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Measuring Pollution Control and Environmental Sustainable Development in China Based on Parallel DEA Method

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Abstract: The purpose of this study is to explore the impact of pollution control on industrial production efficiency in 31 provinces and cities in the Yellow River and Non-Yellow River basins in China from 2013 to 2017, using the methods of the directional distance function (hereinafter referred to as DDF) and the technology gap ratio (hereinafter referred to as TGR) in parallel, while taking the industrial production sector (labor force, total capital formation, energy consumption and industrial water consumption) and the pollution control sector (wastewater treatment funds and waste gas treatment funds) as input variables. Undesirable outputs (total wastewater discharge, lead, SO_2 and smoke and dust in wastewater) and an ideal output variable (industrial output value) are taken as output variables. It is found that the total efficiency of DDF in the Non-Yellow River Basin is 0.9793, which is slightly better than 0.9688 in the Yellow River Basin. Among the 17 provinces and cities with a total efficiency of 1, only Shandong and Sichuan are located in the Yellow River Basin. The TGR values of 31 provinces, cities and administrative regions are less than 1, and the average TGR value of the Yellow River Basin is 0.3825, which is lower than the average TGR value of the Non-Yellow River Basin of 0.5234. We can start by improving the allocation of manpower and capital, implementing the use of pollution prevention and control funds, improving the technical level of industrial production, improving pollutant emission, and increasing output value to improve overall efficiency performance. This study uses the parallel method, taking the industrial production department and the pollution control department as inputs, to objectively evaluate the changes in industrial production efficiency and technology gap in the Yellow River and Non-Yellow River basins, which is conducive to mastering the situation of pollution control and industrial production efficiency, and provides the reference for SDG-6- and SDG-9-related policy making.

Keywords: DDF; TGR; wastewater; waste gas; treatment funds; Yellow River

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1. Introduction

While pursuing industrial and economic development, wastewater and air pollution have short-term and long-term impacts on the environment and human beings [1,2]. Countries around the world have invested a lot of money and resources to try to solve the problems of wastewater and air pollution caused by production and manufacturing. Human beings need to take sustainable actions within the existing environmental resources [3]. Therefore, the agenda for sustainable development sets out 17 sustainable development goals to be achieved by 2030 and will mobilize countries around the world to incorporate sustainable development goals into their national development strategies. Sustainable development goals SDG-6 (sustainable development of water resources) and SDG-9 (development of inclusive sustainable industry) play a vital role in environmental protection, economic development and the promotion of human well-being in achieving these sustainable development goals. In China, since the implementation of the reform and opening-up policy after 1980, prosperity and affluence have gone deep into the mainland from the early coastal areas. According to data released by the World Bank (as shown in Figure 1), we can see the impact of the 2008 financial tsunami and the 2019 COVID-19 pandemic on the global GDP growth rate. In addition, China's GDP growth rate is better than that of the world.

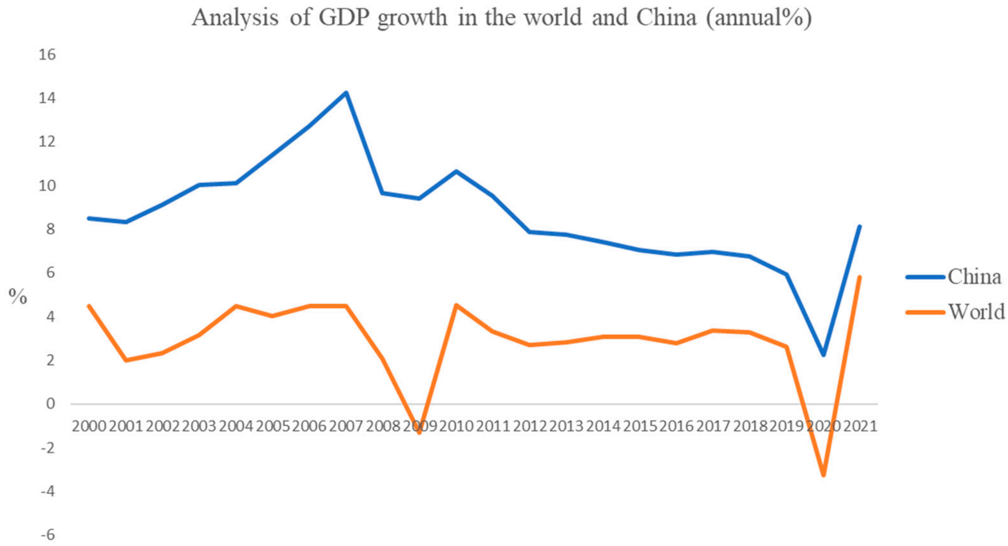
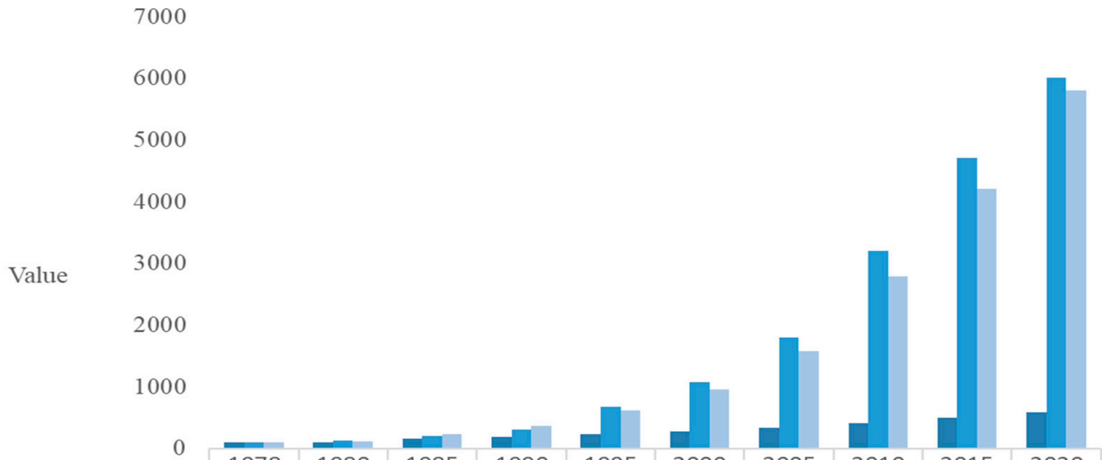


Figure 1. Analysis of GDP growth in the world and China (annual%).

The destruction of environmental resources caused by development has directly affected national health and the environment for human survival. According to China's "industrial classification of national economy", industries are divided into three categories: the primary industry is mainly agriculture, the secondary industry is mainly industry and the tertiary industry is mainly the service industry. According to the data of the National Bureau of Statistics of China (National Bureau of Statistics of China: http://www.stats.gov.cn/tjsj/ndsj/, accessed on 1 February 2022) (as shown in Figure 2), from 1978 to 2020, the fastest growth of China's GDP is in the secondary industry, followed by the service industry. The rapid development of China's economy largely depends on energy consumption, which has caused serious pollution [4,5]. In order to achieve energy conservation and emission reduction and strengthen pollution control [6], we must pay attention to the relevant issues of sustainable development goals SDG-6 and SDG-9. In order to improve environmental quality, improve national health and well-being, maintain environmental resources and pursue sustainable development, which has become a universal common value, the State Council of China put forward the outline of the Yellow River Basin Ecological Protection and High-Quality Development Plan in 2021 (Outline of Ecological Protection and High-Quality Development Plan for the Yellow River Basin (2021): http://www.gov.cn/zhengce/2021-10/08/content_5641438.htm, accessed on 1 February 2022). In addition to investing in pollution prevention and control funds, it also standardized the high energy consumption and high-pollution enterprises in the region. It includes various pollutant discharge standards and monitoring systems to ensure that significant progress will be made in the ecology and development of the Yellow River Basin by 2025.

As mentioned above, the government's policy and financial expenditure on environmental protection have a certain input–output relationship and impact mechanism between regional energy use and pollutant emission (Figure 3). When the industrial production department promotes economic development due to the investment of labor, capital, energy and water resources, the pollution control department is due to the investment of government prevention and control funds. It is beneficial to improve the unintended substances discharged from the production process, such as SO_x and smoke dust in waste gas, heavy metal lead in wastewater, etc., to maintain the natural environment and the health of people. Therefore, this study uses DDF and TGR methods to objectively evaluate the impact of pollution control on the production efficiency of the Yellow River Basin and Non-Yellow River Basin in China from 2013 to 2017. The structure of this study is as follows: Section 2 analyzes the literature on industrial production efficiency, energy efficiency, water efficiency, air pollution emission and treatment; Section 3 introduces the methods; and Section 4 introduces the data, narrative statistics and empirical result analysis. The last part puts forward conclusions and suggestions for future research.



	1978	1980	1985	1990	1995	2000	2005	2010	2015	2020
Primary industry	100	104.6	155.4	190.7	233.1	275.4	331.4	409.7	500.4	590.2
Secondary industry	100	122.8	197.6	302.8	671.4	1072.6	1795.6	3199.3	4703.7	6009.5
Tertiary industry	100	114.4	228.3	361.6	611.4	958.6	1582.8	2784	4202.2	5810.7

Figure 2. China's GDP index from 1978 to 2020.

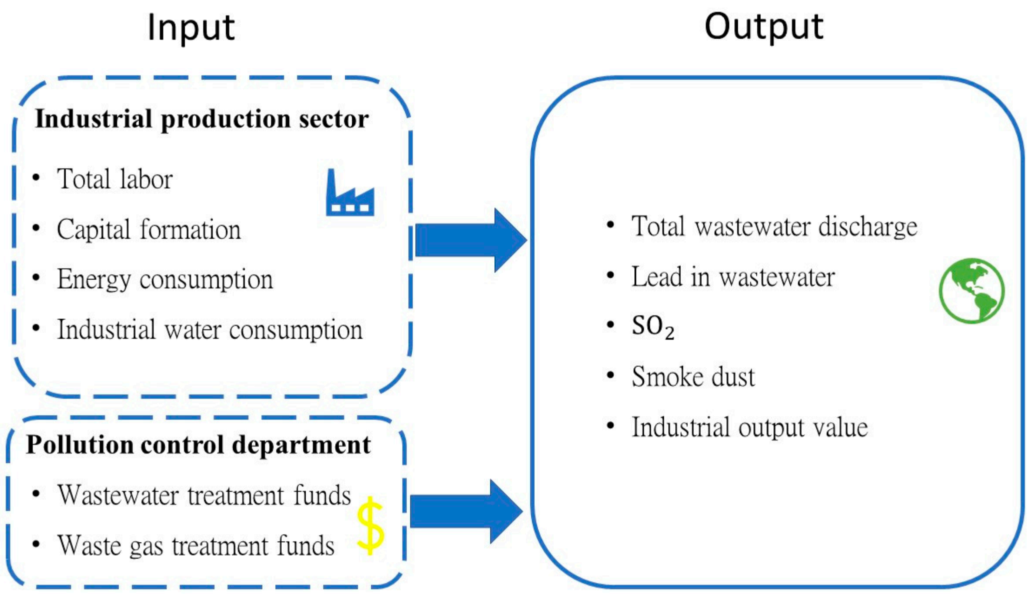


Figure 3. Input and output process of variables in this study.

2. Literature

Previous studies on industrial production efficiency, such as the one conducted by [7], used the SDG-9 index to assess the degree of industrialization of countries, as well as social inclusiveness, less use of natural resources and environmental impact. Ref. [8] using the DEA method, discusses the relationship between the American manufacturing industry and environmental performance. The unintended output is reported as SO_x, NO_x, Co, etc. It is found that air pollution is mainly a by-product of manufacturing activities. The share of the manufacturing industry in the total amount of state-owned products and the share of the polluting industry in the total amount of manufacturing activities are two important factors determining the intensity of pollution. Using DEA, Ref. [9] discuss the energy conservation and carbon reduction efficiency of China's industrial production from 2006 to 2010. The input variables are labor, capital and energy consumption, and the output variables are SO_2, wastewater and GDP. It is found that the energy conservation and emission reduction efficiency in East China is the best. Ref. [10] using the DEA method, evaluated the environmental efficiency of 46 countries in 2002, 2007 and 2011. The input variables are labor, capital and energy use, and the output variables are GDP, CO_2 and NO_x. The study found that the energy efficiency of countries rich in oil and natural gas resources is relatively poor. Ref. [11] using the DEA method, discuss the analysis of the energy and environmental efficiency of two petrochemical plants in China from 2012 to 2013, and divide the output into expected output and unexpected output. It was found that by analyzing the energy efficiency and environmental efficiency of the ethylene production process in complex chemical processes, the energy saving and emission reduction potential of ethylene plants can be obtained, and the efficiency performance of DMU can be improved by improving energy efficiency and reducing carbon emission. Research on energy efficiency by [11] evaluated the efficiency of the water, food and energy (WEF) relationship in 30 provinces and municipalities in China from 2005 to 2017. Inputs were labor force, water resource use, energy use, food consumption and other variables, and outputs were social benefits, wastewater discharge and solid discharge. The researchers analyzed the weight of the WEF relationship, and put forward the strategy of sustainable resource management. Ref. [12] discussing the research results of DEA application in the field of energy and environment from the 1980s to 2010, found that the development process will produce various pollutants to air, water and other types of pollutants which are related to health and climate change. Therefore, it is necessary to strike a balance between economic growth and pollution mitigation. Ref. [13] using the DEA method to explore the impact of U.S. economic growth on the environmental efficiency of the power sector, found that there is a stable n-shape relationship between environmental efficiency and regional economic growth, while in the case of local pollutants, there is an inverted n-shape relationship between environmental efficiency and regional economic growth. For policymakers, climate change needs to consider the relationship between economy, environment and society at the same time. On the research related to water use efficiency, Ref. [14] evaluated the efficiency of SDG-6 and a serious water shortage in the Medjerda Basin in Tunisia. Ref. [15] used the DEA method to explore the water use efficiency of 10 cities in the Minjiang River Basin in China in 2018. The research found that the input of social water and economic water are different, and the output of GDP and unintended wastewater are the factors affecting water use efficiency. Ref. [16] using TFP and Tobit models, discuss the water use efficiency of 30 provinces and municipalities in China from 2006 to 2015. The study found that the efficiency of water use in the administrative regions of provinces and cities is low, so we should establish the awareness of water conservation from the investment of education, so as to balance economic development and water use efficiency. Ref. [17] used the DEA method to explore China's regional ecological efficiency from 2003 to 2014. The input variables were labor force, water consumption, energy consumption, etc., and the output variables were GDP, SO_2, smoke and dust, industrial wastewater, household waste, etc. The study found that the efficiency and progress rate of the eastern region are better than other regions, and there is still room for improvement in China's overall environmental efficiency. Ref. [18] used DDF to evaluate the water resources and wastewater discharge efficiency of China's industrial sector. The input variables were labor, capital and industrial water consumption, and the output variables were industrial output value, chemical oxygen demand, etc. The study found that the eastern region has made progress in science and technology, and the pollutants discharged by industrial production in the western region are more serious. Ref. [19] using the DDF model, evaluated the efficiency of administrative water removal in 31 provinces and cities in China from 2011 to 2015. The study found that there were significant differences between the efficiency performance and technology gap in Eastern, Central and Western China. Ref. [20] evaluating the relationship between China's industrial water efficiency and regional differences from 2005 to 2015, found that the industrial water efficiency values of administrative regions in 31 provinces and cities are less than 1, among which the per capita water resources, R&D investment, regulation formulation, GDP and industrial structure will affect the industrial water efficiency. Ref. [5] using the SBM model, studied the economic production and sewage treatment efficiency of 30 provinces and cities in China from 2011 to 2017. The input variables were labor force, domestic and industrial water, investment in sewage treatment projects and the number of sewage treatment plants. The output variables were GDP, chemical oxygen demand of wastewater discharge and heavy metal pollution. The study found that there are great differences in inefficiency in different regions of China. The efficiency in the economic production stage is significantly higher than that in the sewage treatment stage. The sewage treatment efficiency is the main drag factor of the overall efficiency. Ref. [21] assessed the regional differences of China's provincial air pollution efficiency from 2006 to 2015. The study found that there were significant differences in air pollution emission efficiency in various regions. Air pollution emission efficiency was significantly positively correlated with economic development level, industrial structure optimization, technological innovation and foreign direct investment (FDI), and negatively correlated with energy consumption structure. Ref. [22] used DEA and regression analysis to explore China's energy efficiency performance from 2001 to 2013. Input variables included labor, capital and energy use, and output variables were GDP, industrial wastewater, solid waste and air pollutants. The study found that technological innovation has a positive impact on TFEE. The government should pay attention to technological innovation, which will be conducive to the effectiveness of energy conservation and emission reduction and environmental pollution prevention and control. Research on pollution control costs, such as [23], discusses the efficiency of China's iron and steel industry and pollution control. It is found that the production efficiency of China's iron and steel industry is low and causes serious pollution to the environment. Enterprises must improve the overall efficiency by increasing environmental protection investment, introducing foreign advanced technology and strengthening the R&D of pollutant management.

As for the discussion on energy consumption and pollution control technology, for example, in a paper by [24], it is estimated that Beijing, China, will improve its air quality by adjusting its industrial structure, controlling pollutant emissions, controlling vehicle pollution emissions and other measures and regulations due to rapid industrialization, urbanization and motorization, the continuous growth of energy consumption and the resulting emissions of a variety of pollutants. Ref. [25] assessing the impact of foreign investment on greenhouse gas emissions in developing countries, found that foreign investment enabled technology transfer, improved labor, reduced greenhouse gas emissions, improved energy efficiency and achieved sustainable development goals.

As mentioned above, most previous studies focused on industrial production efficiency, energy efficiency, pollutant emission and control. Therefore, this study uses the DDF method to explore the impact of pollution control on the production efficiency of 31 provinces and municipalities in the Yellow River Basin and Non-Yellow River Basin in China from 2013 to 2017, and uses TGR to measure the change in the technology gap. We objectively evaluate the efficiency difference of pollution control in different provinces and cities to provide an effective reference basis for policy formulation and budget control.

The main contributions of this study are as follows:

(1) Different from the previous literature results, this study uses the parallel method and takes the industrial production department and the pollution control department as

input variables to objectively evaluate the impact of pollution prevention and control funds on industrial production efficiency in 31 provinces and municipalities in China;

(2) This study compares the changes in industrial production efficiency and the technology gap between the Yellow River Basin and Non-Yellow River Basin, which is conducive to mastering the situation of pollution control and production efficiency in 31 provinces and municipalities in China, and provides objective suggestions as a reference for SDG-6- and SDG-9-related policy making.

3. Research Method

Ref. [26] first put forward the concept of a deterministic nonparametric front in 1957. It is used to measure the production level of a decision-making unit. Then, Ref. [27] proposed the CCR model. Ref. [28] proposed the BCC model. Over time, Ref. [29] (1996) proposed the directional distance function (DDF). In addition, Ref. [30] introduced the VRS super-efficiency Nerlove–Luenberger (N–L) model to solve the unreasonable problem. This method can adjust the input and output levels in the same proportion, and the efficiency value obtained under the VRS super-efficiency of DDF can be used for ranking all DMUs. The directional distance function model under variable return to scale (VRS) and the calculation method of efficiency values used in this study are as follows:

3.1. Directional Distance Function, DDF

This study uses [31] to extend the non-oriented method in the DDF model based on the SBM described by [32]. All models can evaluate the general efficiency value (≤ 1) at the same time, and its calculation method is as follows:

Non-oriented DD model

In this case, we have

$$\begin{aligned} &\max \beta \\ &\text{s.t. } X\lambda + \beta g_x \leq x_k \\ &Y\lambda - \beta g_y \geq y_k \\ &\sum \lambda = 1 \\ &\lambda \geq 0 \end{aligned} \tag{1}$$

$$\left(d^{(I)},\ d^{(IN)}, d^{(O)}, d^{(ON)}, d^{(OBad)}\right) = \left(\ x_o^{(I)},\ 0\ , y_o^{(O)}\ , 0\ , y_o^{(OBad)}\ \right) \tag{2}$$

[DD-C]

$$\begin{aligned} &\xi^* = MAX\xi \\ &\text{st.} X^{(I)}\lambda + \xi x_o^{(I)} + s^{(I)} = x_o^{(I)} \\ &X^{(IN)}\lambda + s^{(IN)} = x_o^{(IN)} \\ &Y^{(O)}\lambda - \xi y_o^{(O)} - s^{(O)} = y_o^{(O)} \\ &Y^{(ON)}\lambda - s^{(ON)} = y_o^{(ON)} \\ &Y^{(OBad)}\lambda + \xi y_o^{(OBad)} + x^{(OBad)} = y_o^{(OBad)} \\ &\xi \geq 0\ ,\ \lambda \geq 0\ ,\ s^{(I)} \geq 0,\ s^{(IN)} \geq 0,\ s^{(O)} \geq 0,\ s^{(ON)} \geq 0\ ,\ s^{(OBad)} \geq 0\ . \end{aligned} \tag{3}$$

We define the efficiency value of DMU(x_o, y_o) as

$$\theta^* = 1 - \xi^*.$$

3.2. Technology Gap Ratio, TGR

Since the production boundary of g groups is included in the common production boundary, the technical efficiency under the common boundary must be less than that under the group boundary. The ratio of the two is called the technical efficiency gap ratio (TGR), as follows:

$$\text{TGR} = \frac{\text{Technical efficiency under common boundary}}{\text{Technical efficiency under group boundary}} \tag{4}$$

4. Data Analysis and Empirical Results

4.1. Selection of Data Sources and Variables

This study evaluates the impact of pollution control in 31 provinces and municipalities of China on China's industrial production efficiency from 2013 to 2017. The publicly quantifiable data are obtained from the statistical yearbook of China's National Bureau of Statistics (National Bureau of Statistics of China: http://www.stats.gov.cn/tjsj/ndsj/, accessed on 1 February 2022) from 2013 to 2017, and the efficiency is analyzed through open and objective data. The relevant contents of the selected variables are as follows:

Labor force: including manufacturing, power, heat, gas and water production and supply, and the number of employed persons in urban units. Employed persons refer to persons aged 16 and above who engage in certain social work and obtain labor remuneration or business income. Unit: 10,000 persons.

Total capital formation: refers to the total value of fixed assets acquired by permanent residents less fixed assets disposed of in a certain period of time. Fixed assets are assets produced through production activities with a service life of more than one year and a unit value of more than the specified standard, excluding natural assets. It can be divided into total tangible fixed capital formation and total intangible fixed capital formation. Unit: 100 million yuan.

Energy consumption: electricity consumption by region. Unit: 100 million kWh.

Industrial water consumption: industrial water consumption by region. Unit: 10,000 tons.

Wastewater treatment fund: the completion of wastewater treatment investment generated by industrial pollution. Unit: 10,000 yuan.

Waste gas treatment funds: the completion of waste gas treatment investment generated by industrial pollution. Unit: 10,000 yuan.

Total wastewater discharge: total wastewater discharge by region. Unit: 10,000 tons.

Lead in wastewater: the discharge of main pollutants in wastewater. Unit: kg.

SO_2: emission of sulfur dioxide in waste gas by region. Unit: 10,000 tons.

Smoke and dust: emission of smoke (powder) dust in waste gas by region. Unit: 10,000 tons.

Industrial output value: regional industrial output value. Unit: 100 million yuan.

4.2. Input and Output Variables Statistical Analysis

As shown in the narrative analysis of various variables from 2013 to 2017 (Table 1), the average part shows a growth trend in labor force, total capital formation, energy consumption, waste treatment funds and industrial output value. The amount of industrial wastewater, wastewater treatment funds, lead, SO_2, smoke and dust in wastewater show a downward trend. The total amount of wastewater discharge has little change. In the largest part, labor force, total capital formation, energy consumption, waste gas treatment funds and industrial output value show a growth trend. Lead, SO_2, smoke and dust in wastewater show a downward trend, and other variables change little. In the minimum part, total capital formation, energy consumption, total wastewater discharge and industrial output value show a growth trend, the wastewater treatment funds and waste gas treatment funds show a downward trend, and the other variables have little change.

Table 1. Input–output variables from 2013 to 2017 statistical analysis.

		Labor Force	Total Capital Formation	Energy Consumption	Total Industrial Water Consumption	Wastewater Treatment Funds	Waste Gas Treatment Funds
Average	2013	148.6032	11,812.7645	1723.3352	459,258.0645	45,272.5484	83,133.5484
	2014	182.6548	12,682.8452	1794.7323	453,709.6774	40,284.6129	206,745.4194
	2015	182.1581	13,043.6935	1836.5487	437,548.3871	37,176.5806	254,643.0645
	2016	176.2806	13,773.8355	1927.3248	430,580.6452	38,198.0645	168,325
	2017	170.4032	14,564.3548	2034.7742	421,935.4839	34,916	181,119.3871
Max	2013	561	30,952.9	4956.62	1,931,000	263,797	303,865
	2014	1052.4	33,780.8	5235.23	2,201,000	150,634	701,240
	2015	1046	35,587.4	5310.69	2,380,000	175,141	1,281,351
	2016	1011.7	34,647.1	5610.13	2,390,000	164,863	781,673
	2017	991	39,657.5	5959	2,486,000	158,518	966,722
Min	2013	1.5	899.1	30.65	17,000	922	174
	2014	2.1	1052.1	33.98	17,000	572	466
	2015	2.1	1032	40.53	17,000	90	1453
	2016	2.3	1162.8	49.22	14,000	893	273
	2017	1.6	1376.1	58	16,000	15	47
St. Dev	2013	134.3751	7620.3602	1242.815	440,588.3164	51,282.9423	73,775.0457
	2014	209.0452	8142.8745	1289.1049	460,820.1524	38,242.0501	162,597.069
	2015	211.8303	8407.9079	1365.0845	475,238.4551	37,554.2495	260,514.5884
	2016	205.8528	8924.2812	1451.4981	479,438.3363	41,606.7403	159,393.1626
	2017	200.9428	9999.0218	1520.3991	490,473.7122	38,104.0369	197,602.603
		Total Wastewater Discharge	**Lead in WASTEWA-TER**	**SO_2**	**Smoke and Dust**	**Industrial Output Value**	
Average	2013	224,336.5161	2455.2355	85.181	41.231	8629.4897	
	2014	231,024.1613	2360.7935	63.6906	56.1532	8946.4632	
	2015	237,200.8387	2562.2484	59.9719	49.6135	8874.8148	
	2016	229,385.5806	1707.4355	35.5765	32.6023	9199.2548	
	2017	225,697.129	1237.0387	28.2394	25.6861	9731.27	
Max	2013	862,471	24,318.6	663	131.33	27,426.26	
	2014	905,082	21,609.3	159.02	179.77	29,144.15	
	2015	911,523	18,172.8	152.57	157.54	30,259.49	
	2016	938,261	14,564.8	113.45	125.68	32,650.89	
	2017	882,020	7656.9	73.91	80.37	35,291.83	
Min	2013	5005	2.6	0.42	0.68	61.16	
	2014	5450	2.5	0.42	1.39	66.16	
	2015	5883	3.6	0.54	1.71	69.88	
	2016	6143	5.1	0.54	1.65	86.44	
	2017	7176	3.7	0.35	0.66	102.16	
St. Dev	2013	184,430.1127	4632.3228	114.938	30.1237	7120.6401	
	2014	190,473.1071	4170.2846	39.6557	42.5921	7468.1265	
	2015	195,601.8016	4068.4679	37.3853	38.3135	7741.992	
	2016	194,225.7237	3159.2792	25.0893	26.6502	8400.5834	
	2017	185,112.1309	1898.2696	19.5832	18.5803	9102.946	

4.3. Empirical Results

In this study, 31 provinces and municipalities in China were divided into two groups: the Yellow River Basin and the Non-Yellow River Basin. The DDF method was used to evaluate the difference in industrial production efficiency between the two groups. The common boundary efficiency and group boundary efficiency of the two groups are evaluated by the TGR method to find the technology gap ratio. The results and analysis are as follows.

(1) Industrial production efficiency of DDF in the Yellow River and Non-Yellow River Basins

The empirical results show that (as shown in Figure 4 and Appendix A) the best average value of the total efficiency of the Yellow River and Non-Yellow River basins is 1 in 17 provinces and cities, including Beijing, Tianjin and Hebei, of which only Shandong and Sichuan are located in the Yellow River Basin, and a total of 15 provinces and cities are located in the Non-Yellow River Basin. The average total efficiency of the Non-Yellow River Basin is 0.9793, and the three worst-performing regions are Yunnan (0.7804), Xinjiang (0.9188) and Guizhou (0.9257). The average value of the total efficiency of the Yellow River Basin is 0.9688, which is slightly lower than that of the Non-Yellow River Basin. The three regions with the worst performance of the total efficiency are Gansu (0.8604), Shanxi (0.9417) and Ningxia (0.9592). We further explore the period efficiency of each year in the Non-Yellow River Basin, with the best performance in 2015 and 2016, the efficiency value is 0.982, the worst performance is 0.9741 in 2013, of which Yunnan (0.7197) has the worst efficiency performance. In the part of efficiency in each year of the Yellow River Basin, only 0.9863 performed best in 2013, slightly higher than 0.9741 in the Non-Yellow River Basin. In the next four years, the overall efficiency performance lagged behind the Non-Yellow River Basin. The overall efficiency performance was the worst in 2015 (0.9561), of which Gansu (0.7593) performed the worst in 2015.

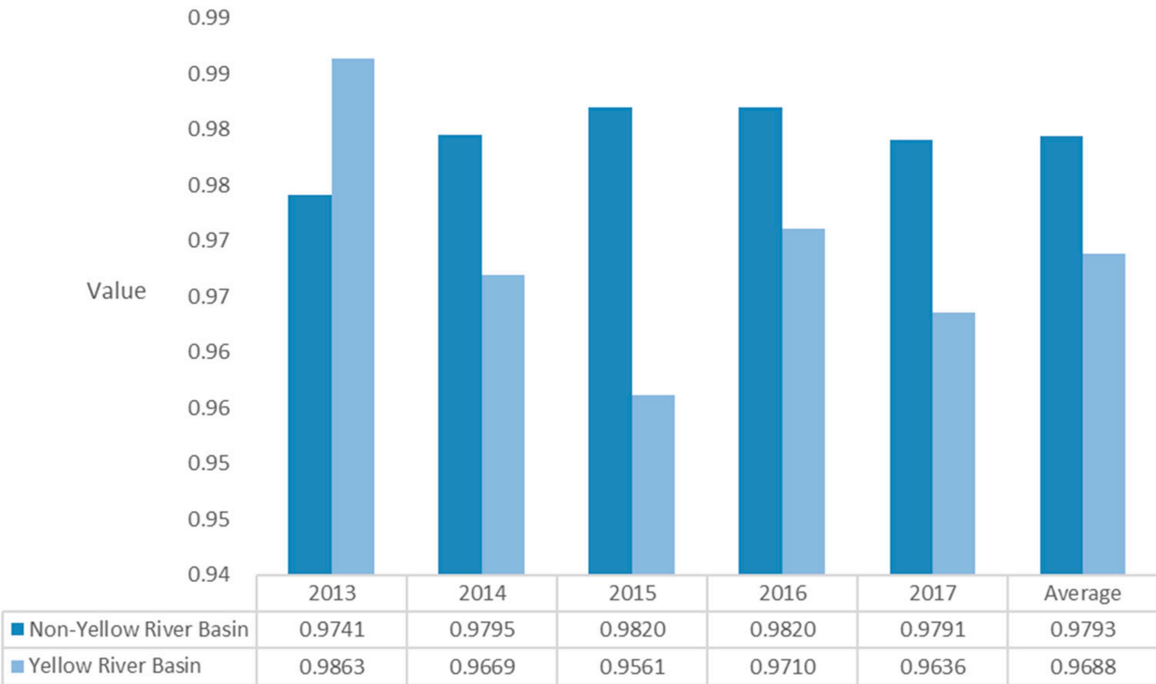


Figure 4. Efficiency of DDF in the Yellow River and Non-Yellow River Basins from 2013 to 2017.

This study further uses the Wilcoxon rank sum test to make $\alpha = 0.05$; the confidence interval is 95%, and the result shows that $z = -3.517$, which indicates that there are regional differences in DDF efficiency between the Yellow River Basin and the Non-Yellow River Basin, and the efficiency value of the Non-Yellow River Basin is better than that of the Yellow River Basin.

(2) Analysis of TGR technology gap ratio between the Yellow River and Non-Yellow River Basins

We use TGR to objectively measure the level of industrial production efficiency. When the TGR value is closer to 1, it means that the industrial production efficiency is relatively high and the efficiency is better. On the contrary, the lower or closer the TGR value is to

0, the more it indicates that there is still room for significant improvement. According to the TGR of 31 provinces and cities in China from 2013 to 2017 (Figure 5 and Appendix B), the TGR values of 22 provinces and cities in the Non-Yellow River Basin are less than 1, indicating that the technical level has not reached the technical level on the common boundary, which can improve the efficiency of industrial production and pollution control. The average value of TGR is 0.5234, and a total of 12 regions are higher than the average value. The better-performing regions are Tibet (0.9876), Hainan (0.8965) and Liaoning (0.8675), the three worst-performing regions are Hubei (0.1413), Guangxi (0.1321) and Hunan (0.1156). The TGR values of nine provinces, cities and administrative regions in the Yellow River Basin are also less than 1. The average TGR value is 0.3825, which is lower than the average TGR value of the Non-Yellow River Basin by 0.5234. In total, the four regions are higher than the average value. The better-performing regions are Ningxia (0.7545), Qinghai (0.5708) and Shandong (0.5411), and the three worst-performing regions are Sichuan (0.1965), Shaanxi (0.1822) and Inner Mongolia (0.1152).

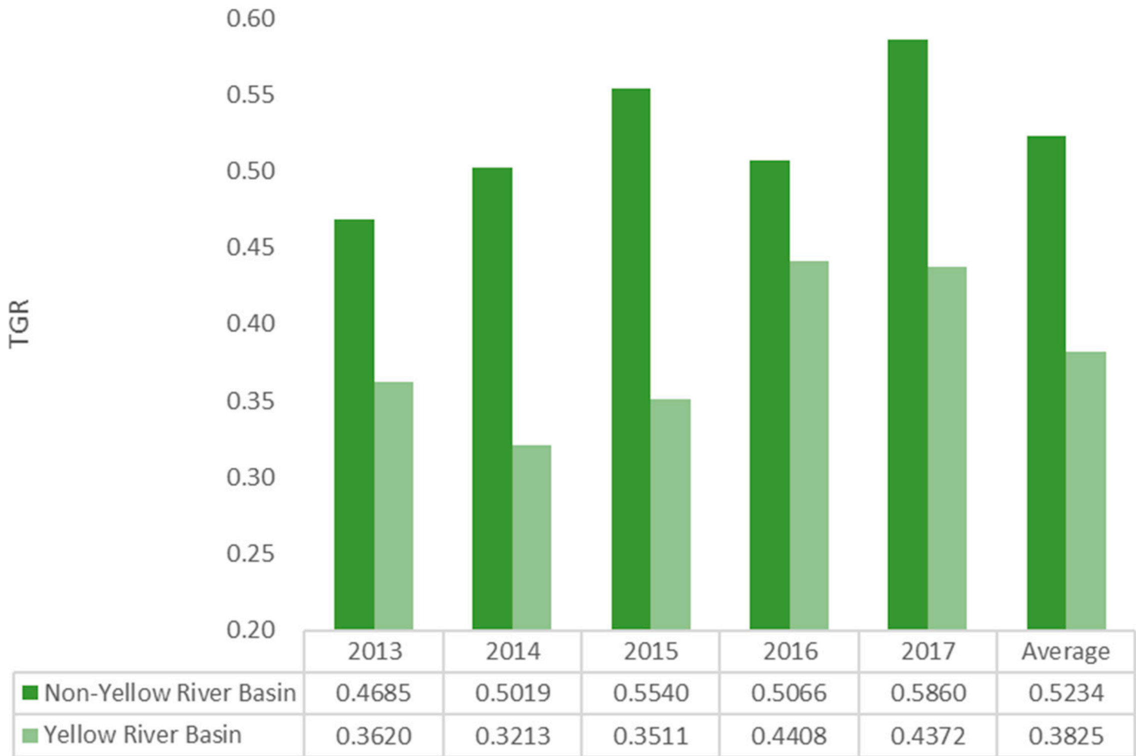
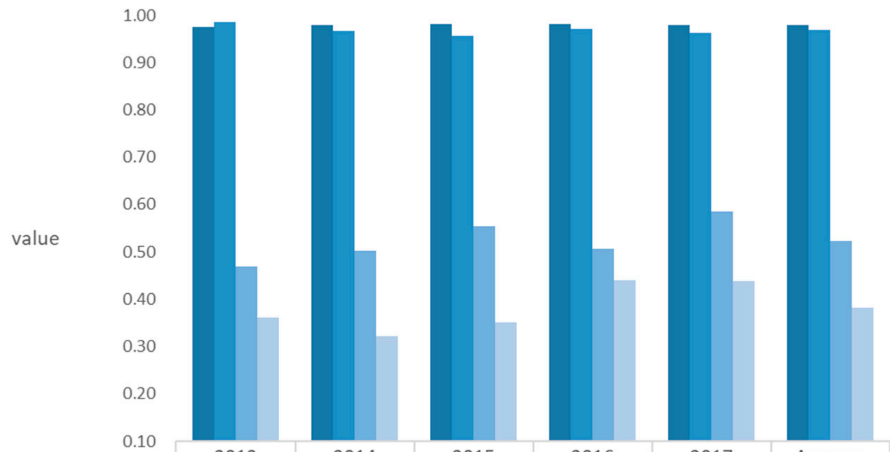


Figure 5. TGR analysis of the Yellow River and Non-Yellow River basins from 2013 to 2017.

Based on the combined analysis of DDF efficiency and TGR results of the Yellow River and Non-Yellow River basins from 2003 to 2007 (Figure 6), the overall efficiency performance of the two regions has little change during the study period. Among them, the Yellow River Basin was only slightly better than the Non-Yellow River basin (0.9863) in 2013 (0.9741), but in the TGR part, the performance of the two regions still has room for significant improvement. Among them, the TGR of the Yellow River Basin is significantly behind the Non-Yellow River Basin. Through reasonable human and capital allocation, we can implement the use of pollution prevention and control funds, and improve the technical level of industrial production to improve pollutant emission and increase output value, to improve the overall efficiency performance.



	2013	2014	2015	2016	2017	Average
DDF efficiency in Non-Yellow River Basin	0.9741	0.9795	0.9820	0.9820	0.9791	0.9793
DDF efficiency in the Yellow River Basin	0.9863	0.9669	0.9561	0.9710	0.9636	0.9688
TGR in Non-Yellow River Basin	0.4685	0.5019	0.5540	0.5066	0.5860	0.5234
TGR in the Yellow River Basin	0.3620	0.3213	0.3511	0.4408	0.4372	0.3825

Figure 6. Analysis of DDF efficiency and TGR in the Yellow River and Non-Yellow River basins from 2013 to 2017.

5. Conclusions and Suggestions

Using DDF and TGR methods, this study invested industrial production departments and pollution control departments in parallel to explore the impact of pollution control on industrial production efficiency in 31 provinces and municipalities in the Yellow River and Non-Yellow River basins of China.

5.1. Conclusions

(1) During the study period, the total efficiency of the Non-Yellow River Basin was 0.9793, slightly better than that of the Yellow River Basin of 0.9688. Among the 17 provinces and cities with a total efficiency of 1, only Shandong and Sichuan were located in the Yellow River Basin, and the other 15 provinces and cities were located in the Non-Yellow River Basin, indicating that the industrial production efficiency still had significant regional differences due to the input of production factors and pollution control funds.

(2) During the study period, the TGR values of 31 provinces and municipalities in the Yellow River Basin and Non-Yellow River Basin were less than 1, while the average TGR value of the Yellow River Basin was 0.3825, which was lower than the average TGR value of Non-Yellow River Basin by 0.5234, indicating that the technical level did not reach the technical level on the common boundary, and there is still room for substantial improvement. In order to achieve the sustainable development goals of SDG-6 and SDG-9, in addition to the cost of pollution prevention and control, clean energy should be developed to reduce pollution, and rational allocation of resources should be used to improve industrial production technology and overall efficiency.

(3) The main contribution of this study is in introducing the method of parallel DEA; in addition to many input variables in the industrial production sector, we also discuss the impact of the financial input of the pollution control department on wastewater, exhaust emissions and total efficiency. In addition, this study covers the research scope of the Yellow River Basin and the Non-Yellow River Basin, which helps to provide broader policy recommendations.

5.2. Research Recommendations

The open and quantifiable data of the Yellow River and Non-Yellow River basins in this study are taken from the database of the National Bureau of Statistics of China. The pollution control is carried out through open and objective data. The analysis of China's industrial production efficiency has restrictions on the selection of input- and output-related variables due to the difficulty in obtaining and omission of some data. It is suggested that, in the future, scholars more widely consider relevant data and extend the observation period to make the research results more objective. In addition, this study mainly focuses on the Yellow River and Non-Yellow River basins. It is suggested that different basins such as the Yangtze River and the Pearl River be added as object of discussions in the future to make a longer-cycle cross-basin comparison with each other, to understand China's efforts in industrial production and pollution control, and to provide analysis and basis for SDG-6 and SDG-9 sustainable development goals and policies.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Efficiency of DDF in the Yellow River and Non-Yellow River basins from 2013 to 2017.

	DMU	2013	2014	2015	2016	2017	Average
Non-Yellow River Basin	Beijing	1	1	1	1	1	1
	Tianjin	1	1	1	1	1	1
	Hebei	1	1	1	1	1	1
	Liaoning	1	1	1	1	1	1
	Jilin	1	1	1	1	1	1
	Black Dragon River	1	1	0.9822	1	0.9153	0.9795
	Shanghai	1	1	1	1	1	1
	Jiangsu	1	1	1	1	1	1
	Zhejiang	1	1	1	1	1	1
	Anhui	1	1	1	1	1	1
	Fujian	0.9452	0.9623	0.9628	0.9739	1	0.9688
	Jiangxi	1	1	1	1	1	1
	Hubei	0.9752	1	1	1	1	0.9950
	Hunan	1	1	1	1	1	1
	Guangdong	1	1	1	1	1	1
	Guangxi	0.9851	0.9599	0.9883	1	0.9535	0.9774
	Hainan	1	1	1	1	1	1
	Chongqing	1	1	1	1	1	1
	Guizhou	0.8202	0.8524	0.956	1	1	0.9257
	Yunnan	0.7197	0.7832	0.8194	0.8017	0.7779	0.7804
	Tibet	1	1	1	1	1	1
	Xinjiang	0.9856	0.9906	0.8959	0.829	0.8928	0.9188
	Average	0.9741	0.9795	0.9820	0.9820	0.9791	0.9793

Table A1. *Cont.*

	DMU	2013	2014	2015	2016	2017	Average
Yellow River Basin	Shanxi	0.9803	0.9184	0.8889	0.9211	1	0.9417
	Inner Mongolia	1	1	1	1	0.9912	0.9982
	Shandong	1	1	1	1	1	1
	Henan	1	0.9553	0.9696	1	1	0.9850
	Sichuan	1	1	1	1	1	1
	Shaanxi	1	1	0.9871	1	1	0.9974
	Gansu	0.9196	0.9101	0.7593	0.8367	0.8763	0.8604
	Qinghai	1	1	1	0.9816	0.9041	0.9771
	Ningxia	0.9771	0.9183	1	1	0.9005	0.9592
	Average	0.9863	0.9669	0.9561	0.9710	0.9636	0.9688

Appendix B

Table A2. TGR analysis of the Yellow River and Non-Yellow River basins from 2013 to 2017.

	DMU	2013	2014	2015	2016	2017	Average
Non-Yellow River Basin	Tibet	0.9999	0.9905	0.9475	0.9999	1.0000	0.9876
	Hainan	0.8629	1.0000	1.0000	0.6278	0.9917	0.8965
	Liaoning	0.7303	0.9488	0.9319	0.8129	0.9134	0.8675
	Black Dragon River	1.0000	0.8539	0.7762	0.8059	0.9007	0.8673
	Beijing	0.3992	0.8811	1.0000	0.9602	1.0000	0.8481
	Tianjin	0.8239	0.8445	0.8448	0.6499	0.9749	0.8276
	Chongqing	0.7837	0.6317	0.8055	0.7210	1.0000	0.7884
	Shanghai	0.6246	0.8022	0.6441	0.5595	1.0000	0.7261
	Hebei	0.5811	0.6070	0.5647	0.5945	0.6271	0.5949
	Jilin	0.6069	0.6110	0.5334	0.4927	0.7060	0.5900
	Jiangsu	0.4275	0.4250	0.4565	0.6617	0.8183	0.5578
	Zhejiang	0.5043	0.5831	0.4352	0.5733	0.5748	0.5341
	Guizhou	0.2885	0.2245	0.6365	0.8179	0.3949	0.4725
	Xinjiang	0.4264	0.4511	0.4149	0.2540	0.2649	0.3623
	Yunnan	0.1555	0.1228	1.2204	0.1098	0.1180	0.3453
	Guangdong	0.2396	0.2759	0.2457	0.2527	0.3327	0.2693
	Fujian	0.1190	0.1098	0.1074	0.5034	0.2717	0.2223
	Anhui	0.1420	0.1688	0.1492	0.2067	0.3441	0.2022
	Jiangxi	0.2279	0.1759	0.1545	0.1403	0.1336	0.1664
	Hubei	0.1083	0.1171	0.1063	0.1685	0.2065	0.1413
	Guangxi	0.1500	0.1202	0.1116	0.1289	0.1498	0.1321
	Hunan	0.1053	0.0971	0.1026	0.1043	0.1685	0.1156
	Average	0.4685	0.5019	0.5540	0.5066	0.5860	0.5234
	DMU	**2013**	**2014**	**2015**	**2016**	**2017**	**Average**
Yellow River Basin	Ningxia	0.7257	0.5888	0.9243	1.0000	0.5335	0.7545
	Qinghai	0.5908	0.5105	0.6123	0.5184	0.6219	0.5708
	Shandong	0.4784	0.5117	0.5014	0.7260	0.4879	0.5411
	Shanxi	0.5274	0.3898	0.2413	0.6932	0.8063	0.5316
	Gansu	0.2921	0.2695	0.2941	0.2438	0.2970	0.2793
	Henan	0.1332	0.1277	0.2076	0.2589	0.6282	0.2711
	Sichuan	0.2343	0.2222	0.1036	0.2253	0.1971	0.1965
	Shaanxi	0.1672	0.1651	0.1600	0.1811	0.2375	0.1822
	Inner Mongolia	0.1090	0.1059	0.1154	0.1205	0.1254	0.1152
	Average	0.3620	0.3213	0.3511	0.4408	0.4372	0.3825

Note: the total average value of TGR in the Yellow River and non yellow river basins is 0.4825.

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