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Measuring water-used and production efficiency in China using the super-efficient directional distance function

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ABSTRACT

This study employs the super-efficiency directional distance function (SDDF) to assess the productivity of each administrative region in China over the period 2013–2017. The focus is on exploring variations in gross domestic production and efficiency related to waste gas and wastewater discharge across regions. The inputs include labor, capitalization, energy usage, and total water consumption, with domestic gross production as the output, and total wastewater and exhaust gas discharges as unintended outputs. The findings highlight Beijing, Tianjin, Hainan, Qinghai, Guangdong, Shanghai, Jiangsu, and Shandong as the most efficient regions, while Zhejiang, Ningxia, Hunan, and others exhibit lower performance. Notably, Guangxi ranks lowest (0.631). Unlike traditional direct distance function models, the SDDF model provides a more accurate estimation of the production efficiency of all 30 administrative regions, and addresses the limitation of generating the same efficiency values of 1 simultaneously for multiple regions. The study emphasizes the need for inefficient regions to reduce water consumption and emissions and enhance productivity, offering valuable insights for policymakers in formulating environmental and production policies.

Key words: direction distance function, environmental policy, production efficiency, super efficient, waste gas, wastewater

HIGHLIGHTS

- Water-used and production efficiency of China are evaluated.
- Analyzing data for the period 2013–2017, changes in gross domestic production are tracked.
- Efficiency varies notably in China among regions.
- The study urges resource reduction in less efficient regions.

1. INTRODUCTION

China's dependence on energy-intensive and polluting industries has led to large emissions of greenhouse gases and exacerbated the environmental problems such as climate change and global warming (Liu *et al.* 2020). Most of China's regional development policies are based on three regions: eastern, central, and western. The 1980s and 1990s open-up policies and coastal development strategies benefitted coastal areas and significantly increased interregional inequalities (Chen & Zheng 2008). China's industry develops from south to north along the eastern coastal areas, with the eastern part becoming China's economic center, and the east-to-west region causing problems such as urban–rural disparity and environmental pollution as a result of uneven development. Urbanization is the engine or main driver of economic growth here. However, urbanization and economic growth in China will bring about a water crisis and will be strongly affected by water resources (Bao & He 2015). As a result of economic growth, population growth and the consequent demand for water will increase. Eventually economic and social development will generate very large water needs.

Water consumption decreased slightly in 2020 owing to the COVID-19 pandemic, but China's economic growth still amplifies the environmental impact. However, the rising trend of pollution with economic development and global warming are global environmental challenges for humanity. As the world's largest developing country and largest carbon emitter (Zheng *et al.* 2019), China has generated a lot of pollution while pursuing gross domestic production (GDP) growth. The unintended output of waste water and waste gas generated simultaneously in the process of economic production has a high impact on the global environment in which we humans live. China's economy today is developing at a high speed accompanied by increasing pollution, which affects China's production efficiency. The Chinese government and local governments are implementing a number of measures to change to and strengthen the promotion of a sustainable economy, hoping to effectively improve toward cleaner production and reduce carbon emissions (Shi & Xu 2018).

In this study, the super-efficiency directional distance function (SDDF) is used to measure the production efficiency of 30 administrative regions in China, and a total of seven input and output items are selected as variables. In addition, a non-directional scale return model is set. Because the application of the traditional directional distance function (DDF) model produces efficiency values of 1 for multiple administrative regions at the same time, this study uses the SDDF model to measure water-used and the production super-efficiency of 30 administrative regions in China, which can simultaneously solve the situation that the DDF model cannot estimate the efficiency value of the same as 1. Also, applying the SDDF model can help accurately calculate the difference variable to measure the optimal resource allocation and it is used to discuss the numerical analysis of wastewater and waste gas discharge in China, analyze the difference in production efficiency among regions, and then improve the overall production efficiency.

2. LITERATURE REVIEW

Air pollution and water pollution are becoming more and more serious problems and have attracted the attention of many researchers across the world. While achieving economic growth, the world also hopes to achieve the sustainable development goals, which include reducing emissions and water pollution, so much related research is focused on how to improve productivity in these spheres.

2.1. Use the data envelope analysis model

Shi *et al.* (2010) assessed the energy efficiency of industries in 28 administrative regions of China between 2000 and 2006. Tanaka (2011) studied the implementation of national policies to improve industrial energy efficiency between 1995 and 2007, and evaluated the relationship between the implementation of specific technologies and related interests. Chiu *et al.* (2012) evaluated the ratio of technological efficiency and technology gap in four different regions: the United States, Europe, Asia, and Africa. Wu *et al.* (2012) studied energy efficiency and CO_2 emission efficiency in the industrial sectors of 28 provinces in China from 1997 to 2008. Wu *et al.* (2013) assessed the performance efficiency of 21 Organization for Economic Co-operation and Development (OECD) countries. Sueyoshi & Yuan (2015) used the dynamic data envelope analysis (DEA) to evaluate policy efficiency, sustainable development, diversified resource allocation, economic development, and air pollution in four types of cities in China from 2013 to 2014. Ren *et al.* (2016) used a two-stage DEA to analyze water-use efficiency in Gansu Province, China, from 2004 to 2013. Zhang *et al.* (2019) studied the dynamic environmental efficiency assessment of 30 industrial water pollution areas in China between 2011 and 2015. Wang *et al.* (2020) evaluated the environmental efficiency of industrial production and waste gas treatment systems using a stochastic two-stage DEA model. Zhou *et al.* (2020) used DEA window analysis to assess urban air quality in China, exploring air quality analysis of particulate matter (PM) 2.5 and PM 10 in 360 cities in China from January 2018 to August 2019. Wang & Feng (2020) also used the super DEA method of two-stage networks to study total factor productivity and environmental governance efficiency in the industrial sector in China from 2004 to 2015. Zhao *et al.* (2022) estimated transportation sector carbon dioxide emissions efficiency (TSCDEE) in 30 provinces of China from 2010 to 2016 using the DEA, epsilon-based measure (EBM) DEA, and spatial Durbin models. The influencing factors were analyzed using the Durbin model. The input items are capital stock, total energy consumption of labor, and energy, and the output items are expected to be the added value of the transportation industry, while the negative output items are the carbon dioxide emissions of the transportation sector.

2.2. Other models

Aziz (2013) used dynamic regression analysis to assess the factors affecting energy demand in 16 developing countries between 1978 and 2003. Apergis *et al.* (2015) used slacks-based measure (SBM)-DEA and productivity index models to explore energy efficiency in the OECD countries from 1985 to 2011. Deng *et al.* (2016) used the SBM-DEA model to explore the water-use efficiency of 31 provinces in China from 2004 to 2013. Moutinho *et al.* (2020) used DEA and stochastic frontier analysis to predict ecoefficiency. Wu *et al.* (2021a) used the triangular (super SBM) model to assess the energy efficiency of G20 economies for 5 years between 2010 and 2014. Lu *et al.* (2020) used DEA (Dynamic Network Slacks-Based Measure (DN-SBM)) to study the impact of forest areas on annual, overall energy and health efficiency in Association of Southeast Asian Nations Plus Three Cooperation (APT) economies across time periods. Expósito & Velasco (2020) used the dynamic DEA–Malmquist index to explore the environmental efficiency of the use of mineral fertilizers in the European agricultural sector between 2001 and 2012. Matsumoto *et al.* (2020) used DEA and the Malmquist–Luenberger indices to study different types of adverse outputs, and assessed the environmental performance of 27 EU countries using cross-sectional and time-varying data for the period 2000–2017. Chen *et al.* (2021) analyzed the true agricultural green total factor productivity (AGTFP) in 30 provinces of China from 2000 to 2017 by using a three-stage DEA model and SBM study. Hao *et al.*(2021) used the Cross-Sectionally Augmented Auto-regressive Distributive Lag (CS-ARDL) model to investigate the effect of environmentally adjusted multifactorial productivity growth (i.e., green growth) on CO_2 emissions in G7 countries from 1991 to 2017. Wang *et al.* (2021) used the dynamic unbiased gray Markov model to predict water consumption data in Shaanxi Province from 2003 to 2019. This model can eliminate the inherent error of the traditional gray model (GM) (1,1), improve the prediction accuracy, and be more reliable. Wu *et al.* (2021b) developed a principal component analysis (PCA) and back propagation (BP) neural network to predict water resources demand in Taiyuan, Shanxi Province, which showed that the PCA-BP model outperformed other models in many evaluation factors. Wang *et al.* (2023) used the variational mode decomposition and improved grasshopper optimization algorithm and long short-term memory neural network (VMD-IGOA-LSTM) model to predict water quality, which was higher than by other models, showing better performance in short-term prediction.

Most of the literature compiled above focuses on energy efficiency or air and water pollution, but unintended output pollution such as wastewater, carbon dioxide, and other exhaust emissions are used as variables, and the SDDF model is rarely used to evaluate efficiency value. Therefore, this study uses the SDDF model and the unguided scale remuneration, takes labor, capital stock, and energy use as input variables, and takes total water consumption, total wastewater discharge, waste gas discharge, and GDP as output variables, to analyze 30 administrative regions in China. By observing the results of changes in the production efficiency of wastewater, waste gas, and production efficiencies that are not intended to be produced in economic production, the goal of regulating air and water pollution to improve overall production efficiency that can be accomplished while increasing GDP is measured.

The remainder of the paper is constructed as follows: In Section 3, we show the process of methodology. In Section 4, the empirical result is displayed. Discussion and policy recommendations are shown in Section 5. In Section 6, we present the conclusions.

3. METHODOLOGY

To measure the impact of air and water pollution on the productivity of 30 administrative regions in China, this study uses SDDF, and in view of the fact that the general DEA model cannot rank the efficient decision-making unit (DMU), the DEA and SDDF theories are described as follows.

3.1. Data envelope analysis method

The production frontier, proposed by Farrell (1957), is used to measure production efficiency and find the optimal allocation of the unit being evaluated, so that no matter how resources are distributed or evaluated, any individual under the assessment will obtain higher benefits without harming other individuals. In 1978, Charnes *et al.* (1978) developed data envelopment analysis as a comprehensive performance measurement index based on the production boundary, which is measured using the mathematical programming model, and presented a more complete explanation of efficiency from the input side and output side using the concept of business efficiency measurement and establishing a mathematical programming model (Charnes, Cooper, and Rhodes (CCR) model) to evaluate efficiency. Banker *et al.* (1984) divided the technical efficiency values (the so-called Banker, Charnes, and Cooper (BCC) model) into scale efficiency and pure technical efficiency. Charnes *et al.* (1987) proposed the additive model, which combines the results of efficiency measurement with Pareto's optimal economic concept. Banker & Morey (1986) used categorical variable analysis to distinguish between the 'uncontrollable' and 'controllable' variables of decision makers and explore the situation when input or output variables are not under the control of managers. Sexton Silkman & Hogan (1986) used cross-efficiency to maximize the evaluation efficiency of DMUs to identify the most efficient DMUs. Land *et al.* (1993) used the DEA to estimate performance by way of statistical probability allocation under uncertain data. When using DEA to evaluate multiple inputs and outputs, the weight values are obtained by the linear programming method, and the inconsistency of the number of inputs and outputs is evaluated according to the weights. Boussofiane *et al.* (1991) identify the most efficient and inefficient evaluation units, measure resource management, and apply them to relatively inefficient units to evaluate efficiency and resource allocation.

3.2. Super-efficiency direction distance function

SDDF (Andersen & Petersen 1993), which removed efficient DMUs from the original data set, recalculates them to form a new efficiency boundary, and then sorts the efficient DMUs on the efficiency leading edge. Because the traditional super-efficiency model excludes the DMU to be evaluated from the production possible set, the efficiency value is calculated as super-efficient or not. Under Variable Remuneration for Scale (VRS), there is an unreasonable possibility of multiple 1s in the efficiency values. Therefore, Chambers (1996) proposed the DDF to try to assess whether DMU is super-efficient when it can increase the input while reducing the output. In addition, Ray (2008) introduced the VRS super-efficiency Nerlove–Luenberger model to solve the unreasonable problem by adjusting the level of input and output items in the same proportion. In addition, the efficiency value obtained under the VRS super-efficiency based on DDF can be used to rank all DMUs. The DDF model and efficiency value calculation method under the traditional fixed-scale remuneration (Constant Returns to Scale Model (CRS)) and VRS are as follows:

(1) CRS-unoriented direction distance function model:

max β

$$\begin{aligned} \text{s.t.}\quad X\lambda + \beta g_x &\le x_k \\ Y\lambda - \beta g_y &\ge y_k \\ \lambda &\ge 0 \end{aligned} \tag{1}$$

(2) VRS-unguided direction distance function model:

max β

$$\begin{aligned} \text{s.t.}\quad X\lambda + \beta g_x &\le x_k \\ Y\lambda - \beta g_y &\ge y_k \\ \sum \lambda &= 1 \\ \lambda &\ge 0 \end{aligned} \tag{2}$$

The three variations of the DDF model that are used (Färe & Grosskopf 2010) to extend the (Tone 2001) SBM basis are input-oriented, output-oriented, and non-oriented. All models can evaluate both general efficiency values (≤ 1) and super efficiencies (>1). See input data format for directional distance models. The data and symbols are provided in Table 1.

3.2.1. Input-oriented DDF model

Apply the following formula to evaluate the efficiency score of DMU. In this case, we have:

$$(d^{(I)},\ d^{(IN)},\ d^{(O)},\ d^{(ON)},\ d^{(OBad)}) = (x_0^{(I)}, 0, 0, 0, y_0^{(OBad)}) \tag{3}$$

Table 1 | DDF data and symbols

Title	Symbol	Description
(I)	$X^{(I)}$	Input-oriented
(IN)	$X^{(IN)}$	No input orientation
(O)	$Y^{(O)}$	Output-oriented
(ON)	$Y^{(ON)}$	No output orientation
$(OBad)$	$Y^{(OBad)}$	Unintended output

Note: Unintended outputs are considered inputs.

[DD-I-C]

$$\xi^* = MAX\xi$$

s.t. $X^{(I)}\lambda + \xi s^{(I)} + s^{(I)} = x_o^{(I)}$

$X^{(IN)}\lambda + s^{(IN)} = x_o^{(IN)}$

$Y^{(O)}\lambda - s^{(O)} = y_o^{(O)}$

$Y^{(ON)}\lambda - s^{(ON)} = y_0^{(ON)}$

$Y^{(OBad)}\lambda + \xi y_0^{(OBad)} + s^{(OBad)} = y_0^{(OBad)}$

$\xi \geq 0\ ,\ \lambda \geq 0\ ,\ s^{(I)} \geq 0,\ s^{(IN)} \geq 0,\ s^{(O)} \geq 0,\ s^{(ON)} \geq 0\ ,\ s^{(OBad)} \geq 0$ (4)

We define the efficiency value of DMU ($X_{0,}$ Y_0) as follows:

$$\theta^* = 1 - \xi^* \quad (5)$$

In variable scale models (directional distance function in variable scale model (DD-I-V)), the limit:

$$e\lambda = 1 \quad (6)$$

Our predictions are as follows:

$x_o^{(I)^*} = x_o^{(I)} - \xi^* x_o^{(I)} - s^{(I)^*}$

$x_o^{(O)^*} = x_0^{(IN)} - s^{(IN)^*}$

$y_o^{(O)}* = y_o^{(O)} + s^{(O)*}$

$y_o^{(ON)^*} = y_o^{(ON)} + s^{(ON)^*}$

$y_o^{(OBad)^*} = y_0^{(OBad)} - \xi^* y_o^{(OBad)} - s^{(OBad)^*}$ (7)

The symbol * indicates the best value.

3.2.2. Output-oriented DDF model

In this case, we have:

$$(d^{(I)},\ d^{(IN)}, d^{(O)}, d^{(ON)}, d^{(OBad)}) = (\ 0\ ,0\ , y_o^{(O)}\ ,0\ ,0\ ) \quad (8)$$

[DD-O-C]

$\xi^* = MAX\xi$

s.t. $X^{(I)}\lambda + s^{(I)} = x_o^{(I)}$

$X^{(I)}\lambda + s^{(IN)} = x_o^{(IN)}$

$Y^{(O)}\lambda - \xi y_o^{(O)} - s^{(O)} = y_o^{(O)}$

$Y^{(ON)}\lambda - s^{(ON)} = y_o^{(ON)}$ (9)

$Y^{(OBad)}\lambda + s^{(OBad)} = y_o^{(OBad)}$

$\xi \geq 0\ ,\ \lambda \geq 0\ ,\ s^{(I)} \geq 0,\ s^{(IN)} \geq 0,\ s^{(O)} \geq 0,\ s^{(ON)} \geq 0\ ,\ s^{(OBad)} \geq 0$

We define the efficiency value of DMU ($X_{0,}\ \ Y_0$) as:

$$\theta^* = \frac{1}{1+\xi^*} \tag{10}$$

3.2.3. Non-oriented DDF model

In this case, we have:

$$(d^{(I)},\ d^{(IN)}, d^{(O)}, d^{(ON)}, d^{(OBad)}) = (\ x_o^{(I)},\ \ 0\ , y_o^{(O)}\ , 0\ , y_o^{(OBad)}\ ) \tag{11}$$

[DD-C]

$$\begin{aligned}
&\xi^* = MAX\xi \\
&\text{s.t.}\quad X^{(I)}\lambda + \xi x_o^{(I)} + s^{(I)} = x_o^{(I)} \\
&X^{(IN)}\lambda + s^{(IN)} = x_o^{(IN)} \\
&Y^{(O)}\lambda - \xi y_o^{(O)} - s^{(O)} = y_o^{(O)} \\
&Y^{(ON)}\lambda - s^{(ON)} = y_o^{(ON)} \\
&Y^{(OBad)}\lambda + \xi y_o^{(OBad)} + x^{(OBad)} = y_o^{(OBad)} \\
&\xi \geq 0\ ,\ \ \lambda \geq 0\ ,\ \ s^{(I)} \geq 0,\ \ s^{(IN)} \geq 0,\ \ s^{(O)} \geq 0,\ \ s^{(ON)} \geq 0\ ,\ \ s^{(OBad)} \geq 0
\end{aligned} \tag{12}$$

We define the efficiency value of DMU ($X_{0,}\ \ Y_0$) as:

$$\theta^* = 1 - \xi^* \tag{13}$$

3.2.4. Ultra-efficient DDF model

Under the variable scale return, the Super-DD model estimates the super efficiency of the decision unit (DMU), which can also solve the situation that the DD model cannot estimate the efficiency value of the same as 1:

$$\text{when } \theta* = 1 \tag{14}$$

Using the above model, we can evaluate DMU($X_{0,}\ \ Y_0$) super-efficiency, set $\lambda_0 = 0$. Therefore, this study will use the model settings for the use of variables as follows:

$$(d^{(I)}, d^{(O)}) = (\ x_o^{(I)},\ \ 0\ , y_o^{(O)}\ , 0\ \ ) \tag{15}$$

$$\begin{aligned}
&\delta^* = MAX\delta \\
&\text{s.t.}\quad X^{(I)}\lambda + \delta x_o^{(I)} + s^{(I)} = x_o^{(I)} \\
&Y^{(O)}\lambda - \delta y_o^{(O)} - s^{(O)} = y_o^{(O)} \\
&\delta \geq 0\ ,\ \ \lambda \geq 0\ ,\ \ s^{(I)} \geq 0,\ \ s^{(O)} \geq 0
\end{aligned} \tag{16}$$

We define the efficiency value of DMU ($X_{0,}\ \ Y_0$) as:

$$\theta^* = 1 - \delta^* \tag{17}$$

This study evaluates the production super-efficiency of 30 administrative regions in China, selects a total of seven variable inputs and outputs, and applies the traditional DDF model to produce multiple administrative regions with an efficiency value of 1 at the same time, so this study applies the SDDF model to measure the production super-efficiency of 30 administrative regions in China, which can simultaneously solve the situation that the DDF model cannot estimate the efficiency value of the same as 1. When $\theta * = 1$, using the above model, we can evaluate the super-efficiency of the administrative area with a production efficiency value of 1. Set $\lambda_0 = 0$.

3.3. Data and descriptive statistics

This study takes 30 administrative regions of China as the main research subject, the research period being from 2013 to 2017 for a total of 5 years, the application of the SDDF model to labor, capital stock, total energy use, total water consumption as input variables, the total waste water discharge, waste gas emissions, and GDP of each administrative region as output variables, which are explained in Table 2. The research uses public and quantifiable data taken from the National Bureau of Statistics of China, and the efficiency analysis can be carried out through public and objective data.

4. EMPIRICAL RESULT

4.1. Descriptive statistical analysis of input items

From Table 3, it can be seen that the overall input items showed an upward trend, with the labor force increasing by 686,800 from 2013 to 2017, capital increasing by 6.4759 trillion yuan from 2013 to 2017, and energy increasing by 339.14 thousand metric tons from 2013 to 2017, but the total water consumption showed a downward trend, decreasing by 47.067 billion cubic meters from 2013 to 2017.

4.1.1. Descriptive statistical analysis of output items

From Table 3, it can be analyzed that the total amount of wastewater discharge first increases and then decreases, the overall waste discharge shows a downward trend, decreasing by 872,460 metric tons from 2013 to 2017, and the overall GDP shows an upward trend, increasing by 778,670 million yuan from 2013 to 2017.

Table 2 | Study the variable definition

Variable		Unit	Definition
Input	Labor force	10,000 people	The economically active population who are able to work and are over 16 years of age
	Capital	100 million yuan	Capital, equipment, and related expenses invested in production
	Energy use	Thousand metric tons	Total final consumption of fuel oil, liquefied petroleum gas, coal, etc.
	Total water	100 million cubic meters	Total water used for the inputs used in production
Output	Wastewater total emissions	1,000 metric tons	Production and consumption of waste water produced
	Exhaust gas emissions	Tons	For the production and consumption of carbon dioxide produced by burning oil and coal mines
	Regional GDP	100 million yuan	The final result of the production activities of the administrative regions of China in a regular period

Note: The National Bureau of Statistics of China; the above relevant content is self-organized.

Table 3 | Average numbers of inputs and outputs from 2013 to 2017

Input	2013	2014	2015	2016	2017	SD
Capital (100 billion RMB)	14,658.8	16,822.8	19,983.1	19,650.9	21,134.7	2,646.8
Labor force (10,000 people)	2,705.99	2,756.51	2,767.02	2,781.4	2,774.67	30.0
Total water consumption (100 billion cubic meters)	2,051,067	2,021,433	2,024,267	2,003,067	2,004,000	19,526.9
Energy use (thousand hectares)	1,779.76	1,853.42	1,896.42	1,989.93	2,118.9	131.2
Output						
GDP (RMB million)	19,904.9	21,578.8	23,086.6	24,992.5	27,691.6	3,023.7
Total wastewater discharge (100 million cubic meters)	231,648	238,577	244,911	236,827	232,981	5,241.6
Exhaust emissions (hectares)	1,847,960	1,928,847	1,746,883	1,168,043	975,500	431,752.1

Note: The National Bureau of Statistics of China; the above relevant content is self-organized.

Table 4 | Average production super-efficiency in 30 administrative regions of China from 2013 to 2017

Region	Average value	SD	Region	Average value	SD
Beijing	1.462	0.0540	Henan	0.873	0.0106
Tianjin	1.181	0.0771	Hubei	0.946	0.0137
Hebei	0.775	0.0173	Hunan	0.948	0.0152
Shanxi	0.755	0.0781	Guangdong	1.198	0.0190
Inner Mongolia	0.867	0.0397	Guangxi	0.631	0.0336
Liaoning	0.839	0.1034	Hainan	2.882	0.1634
Jilin	0.825	0.0257	Chongqing	0.853	0.0133
Heilongjiang	0.743	0.0320	Sichuan	0.89	0.0092
Shanghai	1.133	0.0114	Guizhou	0.776	0.0628
Jiangsu	1.133	0.0084	Yunnan	0.707	0.0470
Zhejiang	0.992	0.0100	Shaanxi	0.827	0.0800
Anhui	0.81	0.0143	Gansu	0.845	0.0261
Fujian	0.854	0.0298	Qinghai	1.714	0.0465
Jiangxi	0.766	0.0295	Ningxia	0.981	0.0432
Shandong	1.093	0.0214	Xinjiang	0.772	0.0395
Average value of all regions	1.002		Standard deviation		0.0120

Note: The National Bureau of Statistics of China; the above relevant content is self-organized.

4.2. Average production super-efficiency in 30 administrative regions of China from 2013 to 2017

From the analysis of Table 4, it can be concluded that the average super-efficiency value of 5 years from 2013 to 2017 is 1.002, of which the efficiency values of Beijing, Tianjin, Shanghai, Jiangsu, Shandong, Guangdong, Hainan, and Qinghai provinces were greater than 1, which reflects the efficient decision-making of these administrative regions. In addition, the best super-efficiency values are that of Hainan (2.882), Qinghai (1.714), and Beijing (1.462). The administrative regions showing below-average performances are Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Zhejiang, Anhui, Fujian, Henan, Hubei, Hunan, Chongqing, Guangxi, Sichuan, Xinjiang, Anhui, Guizhou, Gansu, Yunnan, Jiangxi, Shaanxi, Qinghai, Ningxia, and Xinjiang. The administrative regions with the worst super-efficiency values are Guangxi (0.631), Yunnan (0.707), and Heilongjiang (0.743).

From Table 4, it can be determined that the province with the efficiency value of 0.7–0.9 is the most efficient, concentrated in the central region, including Hainan Island and Qinghai, owing to the special geographical environment. Furthermore, the efficiency of the eastern coastal area is better than that of the other regions, which is related to earlier development and abundant resources. There is a more intuitive representation in Figure 1.

4.3. Compilation of suggestions on the direction and magnitude of improvement of input and output variables in 30 administrative regions of China from 2013 to 2017

From the analysis in Table 5, it can be seen that the recommended average labor adjustment is an increase of 36.113%; however, nine cities such as Beijing, Tianjin, Jilin, Shanghai, Jiangsu, Shandong, Guangdong, Hainan, and Qinghai do not need to be adjusted, and the cities with adjustment values greater than the average value of each administrative region are Chongqing, Hebei, Jiangxi, Shanxi, Sichuan, Xinjiang, Anhui, Henan, Heilongjiang, Guangxi, Guizhou, Gansu, and Yunnan. From 2013 to 2017, the average adjusted value in Yunnan needs to increase by 66.46%. The recommended average value of capital adjustment is a decrease of 35.636%; however, nine cities such as Beijing, Tianjin, Jilin, Shanghai, Jiangsu, Shandong, Guangdong, Hainan, and Qinghai do not need to be adjusted, and the cities with adjustment values greater than the average value of each administrative region are Chongqing, Hebei, Jiangxi, Shanxi, Sichuan, Xinjiang, Anhui, Henan, Heilongjiang, Guangxi, Guizhou, Gansu, and Yunnan. The recommended average value for energy-use adjustment is a decrease of 20.581%, and the average adjustment value in Inner Mongolia needs to be reduced by 66.508% from 2013 to 2017. The recommended average value for the total water-consumption adjustment is a reduction of 43.976%; however, 8 cities including Beijing, Jilin,

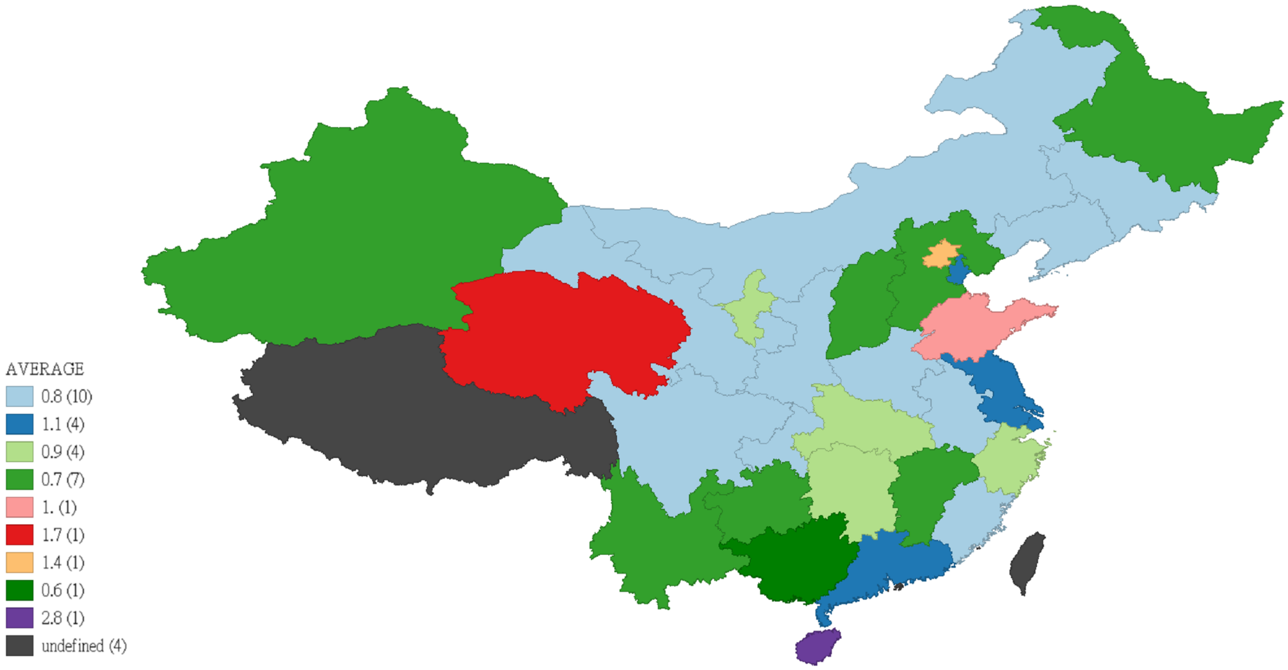

Figure 1 | Average distribution map of super-efficiency in 30 administrative regions in China. *Note*: The National Bureau of Statistics of China; the above relevant content is self-organized.

Shanghai, Jiangsu, Shandong, Guangdong, Hainan, Qinghai, and Tianjin do not need to be adjusted. The recommended average value for the adjustment of total wastewater discharge is 12.493%, but 8 cities including Beijing, Jilin, Shanghai, Jiangsu, Shandong, Guangdong, Hainan, Qinghai, and Tianjin do not need to be adjusted, and the cities with adjustment values greater than the average value in each administrative region are Chongqing, Hebei, Jiangxi, Shanxi, Sichuan, Xinjiang, Anhui, Henan, Heilongjiang, Guangxi, Guizhou, Gansu, and Yunnan. The recommended average adjustment of exhaust emissions is 17.7309%, and the average adjustment value in Guangxi needs to be reduced by up to 42.625% from 2013 to 2017. The recommended average GDP adjustment is an increase of 12.465%, and the maximum increase in the average adjustment value in Guangxi from 2013 to 2017 is 36.949%.

Among the input variables, 43.976% of the total water consumption should be adjusted first, and the administrative regions with the largest suggested adjustment are Xinjiang, Inner Mongolia, Heilongjiang, Guangxi, Jiangxi, Hunan, and Yunnan. Among the output variables, 17.730% of the total amount of exhaust gas should be adjusted first, and the administrative regions with the largest suggested adjustment ranges are Guangxi, Yunnan, Heilongjiang, Shanxi, Jiangxi, Hebei, and Guizhou.

5. DISCUSSION AND POLICY RECOMMENDATIONS

This study proposes the following policy implications for 30 administrative regions in China.

5.1. The trend of input items

There is a decrease in total energy use (−20.58%), total water consumption (−43.97%), labor (−36.69%), and capital (−20.581%). This trend shows that labor and capital allocation are inefficient, so for the reallocation of labor and capital, technical training will help improve production efficiency.

5.2. Output trends

There was a reduction in the total wastewater (−12.493) and total waste gas volume (−17.730), and a total GDP growth (12.4652). This trend shows that wastewater volume and waste gas volume allocation are inefficient, so for pollution prevention and production control reconfiguration, technical control rate improvement will help improve production efficiency.

Table 5 | Suggestions on the direction and magnitude of improvement in the input and output variables for 30 administrative regions of China from 2013 to 2017 (percentage)

DMU	Regional GDP	Total waste water discharge	Waste gas discharge	Total water consumption	Labor	Capital	Energy use
Beijing	0	0	0	0	0	0	0
Tianjin	0	0	0	0	0	0	0
Hebei	22.535	−22.535	−31.079	−29.667	−56.574	−50.867	−47.696
Shanxi	24.454	−24.466	−33.291	−45.878	−55.696	−46.580	−51.440
Inner Mongolia	13.292	−13.292	−23.575	−82.262	−43.090	−62.480	−66.508
Liaoning	16.097	−16.194	−25.403	−39.324	−49.545	−30.357	−38.213
Jilin	17.514	−17.598	−26.471	−68.170	−45.891	−58.734	−17.514
Heilongjiang	25.749	−25.796	−34.338	−88.526	−56.323	−46.661	−25.749
Shanghai	0	0	0	0	0	0	0
Jiangsu	0	0	0	0	0	0	0
Zhejiang	0.897	−0.914	−0.897	−0.897	−5.175	−17.215	−18.155
Anhui	19.048	−19.065	−26.545	−73.676	−63.821	−59.488	−20.617
Fujian	14.573	−14.573	−18.125	−44.57	−37.743	−39.783	−17.965
Jiangxi	23.447	−23.561	−31.589	−84.386	−59.201	−60.975	−23.447
Shandong	0	0	0	0	0	0	0
Henan	12.722	−12.722	−18.427	−13.295	−55.514	−43.805	−12.72
Hubei	5.4176	−5.465	−13.103	−66.062	−47.621	−57.957	−5.417
Hunan	5.2158	−5.383	−14.109	−76.839	−57.727	−60.654	−5.215
Guangdong	0	0	0	0	0	0	0
Guangxi	36.949	−36.976	−42.625	−87.018	−63.089	−58.291	−37.075
Hainan	0	0	0	0	0	0	0
Chongqing	14.700	−14.809	−23.162	−49.523	−41.497	−55.168	−14.700
Sichuan	11.040	−11.068	−18.285	−53.628	−55.967	−53.202	−11.040
Guizhou	22.408	−22.408	−30.203	−67.115	−62.529	−52.952	−32.71
Yunnan	29.280	−29.280	−36.040	−76.318	−66.463	−52.976	−38.789
Shaanxi	17.250	−17.250	−25.851	−59.973	−48.981	−64.108	−27.545
Gansu	15.5488	−15.548	−20.634	−70.494	−64.961	−43.982	−28.887
Qinghai	0	0	0	0	0	0	0
Ningxia	3.0196	−3.103	−7.189	−47.16	−3.169	−4.2542	−15.441
Xinjiang	22.795	−22.795	−30.978	−94.505	−42.804	−48.598	−60.601
Ave.	12.4652	−12.493	−17.730	−43.976	−36.112	−35.636	−20.581

Note: The National Bureau of Statistics of China; the above relevant content is self-organized.

5.3. The average production efficiency for 5 years

Between 2013 and 2017, the production efficiency of 30 administrative regions analyzed in China shows a downward trend. Among them, the 5-year average efficiency value is 1.002, and Beijing, Tianjin, Inner Mongolia, Jiangsu, Guangdong, and Ningxia have aDMU with a super-efficiency value greater than 1. Below average regions include Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Zhejiang, Anhui, Fujian, Jiangxi, Henan, Hubei, Hunan, Chongqing, Guangxi, Sichuan, Xinjiang, Anhui, Henan, Heilongjiang, Guizhou, Gansu, Yunnan, Shaanxi, Ningxia, and Xinjiang. The administrative regions with the worst super-efficiency values are Guangxi (0.631), Yunnan (0.707), Heilongjiang (0.743), and other districts, and the most-adjusted input variable is the reduction in total water consumption (−43.976%). Furthermore, the most-adjusted input variable in Xinjiang is total water consumption, which is recommended to be reduced by 94.505%.

5.4. The impact of air and water pollution on the production efficiency of 30 administrative regions in China

To improve production efficiency, it is recommended to prioritize the reduction of 12.493% of the total amount of wastewater, and toward this Guangxi, Jiangxi, Yunnan, and Heilongjiang should be prioritized. At the same time, the total amount of exhaust gas is reduced by 17.730%, and the administrative regions with the largest adjustment range are Guangxi, Yunnan, Heilongjiang, Shanxi, Jiangxi, Hebei, and Guizhou. It is still necessary to reallocate resources or upgrade technology to achieve sustainable economic development and maintain the balance of the ecological environment.

6. CONCLUSIONS

(1) In this paper, measuring the performance efficiency of China's 30 administrative regions across different years, differences in air and water pollution are determined, which affect China's production efficiency. Production efficiency in China shows a downward trend between 2013 and 2017. SDDF can be ranked above the efficiency value of 1, calculated by the production efficiency and difference variables. The estimated results are displayed as follows.

(2) The administrative regions with the best production efficiency are empirically shown to be Hainan, Qinghai, and Beijing. The regions with below average efficiency are Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Zhejiang, Anhui, Fujian, Jiangxi, Henan, Hubei, Hunan, Chongqing, Guangxi, Sichuan, Xinjiang, Anhui, Henan, Heilongjiang, Guizhou, Gansu, Yunnan, Shaanxi, Ningxia, and Xinjiang. The administrative regions with the worst super-efficiency values are Guangxi (0.631), Yunnan (0.707), and Heilongjiang (0.743).

(3) To improve production efficiency, the three administrative regions with the worst efficiency values need to adjust their variables, with the variable of total water consumption being the most in need of adjustment. It is recommended to reduce the overall water consumption by 43.9765%, while Xinjiang is the administrative region with the largest adjustment value, as it has an arid climate, scarce precipitation, and strong evaporation, and it is recommended to reduce the water consumption here by 94.5056%, to improve production efficiency. It is recommended to reduce the overall total wastewater volume by 12.4936%, and at the same time reduce the total amount of waste gas by 17.7309% to reduce the impact of air and water pollution on production efficiency, for which Guangxi should give priority to adjusting and reducing 42.625% of waste gas discharge and 36.9762% of wastewater discharge.

(4) In the future, the administrative regions with the largest adjustment ranges are predicted to be Yunnan, Heilongjiang, Shanxi, Jiangxi, Hebei, and Guizhou, and other provinces still need to reallocate resources or upgrade technology to achieve sustainable economic development and maintain the balance of the ecological environment.

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Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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