g,\\
&\lambda_f^g, u_f^g \ge 0,\\
&0 \le \theta_o^j, \theta_o^p, \theta_o^q \le 1
\end{aligned} \tag{2}$$

In Model 2, N^g is the number of DMUs in the gth specific group, λ_f^g and u_f^g are the weightings, θ_o^j is the reduced proportion for X_e^j, θ_o^p is the expansion proportion for desirable output Y_d^p, and θ_o^q is the contract proportion for the undesirable output Y_{ud}^q. The efficiency score of DMU_o, belonging to the gth specific group, is

θ_o^g. This model more accurately evaluates efficiency compared with the traditional DDF model because it relaxes the assumption that inputs and outputs should contract or expand at the same proportion.

The efficiency score of DMU_o, which is in the gth specific group, is denoted as θ_o^g. For DMU_o, the potential improvement capacity under the group-frontier (PICG) is denoted as follows:

$$PICG_o = 1 - \theta_o^g \tag{3}$$

If the PICG is equal to 0, it indicates that the province is efficient. If the PICG is between 0 and 1, it indicates that the province is inefficient.

Meta-Frontier DEA Model

In previous studies, scholars noticed differences between different regions of China including different stages of economic development and different geographic locations. However, few of them noted the impact of climate on environmental efficiency. In fact, climate affects people's choices about where they live and where they work. Furthermore, population density can significantly impact the environmental efficiency of a region. Therefore, this study divided 29 provinces in Mainland China into two groups based on the climatic conditions: the tropical and subtropical zones and the temperate zone. Considering regional heterogeneity, the study evaluated and analyzed environmental efficiency in different provinces using a more accurate approach.

Using the meta-frontier, Model 2 was extended to evaluate the environmental efficiency with different technology. In this extended model, all provinces were divided into G ($G > 1$) groups and $\sum_{g=1}^{G} N_g = N$. The DMUs in the gth group formed a group-frontier. The meta-frontier was obtained by enveloping all the group-frontiers. Assume that T^g and T^m represent the specific technologies of the group-frontier and meta-frontier, respectively. For any group g,

if $\{X_e^j, X_{ne}^k, Y_d^p, Y_{ud}^q\} \in T^g$, then $\{X_e^j, X_{ne}^k, Y_d^p, Y_{ud}^q\} \in T^m$;

if $\{X_e^j, X_{ne}^k, Y_d^p, Y_{ud}^q\} \in T^m$, then $\{X_e^j, X_{ne}^k, Y_d^p, Y_{ud}^q\}$ must belong to one of $T^g (g = 1, 2, \ldots, G)$, and $T^m = \{T_1 \cup T_2 \cup \cdots T_G\}$

The environmental efficiency was then evaluated using the following Model 4 and Equation 5 under the meta-frontier.

$$\min \theta_o^m = \frac{\frac{1}{2}\left[\left(1 - \frac{1}{J}\sum_{j=1}^{J} \theta_o^j\right) + \left(1 - \frac{1}{Q}\sum_{q=1}^{Q} \theta_o^q\right)\right]}{1 + \frac{1}{P}\sum_{P=1}^{P} \theta_o^p}$$

$$\begin{aligned} \text{s.t.} & \sum_{g=1}^{G}\sum_{f=1}^{N^g}(\lambda_f^m + u_f^m)X_e^j \le X_{eo}^j - \theta_o^j X_{eo}^j, \; j = 1, \ldots, J, \\ & \sum_{g=1}^{G}\sum_{f=1}^{N^g}(\lambda_f^m + u_f^m)X_{ne}^k \le X_{neo}^k, \; k = 1, \ldots, K, \\ & \sum_{g=1}^{G}\sum_{f=1}^{N^g}\lambda_f^m Y_d^p \ge Y_{do}^p + \theta_o^p Y_{do}^p, \; p = 1, \ldots P, \\ & \sum_{g=1}^{G}\sum_{f=1}^{N^g}\lambda_f^m Y_{ud}^q = Y_{udo}^q - \theta_o^q Y_{udo}^q, \; q = 1, \ldots, Q, \\ & \sum_{g=1}^{G}\sum_{f=1}^{N^g}(\lambda_f^m + u_f^m) = 1, \; f = 1, \ldots N^g, \\ & \lambda_f^m, u_f^m \ge 0, \\ & 0 \le \theta_o^j, \theta_o^p, \theta_o^q \le 1 \end{aligned} \tag{4}$$

In Model 4, λ_f^m and u_f^m represent the weightings and θ_o^m represents the environmental efficiency of the oth provinces.

The variable θ_o^m is the efficiency score of the oth DMU under the meta-frontier. For DMU_o, the potential improvement capacity under the meta-frontier (PICM) is denoted as follows:

$$PICM_o = 1 - \theta_o^m \tag{5}$$

Under the meta-frontier, if the PICM is equal to 0, it indicates that the province is efficient. If the PICM is between 0 and 1, it indicates that the province is inefficient.

Environmental Efficiency Difference Between Group-Frontier and Meta-Frontier

In Model 4, all DMUs served as reference units. In contrast, only DMUs in the gth group were treated as reference units in Model 2. Therefore, the frontier of Model 4 represents the best production technology. The environmental efficiency measured based on the meta-frontier (θ_o^m) cannot exceed the environmental efficiency measured based on the group-frontiers (θ_o^g), that is, $\theta_o^m \le \theta_o^g$.

To compare the difference in environmental efficiency between the group-frontier and meta-frontier, the TGR index of environmental efficiency was constructed using Equation 6, according to O'Donnell, Rao, and Battese (2008).

$$TGR_o = \theta_o^m / \theta_o^g \tag{6}$$

The closer TGR_o gets to 1, the smaller the technology heterogeneity is. This means that there is only a small difference between the environmental efficiency measured on the basis of the group-frontier and the efficiency measured on the basis of the meta-frontier. In contrast, the closer TGR_o gets to 0, the greater the technology heterogeneity is.

The inefficiency of the DMU under the meta-frontier was further decomposed into technology inefficiency and management inefficiency (Chiu, Liou, & Wu, 2012; Sun et al., 2018). In other words, the potential improvement capacity (PICM) of the province with respect to environmental efficiency can be decomposed into MP and TP, as shown in Equations 7 and 8, respectively.

$$\mathrm{MP}_o = \mathrm{PICG}_o = 1 - \theta_o^g \quad (7)$$

In this expression, θ_o^g is measured based on the group-frontier in which DMUs have similar techniques. As such, the inefficiency of the DMU_o originates from poor management.

$$\begin{aligned}\mathrm{TP}_o &= \mathrm{PICM}_o - \mathrm{PICG}_o = (1 - \mathrm{TCR}_o)\mathrm{PICG}_o \\ &= (1 - \theta_o^m) - (1 - \theta_o^g) = \theta_o^g - \theta_o^m\end{aligned} \quad (8)$$

As noted earlier, θ_o^g is the environmental efficiency of $\mathrm{DMU_o}$ measured based on the group-frontier; the variable θ_o^m is the environmental efficiency of $\mathrm{DMU_o}$ measured based on the meta-frontier. For the same DMU, technology heterogeneity is the only reason for a difference between θ_o^m and θ_o^g. The gap between θ_o^m and θ_o^g is defined as TP_o.

Therefore, the potential improvement capacity of the $\mathrm{DMU_o}$ measured on the basis of the meta-frontier can described by Equation 9:

$$\mathrm{PICM}_o = \mathrm{TP}_o + \mathrm{MP}_o = 1 - \theta_o^m \quad (9)$$

The PICM represents the distance from DMU to the meta-frontier. This distance can be further divided into two parts: one is from DMU to the group-frontier (MP) and one from the group-frontier to meta-frontier (TP).

Figure 1 depicts the general idea of environmental efficiency based on the group-frontier and meta-frontier. The meta-frontier represents the most advanced technology for all sample provinces and envelopes the two group-frontiers. The two group-frontiers represent the best benchmark for provinces in the subtropical and tropical zones and temperate zone. The distance between Point A and Point B represents the total inefficiency of DMU, named *A* on the basis of the meta-frontier. To improve its environmental efficiency, this DMU should move along line AC, consisting of two parts: AB (MP) and BC (TP). Moving from Point A to Point B means improving management; moving from Point B to Point C means improving technology.

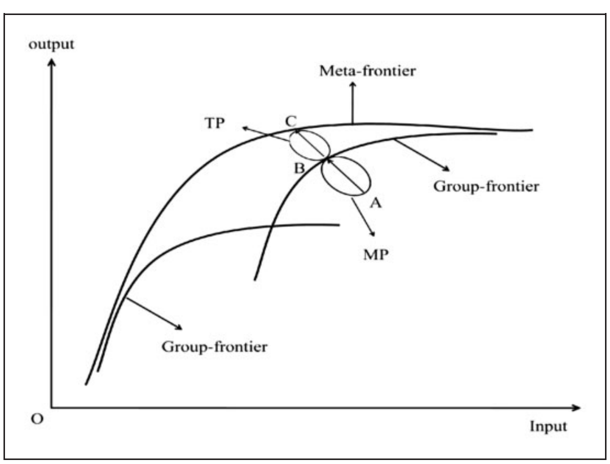

Figure 1. Decomposition of environmental inefficiency. MP = management potential; TP = technology potential.

Source of Data and Variables Description

In this study, seven indicators were used to evaluate the environmental efficiency of Mainland China. Energy consumption equaled the total of primary energy consumption, including coal, oil, gas, and electricity. These were transformed into the standard coal equivalent in advance based on the corresponding energy folding standard (Choi et al., 2012; Q. Wang et al., 2013). Capital stock was calculated using 2000 prices, by adopting the perpetual inventory method according to the results of Shan (2008). Labor was measured by the number of employees of each province at the end of the year. The nominal GDP of the provinces was transformed into real GDP by adjusting to the 2000 constant price to eliminate inflation effects. Sulfur dioxide, dust, and nitric oxides were measured using each province's emissions (Choi et al., 2012; Q. Wang, Zhou, & Zhou, 2012; Wei, Ni, & Du, 2012).

Of these indicators, labor and capital stock were selected as nonenergy inputs. Total primary energy consumption was represented by energy input; GDP was treated as a desirable output. Sulfur dioxide, dust, and nitric oxides were considered undesirable outputs. Table 1 summarizes the descriptive statistics of the input and output variables from 2006 to 2016. Data were collected from the China Statistical Yearbook (National Bureau of Statistics of China [NBSC], 2007–2017) and the China Energy Statistical Yearbook (NBSC, 2007–2017).

Of the 31 provinces in Mainland China, Tibet and Qinghai are in the plateau climate zone. The other 29 provinces are located in the tropical, subtropical, and temperate zones. Therefore, the 2 plateau climate provinces were excluded from this empirical study, and the 29 provinces of Mainland China served as the sample set from 2006 to 2016.

The sample provinces in Mainland China were categorized into two groups, based on whether they were in the subtropical and tropical zones or in the temperate zone. The subtropical and tropical zones

Table 1. Descriptive Statistics of Inputs and Outputs (2006–2016).

Category	Variable	Units	Mean	Minimum	Maximum	*SD*
Inputs	Capital stock	Billion CNY	268.23	30.39	672.64	169.31
	Labor	100,000	3,023.60	165.50	12,973.95	2,405.64
	Energy	Million tons of coal equivalent	134.91	9.20	388.99	80.66
Desirable output	GDP	Billion CNY	1,237.60	55.97	5,771.09	1,028.50
Undesirable outputs	Sulfur dioxide	10,000 tons	72.06	1.70	196.20	42.28
	Nitric oxides	10,000 tons	64.34	4.00	180.11	40.58
	Dust	10,000 tons	39.49	0.20	179.77	29.40

Note. SD = standard deviation; GDP = gross domestic product; CNY = Chinese Yuan.

Table 2. Environmental Efficiency Under Group-Frontier and Meta-Frontier.

Subtropical and tropical zones	MEE	GEE	TGR	Temperate zone	MEE	GEE	TGR
Shanghai	0.89686	0.89686	1.00000	Beijing	0.65190	0.98294	0.66321
Jiangsu	0.52614	0.52735	0.99771	Tianjin	0.51429	0.87807	0.58571
Zhejiang	0.47119	0.47818	0.98538	Hebei	0.19726	0.37777	0.52217
Anhui	0.34623	0.36100	0.95909	Shanxi	0.11415	0.16966	0.67285
Fujian	0.52266	0.53730	0.97275	Inner Mongolia	0.14602	0.18350	0.79579
Jiangxi	0.35035	0.36985	0.94725	Liaoning	0.28460	0.75430	0.37730
Hubei	0.28641	0.30383	0.94269	Jilin	0.27433	0.35784	0.76663
Hunan	0.35072	0.36290	0.96644	Heilongjiang	0.38720	0.85492	0.45291
Guangdong	0.99226	0.99226	1.00000	Shandong	0.34483	0.97172	0.35487
Guangxi	0.29989	0.33081	0.90652	Henan	0.27505	0.49170	0.55939
Chongqing	0.81540	0.87576	0.93108	Shaanxi	0.22803	0.30786	0.74069
Hainan	0.31960	0.34165	0.93545	Ganshu	0.21920	0.54248	0.40408
Sichuan	0.31159	0.31673	0.98378	Ningxia	0.65523	0.65683	0.99756
Guizhou	0.15359	0.16219	0.94699	Xinjiang	0.13838	0.23774	0.58206
Yunnan	0.29935	0.31949	0.93698				
Subtropical and tropical (mean)	0.46282	0.47841	0.96080	Temperate (mean)	0.31646	0.55481	0.60537

Note. GEE = group-frontier environmental efficiency; MEE = meta-frontier environmental efficiency; TGR = technology gap ratio.

include Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Hunan, Guizhou, Guangxi, Hubei, Chongqing, Guangdong, Yunnan, Sichuan, and Hainan. The temperate zone includes Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Helongjiang, Shandong, Henan, Ganshu, Shaanxi, Ningxia, and Xinjiang. (The classification is explained in Appendix A.)

Compared with the provinces in the temperate zone, the provinces in the subtropical and tropical zones have a more developed economy and a higher population density. Using the year 2017 as an example, in the temperate zone, the per capita GDP was $8,431 and the population density was 2,796 persons per square kilometer. In contrast, in the tropical and subtropical zones, the per capita GDP was $9,504 and the population density was 2,811 persons per square kilometer. Based on economic development and population movement, the gap between per capita GDP and population density between the tropical and subtropical zones and the temperate zone may further widen in the near future.

Results

Analysis of Environmental Efficiency

According to Equations 2, 4, and 6, Table 2 shows the average environmental efficiencies from 2006 to 2016 for the 29 provinces in Mainland China, based on the group-frontier environmental efficiency (GEE), meta-frontier environmental efficiency (MEE), and TGR.

Under the meta-frontier, the average environmental efficiency of all provinces was 0.39216. The average environmental efficiencies of the provinces in the subtropical and tropical zones and in the temperate zone were 0.46282 and 0.31646, respectively (Table 2). The environmental efficiency of the temperate zone was significantly lower compared with the tropical and subtropical zones. (The results of independent sample *t* test are shown in Appendix B). Based on this efficiency score, the 29 provinces could achieve an overall improvement of 60.78% (Table 2). The provinces in the tropical and subtropical zones and the provinces in the temperate zone could improve by up to 53.72% and 68.35%, respectively (Table 2).

These results show that the overall environmental efficiency of the provinces in Mainland China has significant room for improvement. The pattern in the change in environmental efficiency indicates that the average environmental efficiency of all sample provinces increased from 0.39740 in 2006 to 0.49612 in 2016. The average environmental efficiency of provinces in the subtropical and tropical zones and the efficiency of provinces in the temperate zone increased from 0.46449 and 0.32552 in 2006 to 0.57468 and 0.41194 in 2016, respectively. This suggests the overall environmental efficiency of provinces in Mainland China significantly increased.

For all provinces, the environmental efficiency based on the meta-frontier is no more than the efficiency based on the group-frontier (Table 2). Beijing, in the temperate zone, is discussed as an example. The average environmental efficiency based on the meta-frontier was 0.65190, with an improvement potential of 34.81%. When based on the group-frontier, the average environmental efficiency of Beijing was 0.98222, with an improvement potential of 1.78%. This was a far lower value than the efficiency based on the group-frontier (Table 2). This finding was consistent with the previous theoretical analysis discussed in "Methods" section.

Table 3. Kruskal–Wallis Test Result of Technology Gap Ratio.

Null hypothesis	Kruskal–Wallis *H* statistics score	*p*
The two distributions have the same center position	129.397	.000

To measure the degree of the technology gap between different groups, the TGR of each province was calculated using Equation 6. Then, the Kruskal–Wallis method was used to test whether the two groups are independent. Table 3 shows that the Kruskal–Wallis result rejects the null hypothesis ($p < .01$), indicating that the TGR of provinces across the two different groups was statistically significantly different from 0 at the 1% level.

Figure 2 and Figure 3 present the quartile and frequency, respectively, of the two groups' TGR. The figures show that the average TGR score of the provinces in the subtropical and tropical zones was greater than the mean of all samples. The average TGR scores of provinces in the temperate zone are less than the average of all the samples.

All these findings, derived from Table 3, Figure 2, and Figure 3, indicate that there is technology heterogeneity between provinces in the subtropical and tropical zones and the temperate zone.

Decomposition of Environmental Inefficiency

Table 4 shows the TP and MP, which represent the environmental efficiency loss derived from technology gap and poor management, when calculated using Equations 7 and 8, respectively. For the provinces in the subtropical and

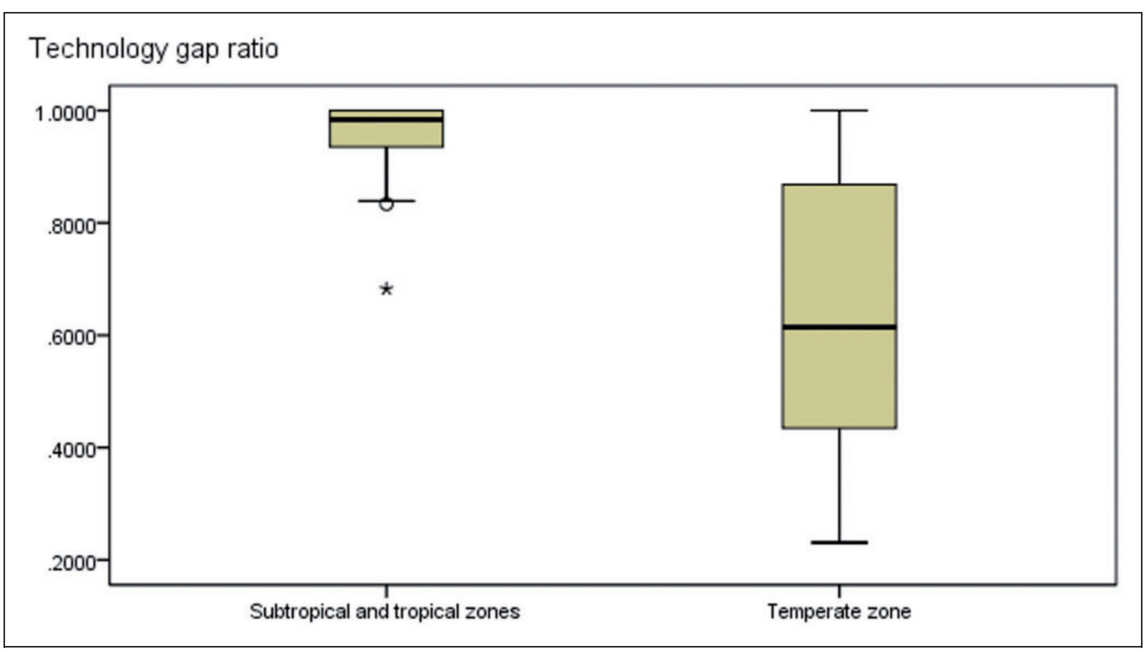

Figure 2. Quartile distribution of the two groups' technology gap ratio.

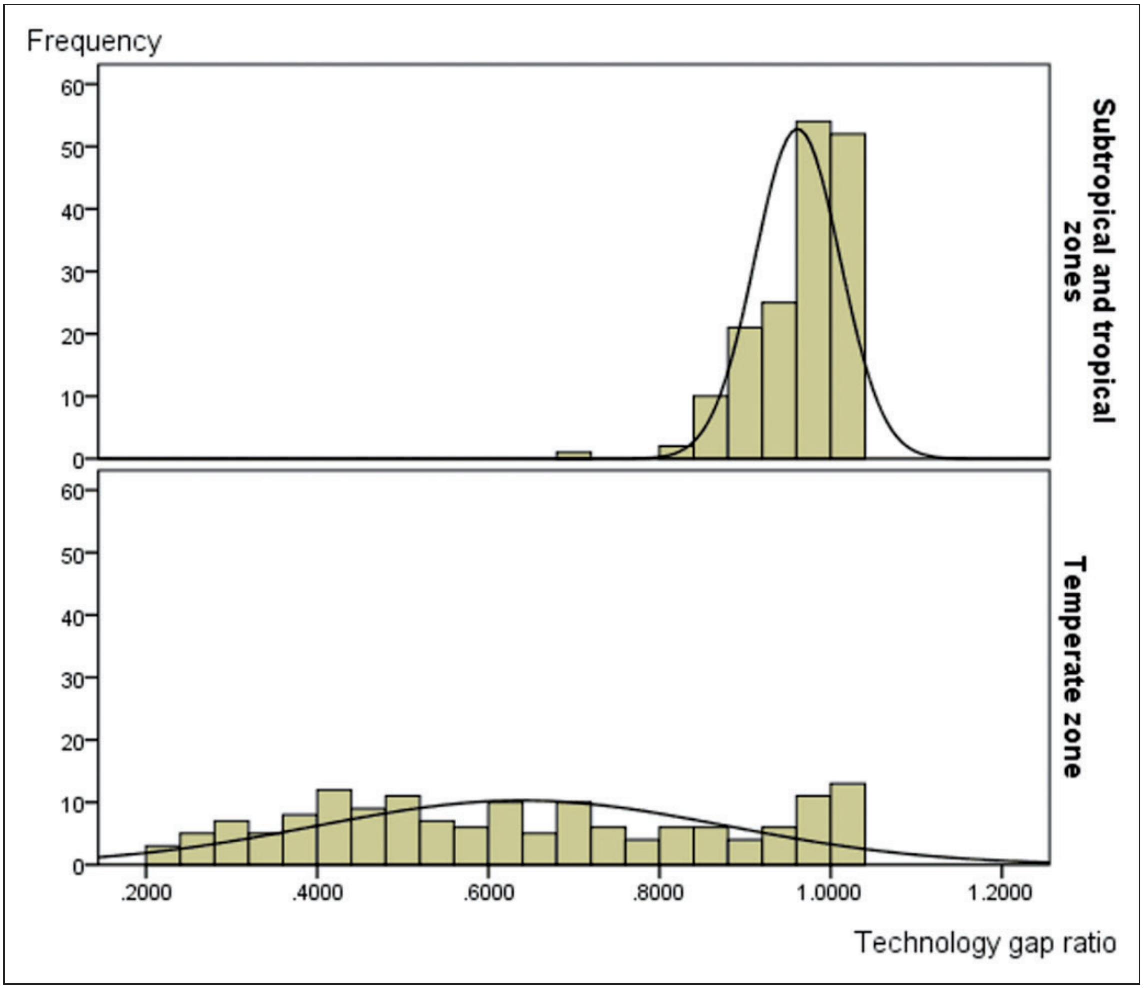

Figure 3. Frequency of each group's technology gap ratio.

Table 4. Decomposition of Environmental Inefficiency Across Provinces.

Subtropical and tropical zones	TP	MP	Temperate zone	TP	MP
Shanghai	0.00000	0.10314	Beijing	0.33105	0.01706
Jiangsu	0.00121	0.47265	Tianjin	0.36378	0.12193
Zhejiang	0.00699	0.52182	Hebei	0.18051	0.62223
Anhui	0.01477	0.63900	Shanxi	0.05550	0.83034
Fujian	0.01464	0.46270	Inner Mongolia	0.03747	0.81650
Jiangxi	0.01951	0.63015	Liaoning	0.46970	0.24570
Hubei	0.01741	0.69617	Jilin	0.08351	0.64216
Hunan	0.01218	0.63710	Heilongjiang	0.46772	0.14508
Guangdong	0.00000	0.00774	Shandong	0.62688	0.02828
Guangxi	0.03092	0.66919	Henan	0.21665	0.50830
Chongqing	0.06036	0.12424	Shaanxi	0.07983	0.69214
Hainan	0.02205	0.65835	Ganshu	0.32328	0.45752
Sichuan	0.00514	0.68327	Ningxia	0.00160	0.34317
Guizhou	0.00860	0.83781	Xinjiang	0.09936	0.76226
Yunnan	0.02013	0.68051			
Subtropical and tropical (mean)	0.01559	0.52159	Temperate (mean)	0.23835	0.44519

Note. MP = management potential; TP = technology potential.

tropical zones, the average environmental inefficiency was 0.53718, the technical gap inefficiency was 0.01559, and the managerial inefficiency was 0.52159. For the provinces in the temperate zone, the average environmental inefficiency was 0.68354, the technology gap inefficiency was 0.23835, and the managerial inefficiency was 0.44519.

Overall, technology gaps and poor management are main sources of inefficiency. For the provinces in the subtropical and tropical zones, poor management led to an approximately 97.10% loss in environmental efficiency (Table 4). Improving the management level should be emphasized in these provinces. In contrast, management and technical factors were responsible for 65.13% and 34.87%, respectively, of the inefficiency in the provinces in the temperate zone (Table 4). This shows that the provinces in the temperate zone should improve their technical levels with respect to energy utilization and pollutant discharge while also strengthening management.

Discussion

Improving environmental efficiency is one of the most critical ways to reduce pollutant emissions from energy consumption. Based on the previous studies, this study focused on analyzing the impact of climate conditions on regional environmental efficiency. An improved DEA model based on the group-frontier and meta-frontier was applied to evaluate the environmental efficiency of 29 provinces in Mainland China from 2006 to 2016. Unlike other studies, this study divided the 29 provinces into the subtropical and tropical zones and the temperate zone. When environmental efficiency is associated with the group-frontier, it means the inefficiency is mainly caused by management problems under the existing technology circumstances. In contrast, an efficiency score based on the meta-frontier indicates that the efficiency loss was derived not only from management but also from the difference between the meta-frontier and group-frontier. This study's empirical research led to the following conclusions.

1. Under the meta-frontier, the average environmental efficiency of all provinces was 0.39216, the average environmental efficiency of the provinces in the subtropical and tropical zones was 0.46282, and the average environmental efficiency in the temperate zone was 0.31646 (Table 2). This indicates that the overall environmental efficiency of the provinces in China has significant room for improvement. In terms of the changing trends, the environmental efficiency of provinces in Mainland China increased significantly from 2006 to 2016. The environmental efficiency in the temperate zone was significantly lower compared with the subtropical and tropical zones. The movement of population and economic activity to coastal areas in the tropical and subtropical zones has supported the improvements in the environment efficiency of Mainland China. Therefore, it is unwise to advance policies that impede population migration to coastal areas.
2. Overall, the technology gap and poor management are both main sources of inefficiency. Relatively speaking, ineffective management is the main source of environmental efficiency losses in tropical and subtropical provinces. For temperate provinces, in addition to ineffective management, technology underdevelopment also plays a role. This may be because the technical levels of some provinces in the temperate zone are relatively underdeveloped, and many talented people have migrated to coastal areas. This is also the case for the three provinces in northeast China, leading to a further widening of the technological gap between provinces in the temperate zone and provinces in the tropical and subtropical zones.
3. Guangdong and Shanghai in the tropical and subtropical zones and Beijing in the temperate zone are provinces with higher environmental efficiency. This is mainly because as coastal provinces, Guangdong and Shanghai enjoy both an advantageous location and large concentration of population, making the tertiary industry the leading industry. Furthermore, an advanced rail transit system has effectively curbed environmental pollution. In the case of Beijing, its recent focus on promoting the internet industry has created a win–win situation, simultaneously supporting both environmental protection and economic growth.

Implications for Conservation

Based on the aforementioned discussion , this section proposes three key policy recommendations:

1. Around the world, populations continue to shift to large coastal cities. The urbanization rate in Mainland China rose from 44.30% in 2006 to 57.35% in 2016 (NBSC, 2007–2017). The acceleration of urbanization will result in more population migrating to the eastern coastal area, especially to large cities in the tropical and subtropical zones. Therefore, the market mechanisms involved in resource allocation should be given full play, and the free flow of production factors such as population should not be hindered. For large cities in the subtropical and tropical zones, such as Shanghai, population agglomeration can maximize the advantages of economies of scale. This can encourage the transformation of the industrial structure from the former high-energy industry to the low-energy service industry. This can reduce environmental pollution while advancing economic development, ultimately improving environmental efficiency.

2. Each province should make relevant countermeasures for improvement based on the causes of efficiency loss. To improve environmental efficiency, provinces in the temperate zone can achieve this by introducing technologies to transform traditional industries and improving their management level. In contrast, the tropical and subtropical provinces should try to identify the causes of their efficiency losses and take countermeasures by cooperating with and learning from more efficient enterprises in the region.
3. Pursuing economic development while also protecting the environment is crucial to the sustainable development of China's economy and society. Therefore, each province should strive to improve its environmental efficiency by taking advantage of their comparative advantages, such as economic development stage, resource endowment, and industrial structure. At the same time, provinces should establish stable cooperative relationships and exchange mechanisms with other provinces, to jointly develop new technologies for environmental efficiency and to share successful management experiences.

Appendix A

There is no perfect match between administrative regions and climatic zones. As such, a trade-off between effectiveness and accuracy was required for this empirical study.

Table A1 shows that the provinces with administrative regions completely located in the tropical and subtropical zones include Shanghai, Zhejiang, Fujian, Jiangxi, Hunan, Guizhou, Guangxi, Hubei, Chongqing, Guangdong, and Hainan. Provinces with administrative regions completely in the temperate zone include Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Helongjiang, Shandong, Ningxia, and Xinjiang. The seven provinces that cross the subtropical zone and the temperate zone include Jiangsu, Anhui, Sichuan, Ganshu, Shaanxi, Yunnan, and Henan. Economic activities are mostly concentrated in cities; as such, this study further analyzed the climatic zones of the prefecture-level cities in the seven provinces crossing the two zones. Their climate group was then determined based on the main locations where economic activities occur in each province.

Table A1. Climate Zones of the Provinces of Mainland China.

Climatic zone	Provinces
Subtropical and tropical zones	Shanghai, Zhejiang, Fujian, Jiangxi, Hunan, Guizhou, Guangxi, Hubei, Chongqing, Guangdong, and Hainan
Temperate zone	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Helongjiang, Shandong, Ningxia, and Xinjiang
Cross temperate zone and subtropical zone	Jiangsu, Anhui, Sichuan, Ganshu, Shaanxi, Yunnan, and Henan

In Jiangsu, 8 of the 13 prefecture-level cities are located in the subtropical zone, 3 are in the temperate zone, and 2 are in the temperate and subtropical junctions. Using the year 2016 as an example, the GDP of the eight prefecture-level cities located in the subtropical zone accounted for 76.80% of the GDP of all prefecture-level cities. Furthermore, the eight prefecture-level cities included the five most economically developed cities of Jiangsu: Suzhou, Nanjing, Wuxi, Nantong, and Changzhou. Therefore, Jiangsu was included in the tropical and subtropical group.

Similarly, 10 of the 16 prefecture-level cities in Anhui are located in the subtropical zone, 4 prefecture-level cities are located in the temperate zone, and 2 prefecture-level cities are located at the junction of the tropical zone and temperate zone. The GDP of the four prefecture-level cities in the temperate zone accounted for only 18.65% of the GDP of all prefecture-level cities. Anhui was listed in the temperate group.

Only 2 of the 21 prefecture-level cities in Sichuan are located in the temperate zone and the remaining 19 prefecture-level cities are located in the subtropical zone. As such, this study placed Sichuan in the tropical and subtropical group. For Gansu, there is only one prefecture-level city at the junction of the temperate and subtropical zones; the other 13 prefecture-level cities are located in temperate zone. As such, Gansu province was included in the temperate group.

Shaaxi was assigned to the temperate group, because 8 of its 11 prefecture-level cities are located in the temperate zone, only 2 are in the subtropical zone, and 1 is at the junction of the temperate and subtropical zones. In Yunnan, 12 of the 16 prefecture-level cities are located in the tropical and subtropical zones and 4 are at the junction of the subtropical and temperate zones. As such, Yunnan is listed in the tropical and subtropical group. Finally, Henan has only 3 of its 17 prefecture-level cities at the junction of temperate and subtropical zones and the remaining 14 are in the temperate zone. As such, Henan was grouped in the temperate zone (Yan, Shen, & Mao, 2002).

Appendix B

Table B1 shows the descriptive statistics of the environmental efficiencies of the provinces in the two groups.

Table B1. Group Statistics.

X	Group	*N*	Mean	Standard deviation	Standard error of the mean
	Subtropical and tropical zones	15	0.46282	0.24827	0.06410
	Temperate zone	14	0.31646	0.17757	0.04746

Table B2. Independent Samples Test.

	Levene's test for equality of variances		t Test for equality of means				
	F	Sig.	*t*	*df*	Sig. (two-tailed)	Mean difference	Standard error difference
Equal variances assumed	1.296	.265	1.814	27	.081	0.14635	0.08068
Equal variances not assumed			1.835	25.351	.078	0.14635	0.07976

According to the result of Levene's test in Table B2, the significance level of 0.265 indicates that the sample variances are statistically equal. In view of this, we only use the result of T-test in the first row ("Equal variances assumed"). The T ratio of 1.814 and the significance level of 0.081 indicate that the null hypothesis ($P<0.1$) is rejected, which means that environmental efficiencies of the two groups are statistically different at the 10% level. Considering the mean scores of the two groups in Table B1, we conclude that the environmental efficiencies of provinces in the temperate zone are significantly lower than those of provinces in the tropical and subtropical zones.

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