

## Evaluation of Green Total Factor Productivity in the Yellow River Basin of China

Jingcheng Li<sup>1</sup>, Guangwei Rui<sup>2</sup> and Xinyi Mei<sup>3\*</sup>

<sup>1</sup>*School of Economics and Management, Beijing Jiaotong University, China*

<sup>2</sup>*School of Economics and Management, Beijing Jiaotong University, China*

<sup>3</sup>*Beijing Laboratory of National Economic Security Early-warning Engineering, Beijing Jiaotong University, China*

**\*Corresponding Author:** Xinyi Mei, Beijing Laboratory of National Economic Security Early-warning Engineering, Beijing Jiaotong University, Beijing, China.

**Received:** May 31, 2022; **Published:** June 10, 2022

**DOI:** 10.55162/MCET.03.053

### Abstract

The Yellow River Basin is an important energy production base, heavy industry base, and grain production area in China. Meanwhile, the ecological environment in this area is also very fragile. The success of carbon emission control in this region is related to whether China can complete its vision of carbon peak and carbon neutralization on time. Taking carbon emissions as the non-ideal output of the economy into the nonparametric DEA Malmquist index model, this paper measures the green Malmquist index of 9 provinces in the Yellow River Basin from 2014 to 2020 and analyzes the impact of the green Malmquist index, green technology efficiency and green technology progress rate on the regional economic growth gap and its time evolution trend. The results show that the green total factor productivity of the region shows a fluctuating upward trend from 2014 to 2020, but the direction of efficiency progress is negative. Therefore, the Yellow River Basin needs to reform the management system of high energy-consuming industries and strengthen environmental supervision in the future. In addition, the changes in green total factor productivity in various provinces show high heterogeneity, which poses new challenges to the formulation of emission reduction policies.

**Keywords:** The Yellow River Basin; Energy industry; Carbon control; Green total factor productivity

### Abbreviations

GTFP: Green total factor productivity.

ML: Malmquist-Lunberger index.

EC: Efficiency changes in technology.

TC: Technology changes.

### Introduction

Continued climate warming has caused irreversible damage to the global ecological, social, and economic environment. China, currently the largest source of carbon emissions, has announced its ambitious vision for carbon reduction. The nine provinces located in the Yellow River Basin (Shandong, Henan, Shanxi, Inner Mongolia, Ningxia, Shaanxi, Sichuan, Gansu, and Qinghai) face several challenges such as resource depletion and ecological degradation, which require more refined carbon emission control strategies [1]. Especially after the Chinese government promulgated the Outline of the Plan for Ecological Protection and High-Quality Development of the Yellow River Basin on October 8, 2021, this region has attracted more academic attention. The Yellow River Basin plays an essen-

tial role in China's food security and energy security. Therefore, it is necessary to evaluate the green transition status of this region [2].

Total factor productivity has been widely used to study the sources of economic growth and factors related to economic and social sustainability. On the premise that the input level of various production factors remains unchanged, the additional production efficiency is total factor productivity. For example, if a country's input factors, such as capital and labor, increase by 10% respectively, and if there is no productivity progress, the increase of output should also be 10%; if the output increases by more than 10%, such as 15%, the additional 5% is statistically "residual", which is the contribution of total factor productivity to output in industrial economics. Scholars generally believe that one way to improve total factor productivity is to improve production efficiency through technological progress, and the other is to improve allocation efficiency through the re combination of production factors. From the micro level, enterprises adopt new technologies and processes, which can improve total factor productivity. At the macro level, total factor productivity can be improved through resource reallocation, such as the transfer of labor force from agricultural production sector to efficient service industry.

However, in the process of measuring economic growth, the traditional total factor productivity does not take resources and environmental factors into account. The calculated results will not be conducive to the accurate evaluation of social welfare changes and economic performance, and may mislead the policy suggestions, making the economic development in the direction of "only GDP" and not conducive to the construction of an environment-friendly society. Especially after the 21st century, with the development of science, the popularity of the concept of green development and the deterioration of environmental pollution, the academic community began to pay more attention to the role of environment, which is no longer an endogenous variable of economic development, but also a rigid constraint of high-level economic development [3]. Since Chung (1997), scholars have tried to incorporate environmental factors into the measurement system of total factor productivity and named it green total factor productivity or environmental total factor productivity [4].

Pittman's research began to incorporate undesirable outputs, such as carbon emissions and sewage, into the production efficiency evaluation system [5], and Chung's innovation was made on this evaluation system. An environmental regulation behavior analysis model Activity Analysis Model based on Directional Distance Function is proposed by Chung et al. The introduction of Directional Distance Function is a methodological breakthrough, which can reasonably fit the restrictive effect of environmental factors in the production process and make it possible to capture the real economic effect of environmental regulation.

In order to comprehensively evaluate the current status of green transformation in the Yellow River Basin and make targeted recommendations, this paper chooses to assess the green total factor productivity of this region.

## Materials and Methods

### Study area

The Yellow River originates from the Qinghai-Tibet Plateau and enters the sea in Shandong Province, spanning 5400 km. According to the planned scope of the Outline of the Plan for Ecological Protection and High-Quality Development of the Yellow River Basin, promulgated by the State Council of China, the Yellow River Basin contains nine provinces: Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shanxi, Shaanxi, Henan, and Shandong. As Figure 1 shows.

### Model introduction

According to the definition of [6], we calculated the DDF as

$$\bar{D}_0(x, y, b; g_y, -g_b) = \sup\{\beta: (y + \beta g_y, -\beta g_b) \in p(x)\} \quad (1)$$

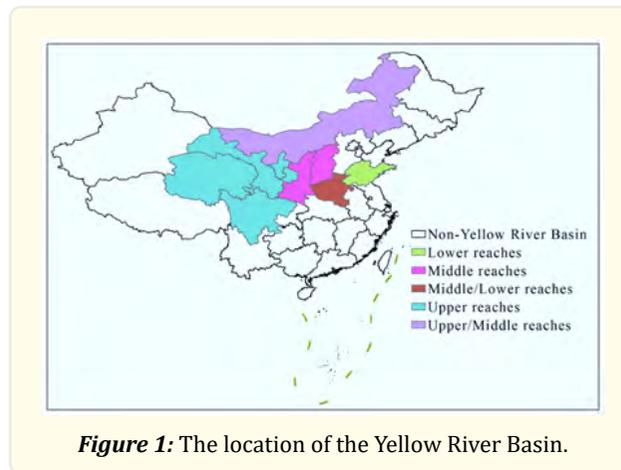


Figure 1: The location of the Yellow River Basin.

We used the SBM - Undesirable model and Malmquist - Lunberger index to construct a green total factor productivity index for each province in the Yellow River Basin for the period 2014-2020 [7, 8].

**SBM-Undesirable model**

Data Envelopment Analysis (DEA) is widely used in the field of efficiency evaluation in management and economics. As a non-parametric frontier method, DEA method can evaluate efficiency without setting the specific form of the production function and the weights of environmental indicators and has a higher objectivity. Traditional radial DEA does not address the input-output relaxation problem, which may lead to biased results, so Tone [9] introduced a more effective SBM model, which can effectively avoid the errors caused by radial and angular selection.

Suppose a system has n decision units ( $DMU_j, j = 1, 2, \dots, n$ ) and each decision unit has three types of input-output indicators ( $i = 1, 2, \dots, m$ ). Each DMU has three types of input-output indicators, including m inputs ( $i = 1, 2, \dots, m$ ),  $s_1$  desired outputs and  $s_2$  non-desired outputs, represented by vectors:  $x \in R^m, y^g \in R^{s_1}, y^b \in R^{s_2}$ , and the matrices X,  $Y^g, Y^b$  are defined as follows:

$$X = [x_1, x_2, \dots, x_n] \in R^{m \times n}, Y^g = [y_1^g, y_2^g, \dots, y_n^g] \in R^{s_1 \times n}, Y^b = [y_1^b, y_2^b, \dots, y_n^b] \in R^{s_2 \times n}.$$

According to the input-output reality, where  $X > 0, Y^g > 0, Y^b > 0$ . Therefore, the production possibility set under the condition of constant payoff to scale (CRS) is defined as:

$$P = \{(x, y^g, y^b) \mid x \geq \lambda X, y^g \leq \lambda Y^g, y^b \geq \lambda Y^b, \lambda \geq 0\} \quad (2)$$

In the Equation (2),  $\lambda$  is a weighting variable with a non-negative value. The formula indicates that the actual input is not lower than the frontier input level, the actual desired output does not exceed the frontier desired output, and the actual non-desired output is not lower than the frontier non-desired output.

The expression of the SBM model is as follows.

$$\begin{aligned} \min \rho = & \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left( \sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b} \right)} \\ & \begin{cases} x_0 = \lambda X + s^- \\ y_0^g = \lambda y^g + s^g \\ y_0^b = \lambda y^b + s^b \end{cases} \quad (3) \\ & s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{aligned}$$

Where  $s$  denotes the slack variables and  $\lambda$  is the weight vector. When  $\rho=1$ , the slack variables are all zero, the corresponding decision unit is valid; when  $0 < \rho < 1$ , the corresponding decision unit is invalid, and the input-output can be improved by eliminating the slack.

**Malmquist -Lunberger index**

In 1953, the Swedish economist Sten Malmquist introduced the idea of using the ratio of scaling factors to construct an index of consumption quantities, which is actually the number of times a given consumption mix needs to be scaled in order to reach a certain non-differentiable surface [10]. This idea was applied to productivity analysis by many researchers and named the Malmquist productivity index [11]. The Malmquist index does not take into account negative output, so Chung et al. extended the Malmquist index to the Malmquist-Lunberger index (later referred to as the ML index) by adding environmental factors to the Malmquist index.

We can define the Malmquist -Lunberger index from period  $t$  to period  $t + 1$  as:

$$ML\_TFP_t^{t+1} = \left[ \frac{(1 + \bar{D}_0^t(x^t, y^t, b^t, -b^t))}{(1 + \bar{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}, -b^{t+1}))} \times \frac{(1 + D_0^{t+1}(x^t, y^t, b^t, -b^t))}{(1 + \bar{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}, -b^{t+1}))} \right]^{\frac{1}{2}} \quad (4)$$

Where  $ML\_TFP > 0$  indicates green total factor productivity growth and  $ML\_TFP < 0$  indicates green total factor productivity decline. ML can be further decomposed into an index of efficiency change and an index of technological change, both of which are calculated as follows.

$$ML_t^{t+1} = ML\_EFFCH \times ML\_TECH \quad (4)$$

$$ML\_EFFCH_t^{t+1} = \frac{(1 + \bar{D}_0^t(x^t, y^t, b^t, -b^t))}{(1 + D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}, -b^{t+1}))} \quad (5)$$

$$ML\_TECH_t^{t+1} = \left[ \frac{(1 + \bar{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}, -b^{t+1})) (1 + D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}, -b^{t+1}))}{(1 + \bar{D}_0^t(x^t, y^t, b^t, -b^t))} \right]^{\frac{1}{2}} \quad (6)$$

Where  $ML\_EFFCH$  denotes output growth caused by changes in production efficiency and  $ML\_TECH$  denotes output growth caused by technological progress.  $ML\_EFFCH > 0$  and  $ML\_TECH > 0$  denote technical efficiency increase and technological progress, respectively, and conversely,  $ML\_EFFCH < 0$  and  $ML\_TECH < 0$  denote technical efficiency decline and technological regression, respectively. The calculation of Equation (6) requires solving four directional distance functions, including the current period directional distance functions  $\bar{D}_0^t(x^t, y^t, b^t, -b^t)$  and  $D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}, -b^{t+1})$ , and two mixed directional distance functions  $\bar{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}, -b^{t+1})$  and  $D_0^{t+1}(x^t, y^t, b^t, -b^t)$ .

**Data source**

The factors for the ML index calculation in this paper are shown in Table 1.

Indicators	Variables	Data source	Unit
Input	Capital	Follow the method of [12]	100 million yuan
	Labor	Statistical Yearbook by Province	10,000 people
	Energy	Energy Statistics Yearbook	10,000 tons of standard coal
Output	GDP (Desired output)	National Statistical Yearbook (2013 constant prices)	100 million yuan
	CO2 (Non-desired outputs)	CEADS [13]	Million tons

**Table 1:** Factors in the ML index.

Descriptive statistics of all parameters are shown in Table 2.

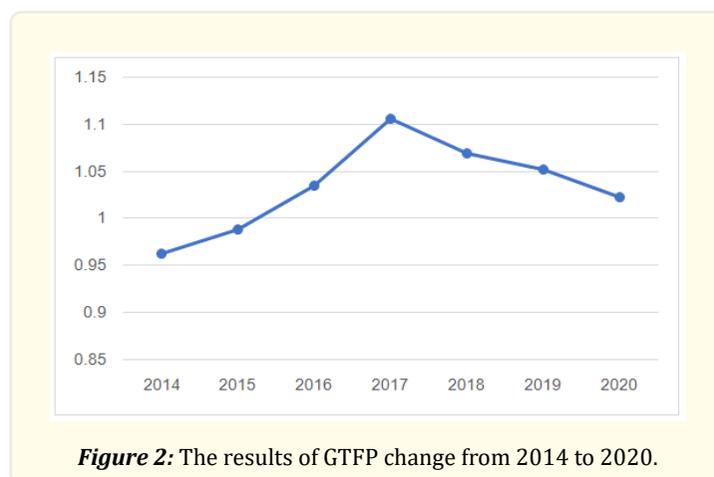
<i>Variables</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>Standard deviation</i>
Capital	2602.997	6737	314.2	2013.745
Labor	13830.282	37036.11585	2222.98	10898.491
Energy	17027.180	42000	3768	10313.852
GDP	23635.717	73129	2122.06	20558.001
CO2	394.942	992.4525723	47.9	256.265

**Table 2:** Descriptive statistics of variables.

## Results and Discussion

MaxDea8 software was used to calculate the green total factor productivity GML for the relevant input-output indicators, and the results are as follows.

### Time Series Analysis



**Figure 2:** The results of GTFP change from 2014 to 2020.

As can be seen from Figure 2, the green ML index of the Yellow River Basin provinces shows an overall increasing trend during 2014-2020. However, after 2017, the GTFP in the Yellow River Basin, although still positive, grew at a significantly slower rate than in 2016 and 2017. This indicates that the effect of the original green transformation policy has diminishing marginal effect after 2017, and the related policy design needs to be upgraded and updated.

Further analysis of GTFP changes across provinces was conducted (Figure 3). We find significant variation in GTFP changes across provinces, with several provinces excelling in this indicator; especially in Qinghai and Ningxia, where the change from ML less than 1 to ML greater than 1 was achieved around 2016, indicating that the green total factor productivity of the two places has increased significantly. In 2020, among the nine provinces, only Shanxi and Gansu have ML less than 1. Compared to the previous time period when they were in a more inefficient state, both Shanxi and Gansu experienced fluctuations in ML, which had reached a level of 1.32 in 2017, but did not maintain this growth trend afterwards. Apart from Shanxi and Gansu, Shaanxi's ML is around 1 in 2020, indicating that its green total factor productivity did not improve significantly in that year.

Further decomposing the green total factor productivity of each province, it is found that the contribution of efficiency changes (EC), is much lower than that of technology changes (TC).

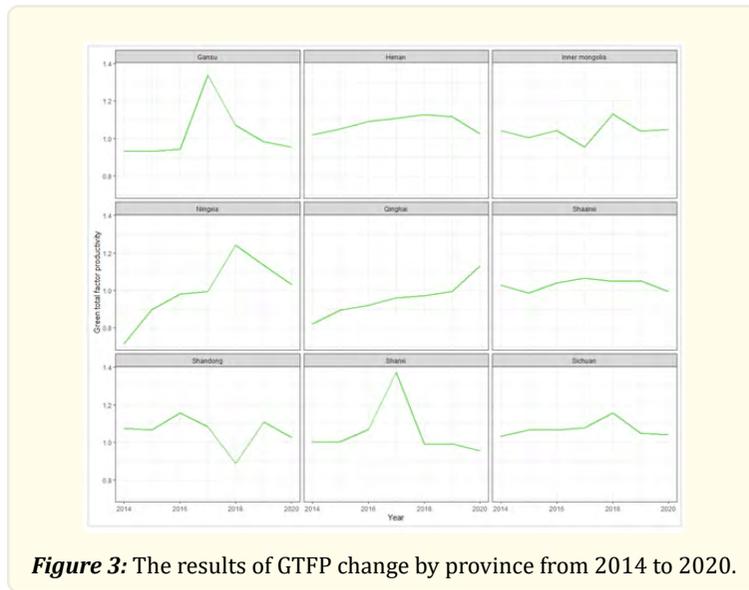


Figure 3: The results of GTFP change by province from 2014 to 2020.

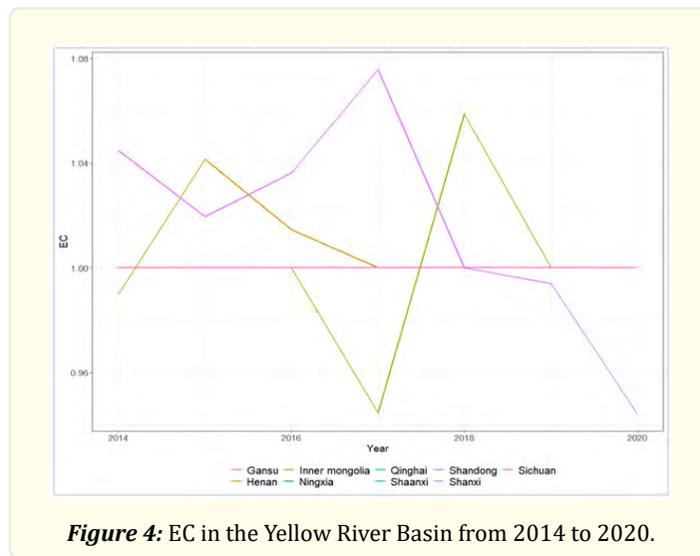
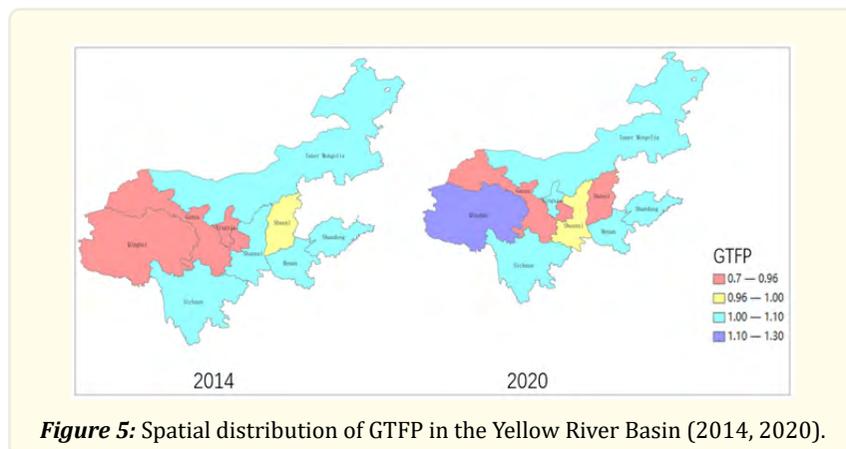


Figure 4: EC in the Yellow River Basin from 2014 to 2020.

It can be seen from figure X that most provinces show a stable EC of 1, and only Henan, Inner Mongolia and Shanxi have changed in efficiency. From 2014 to 2016, the efficiency of Henan Province showed a positive change, while that of Inner Mongolia showed a fluctuating trend, but it remained stable around 2020.

Shanxi is the only province with a continuous decline in EC, which needs to be paid enough attention. Before 2012, Shanxi Province took large-scale coal mining as its pillar industry, resulting in environmental pollution, insufficient power for industrial upgrading and many other problems. With the depletion of coal resources, Shanxi Province has experienced a large-scale industrial adjustment, its tertiary industry has gradually become the leading industry, and people’s work choices have also shifted from industry to service industry.

*Spatial analysis*



**Figure 5:** Spatial distribution of GTFP in the Yellow River Basin (2014, 2020).

From the perspective of spatial distribution of green total factor productivity (Figure 5), there was a great difference between the upper and middle lower reaches of the Yellow River Basin in 2014. Specifically, Qinghai, Gansu and Ningxia provinces have experienced a decline in green total factor productivity. Except Shanxi Province, the middle and lower reaches have shown an upward trend, and the GTFP score of Shanxi Province is also greater than 0.96, which is in a weak recession. In 2020, Qinghai Province, located in the upper reaches of the Yellow River, has made great progress in GTFP, which is the only province with a score of more than 1.1. Ningxia also shows a trend of progress, but it is worrying that Gansu Province is still lower than 0.96. In the middle and lower reaches, the GTFP level of Shanxi Province has declined significantly. Compared with 2014, the GTFP level of Shaanxi Province has declined slightly. From 2014 to 2020, the GTFP of Inner Mongolia, Shandong, Henan and Sichuan provinces is still higher than 1, showing a positive trend of green transformation.

The average ML indices, EC and TC, for the upper and middle reaches of the Yellow River for the time period 2014 to 2020 are shown in Table 3. The change in the ML index of the Yellow River Basin is consistent with the economic level, with the downstream areas located in the eastern region making the greatest progress, followed by the midstream provinces located in the central region, and the upstream provinces located in the western region making the least progress. Despite the fragile ecological environment, backward agriculture and unreasonable industrial structure, the western region has maintained positive progress in efficiency and technology, which demonstrates the effectiveness of the “Western Development” policy.

<i>Province</i>	<i>ML index</i>	<i>EC</i>	<i>TC</i>
Henan	1.0765	1.0066	1.0697
Shandong	1.0573	1.0000	1.0573
Downstream	1.0700	1.0030	1.0635
Shaanxi	1.0312	1.0000	1.0312
Shanxi	1.0540	1.0164	1.0349
Midstream	1.0426	1.0082	1.0331
Qinghai	0.9566	1.0000	0.9566
Gansu	1.0214	1.0000	1.0214
Sichuan	1.0694	1.0000	1.0694
Inner mongolia	1.0373	1.0005	1.0363
Ningxia	0.9996	1.0000	0.9996
Upstream	1.0169	1.0001	1.0167

**Table 3:** Average index by province (ML, EC and TC).

## Conclusion

We analyze the green economic efficiency of the Yellow River Basin from a static perspective and find that the average efficiency value of the downstream region is the highest and has a steady increasing trend, the upstream region is the most stable, and the mid-stream region has the highest variation. Looking at green total factor productivity (GTFP) from a dynamic perspective reveals that most of the provinces in the Yellow River Basin show an increasing trend in the ML index, while Qinghai and Ningxia show a decrease in the ML index during this period, which requires more attention from local governments.

The GTFP decomposition of each province revealed that the trend of ML index in Shandong, Shaanxi, Sichuan, Gansu, Qinghai and Ningxia is completely consistent with TC which means the change of GTFP is almost entirely from technological progress. While the change of GTFP in Shanxi mainly from technical efficiency improvement, and the change in GTFP in Henan and Inner Mongolia is partly from technical efficiency improvement and partly from technical progress.

The GTFPs of Shaanxi, Henan, and Sichuan provinces are relatively stable. Shandong and Inner Mongolia show a W-shaped fluctuation, indicating that their attitudes toward environmental protection have undergone a shift during this period. Ningxia, Gansu, Sichuan and Shanxi show inverted-V shifts, indicating that their green transformation is not sustainable. In terms of spatial distribution, the green transformation in the lower reaches of the Yellow River basin is faster than in the middle and upper reaches. Compared with the upstream areas, the midstream areas face more pressure for green transformation. It is necessary to improve the technical efficiency and Overall, the GTFP of the nine provinces in the Yellow River Basin for 2014-2020 is stable and trending in a positive direction, but the changes vary significantly from province to province, and the Yellow River basin and the economic development of the nine provinces it passes through have their own characteristics. Therefore, there is no need to determine a pattern, and each province should formulate relevant policies to improve GTFP according to the local actual situation.

Faced with the spatial variability of GTFP in the Yellow River Basin, Shandong, Henan, Gansu, and Sichuan should focus on the improvement of technical efficiency (EC). Shanxi, Shaanxi, and Inner Mongolia should pay more attention to technological progress (TC). Ningxia and Qinghai should balance technical progress and technical efficiency to improve GTFP.

## Reference

1. Y Chen., et al. "Sustainable development in the Yellow River Basin: Issues and strategies". *Journal of Cleaner Production* 263 (2020): 121223.
2. C Kennedy., et al. "Greenhouse Gas Emissions from Global Cities". *Environ. Sci. Technol* 43.19 (2009): 7297-7302.
3. C Chen, Q Lan, M Gao and Y Sun. "Green Total Factor Productivity Growth and Its Determinants in China's Industrial Economy". *Sustainability* 10.4 (2018): 4.
4. YH Chung, R Färe and S Grosskopf. "Productivity and Undesirable Outputs: A Directional Distance Function Approach". *Journal of Environmental Management* 51.3 (1997): 229-240.
5. RW Pittman. "Multilateral productivity comparisons with undesirable outputs". *The Economic Journal* 372 (1983): 883-891.
6. YH Chung, R Färe and S Grosskopf. "Productivity and Undesirable Outputs: A Directional Distance Function Approach". *Journal of Environmental Management* 51.3 (1997): 229-240.
7. B Wang and G Liu. "Energy Conservation and Emission Reduction and Green Economic Growth in China - A Total Factor Productivity Based Perspective". *China's Industrial Economy* 05 (2015): 57-69.
8. S Chen. "China's Green Industrial Revolution: An Explanation Based on an Environmental Total Factor Productivity Perspective (1980-2008)". *Economic Research* 45.11 (2010): 21-34+58.
9. WW Cooper, LM Seiford and J Zhu. "Handbook on Data Envelopment Analysis". Springer Science & Business Media (2011).
10. S Malmquist. "Index numbers and indifference surfaces". *Trabajos de estadística* 4.2 (1953): 209-242.
11. DW Caves, LR Christensen and WE Diewert. "The economic theory of index numbers and the measurement of input, output, and productivity". *Econometrica: Journal of the Econometric Society* (1982): 1393-1414.

12. J Zhang and Y Zhang. "Re-estimation of China's capital stock K". Economic Research 7.35243 (2003): 675-699.
13. CEADs: Carbon Emission Accounts and Datasets for emerging economies (2021).

**Volume 3 Issue 1 July 2022**

**© All rights are reserved by Xinyi Mei., et al.**