Analysis of Grain Production Efficiency Differences in China Based on DEA-Malmquist Index

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Abstract. This paper presents a cross-sectional analysis of the data related to the input and output of grain production efficiency in 31 provinces of China in 2020 through the DEA-BCC model. It is concluded that the overall pure technical efficiency of grain production in China is good and the scale efficiency is weak, while the comprehensive efficiency development is influenced by both pure technical efficiency and scale efficiency. At the same time, a longitudinal analysis of production efficiency was carried out using the Malmquist index method with time as the axis. The study concluded that from 2011 to 2020, the value of grain TFP in China showed an upward trend, while the efficiency of technological progress showed an inverse trend to technical efficiency. It indicates that China's grain production suffers from the problems of uncoordinated inputs and outputs, poor infrastructure and low efficiency in transforming production resources.

Keywords: Grain production efficiency · DEA model · Malmquist index

1 Introduction

At present, the government attaches great importance to the issue of food security and ensures stable and increased grain production in China by implementing policy measures such as stabilising the cultivated area, improving the quality of cultivated land, increasing farmers' farming returns, and development and dissemination of good seeds. It is of great theoretical significance to study the factors affecting grain production efficiency and analyse the rationality of grain production indicators.

The evaluation of productivity plays a central role in food-output theoretical research, and a common analytical method is data envelopment analysis (DEA). Some scholars have conducted numbers of studies by using DEA models. He Zejun et al. [1] used the DEA-Malmquist index method to measure the variation characteristics of total factor productivity(TFP)in Chinese agriculture from 2007–2015 in time series and spatial regions; Hou Lin et al. [2] used the super-efficient DEA model and Malmquist index to analyse the agricultural production efficiency of 29 provinces in China from 1990 to 2016; Yang Jinying et al. [3] used Malmquist-DEA model to analyse the grain production efficiency in China from 2004 to 2010; Li Zhongdong et al. [4] used super-efficient

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DEA and Malmquist index to agricultural production efficiency in Shandong province from 2011–2016; Xu Qiuyan et al. [5] used a DEA model to analyse garlic production efficiency; Fu Qingyan et al. [6] used the data envelopment analysis (DEA) method to analyse the agricultural production efficiency of 18 cities in Henan province in 2012; Yan Shuxia et al. [7] used a grey DEA model to analyse the agricultural production efficiency of 18 cities in Henan province from 2008–2013, which shows the current factor allocation of agricultural production was considered to be optimal.

Based on the above research, this paper uses the DEA-BCC model from a static perspective to measure the efficiency of food production horizontally in 2020. From a dynamic perspective, the Malmquist index method is used to analyse the specific differences in the annual TFP values of each province and to find a breakthrough in the existing problems and thus improve the efficiency of food production.

2 Research Methodology

2.1 DEA Model

This paper uses the DEA-BCC model for empirical analysis, which is effective for analysing the relative effectiveness of similar sectors or units. The DEA model, after applying linear programming analysis indicators, yields the efficiency values of each decision making unit (DMU) and the degree of inefficiency of non-effective DMU. This paper uses the BCC model in the DEA approach, which is defined as follows [8]:

$$\begin{cases} min\theta \\ s.t. \sum_{j=1}^{n} \lambda_j x_j + s^- = x0 \\ \sum_{j=1}^{n} \lambda_j x_j - s^+ = y \\ \lambda_j \geq 0, j = 1, 2, \ldots, n \\ s^+ \geq 0, s^- \geq 0 \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases} \tag{1}$$

We can tell whether it achieves DEA validity by calculating the DMU value. Based on the last equation validity judgement theorem. If the optimal value $\theta = 1$ exists, then the corresponding DMU is weakly DEA valid; when the optimal value $\theta = 1$ and an optimal solution exists, i.e. the input relaxation variable s- = 0, the input-output variable s + = 0, the corresponding DMU is DEA valid.

2.2 Malmquist Index

The Malmquist index is an all-encompassing model that dynamically measures the total factor productivity (TFP) of a decision unit. To reflect the development of grain production efficiency in China, this paper uses the Malmquist index method to calculate grain production efficiency in China from 2011–2020 and to analyse the resulting efficiency values. The decomposition formula of the TFP index is as follows [9]:

$$\text{TFP} = \text{TP} \times \text{PTE} \times \text{SE} \tag{2}$$

The TFP index refers to the product of the rate of technological progress (TP), pure technical efficiency (PTE), and scale efficiency (SE). The solution process is:

$$M_i\left(x_i^t, y_i^t, x_i^{t+1}, y_i^{t+1}\right) = \frac{D_i^{t+1}(x_i^{t+1}, y_i^{t+1})}{D_i^t(x_i^t, y_i^t)} \times \left[\frac{D_i^t(x_i^{t+1}, y_i^{t+1})}{D_i^{t+1}(x_i^t, y_i^t)} \times \frac{D_i^t(x_i^t, y_i^t)}{D_i^{t+1}(x_i^t, y_i^t)}\right]^{\frac{1}{2}} \quad (3)$$

If the value is bigger than 1, it means that the level of payoffs to scale and technical efficiency is increasing every year, and vice versa; if the rate of technological progress and total factor productivity is bigger than 1 in the Malmquist index analysis, it means that the level of technological growth and productive efficiency is increasing every single year, and vice versa.

3 Indicators and Data Sources

In this paper, the food production efficiency evaluation system is divided into production inputs and production outputs, and the input variables are selected as total sown area of crops X1 and effective irrigated area X2. The output variable is selected as the total agricultural output value Y1 and value added of primary sector production Y2. The output variables are selected as the source of data from [10].

In order to ensure the authenticity and validity of the data, 31 provinces were selected for the relevant data from 2011–2020, and the relevant data used in this paper were obtained from local statistical bureaus and the National Statistical Yearbook.

4 Static Analysis of the Efficiency of Our Food Production in 2020

4.1 DEA Model Static Analysis

This paper uses the input radial as a hypothesis. Using DEAP Version 2.1 software, food production efficiency values can be derived for 2020, as shown in Table 1.

Integrated efficiency analysis.

Aggregate efficiency is an overall assessment of the use of food resources and the efficiency of output in all areas. The efficiency value obtained can objectively reflect the situation of food production in each province. As can be seen from Table 1, Hainan has three efficiency values of 1, which is DEA effective, accounting for 3.23% of the total, indicating that Hainan's production technology, returns to scale and resource factors are optimally allocated. And other 10 provinces including Sichuan have not reached DEA effective, the overall performance of food resource utilisation is good. While 20 provinces such as Hubei, Hunan and Jiangxi have an overall efficiency below the average, accounting for 64.52%, which is a relatively large proportion, the later development should enhance the corresponding production efficiency while improving the revenue. If we want to improve the comprehensive efficiency, we should focus on solving the problem of low efficiency, improving the corresponding policies and institutional mechanisms, and expanding the scale and scope of technology introduction.

Table 1. Efficiency values for food production in China in 2020

DMU	Integrated efficiency crste	Pure technical efficiency vrste	Scale efficiency scale	Benefits of scale
Yunnan	0.490	0.740	0.663	drs
Sichuan	0.525	1.000	0.525	drs
Chongqing	0.763	0.929	0.822	drs
Guizhou	0.797	1.000	0.797	drs
Hubei	0.378	0.790	0.479	drs
Hunan	0.352	0.793	0.444	drs
Jiangxi	0.283	0.454	0.623	drs
Jiangsu	0.424	0.914	0.464	drs
Anhui	0.222	0.589	0.376	drs
Zhejiang	0.642	0.765	0.839	drs
Shanghai	0.418	0.437	0.957	irs
Hebei	0.326	0.754	0.433	drs
Shanxi	0.237	0.345	0.686	drs
Liaoning	0.421	0.587	0.717	drs
Jilin	0.216	0.320	0.675	drs
Heilongjiang	0.219	0.648	0.338	drs
Fujian	0.998	1.000	0.998	drs
Shandong	0.367	1.000	0.367	drs
Henan	0.382	1.000	0.382	drs
Guangdong	0.709	1.000	0.709	drs
Hainan	1.000	1.000	1.000	–
Shaanxi	0.701	0.943	0.744	drs
Gansu	0.355	0.481	0.739	drs
Qinghai	0.392	0.461	0.851	irs
Inner Mongolia	0.177	0.374	0.474	drs
Guangxi	0.631	0.884	0.713	drs
Tibet	0.330	0.362	0.912	irs
Ningxia	0.262	0.309	0.848	drs
Xinjiang	0.362	0.697	0.519	drs
Beijing	0.848	1.000	0.848	irs

(*continued*)

Pure technical efficiency.

Table 1. (*continued*)

DMU	Integrated efficiency crste	Pure technical efficiency vrste	Scale efficiency scale	Benefits of scale
Tianjin	0.422	0.429	0.984	irs
Average	0.473	0.710	0.675	

Pure technical efficiency is an important indicator of the transformation of production technology. The closer the value of the obtained production conditions and technical proficiency is to 1, the higher the efficiency of pure technical conversion is. As shown in Table 1, among the non-DEA effective, seven provinces such as Sichuan, Guizhou and Fujian have a pure technical efficiency of 1 and are at the frontier of technology. While nine provinces such as Yunnan, Chongqing and Hubei have above-average pure technical efficiency and are good developed overall. The remaining 12 provinces are all below 0.6, especially Shanxi, Jilin, Inner Mongolia and Ningxia, where the overall efficiency and pure technical efficiency are low, and also input redundancy may exist. Input resources should be used rationally, the corresponding regulation mechanism should be improved, and appropriate management methods and technical means should be used to improve the efficiency of grain production.

Scale efficiency.

Scale efficiency is an important indicator to measure whether the inputs and outputs in the food production process can reach the optimal scale. As can be seen from Table 1, among the non-DEA effective provinces, 17 provinces, including Chongqing, Guizhou and Zhejiang, are above the average, accounting for 56.67% of the non-DEA effective provinces. The scale efficiency of 2 provinces, Yunnan and Jiangxi, lies between the range of 0.600–0.675. The remaining 11 provinces are below 0.6, especially Anhui, Heilongjiang, Shandong and Henan, where scale efficiency is below 0.4 and in a low state. In addition, from the perspective of scale efficiency, there are five provinces with increasing scale, namely Shanghai, Qinghai, Tibet, Beijing and Tianjin, which should increase the investment of resources and use cutting-edge high technology to achieve the best scale efficiency; while there are 25 provinces with decreasing scale, which have not been effectively integrated with food production resources, and should appropriately adjust the scale of food production in the later development to achieve supply and demand balance.

5 Analysis of the Dynamics of Food Production Efficiency in China

5.1 Dynamic Analysis of the DEA Model

In order to visualise the current state of development of food production efficiency in the period 2011–2020, this paper uses the Malmquist index method to analyse the dynamics of production efficiency by calculating the TFP values one by one.

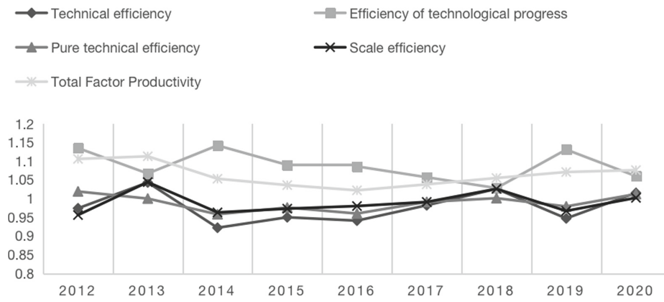

Fig. 1. The evolution of the Malmquist index of grain production efficiency from 2011 to 2020

Comprehensive numerical analysis.

As can be seen from Fig. 1, the average value of grain TFP in China is 1.063, with an annual rise rate of 6.3%, which is a good overall development. Technical efficiency, on the other hand, is 0.977, which is a slower development compared to other efficiency values and has not reached its production limit. Pure technical efficiency is in parallel with scale efficiency, falling by 1.2%, 1.1% respectively. From this it can be concluded that technical efficiency is growing slowly and this has become the key to efficiency growth. Technical progress efficiency shows a positive growth, around 8.8%, which has become the core of TFP value growth. Thus, the key factor affecting the TFP value of food is technical efficiency.

Specific numerical analysis.

In order to find the reason for the changes in efficiency values, this paper analyses the average value of each efficiency value and dynamically analyses the development trend of efficiency values. By year, China's grain TFP values from 2011 to 2020 are all greater than 1. After reaching a peak in the second year, there are small fluctuations later on, and the overall fluctuations are not significant. After 2016, there is a steady upward trend, indicating that the country has obvious advantages in grain production and greater potential. As can be seen from Fig. 1, TFP values and technical progress efficiency are superimposed on each other, which further indicates that TFP values fluctuate with changes in technical progress efficiency; technical efficiency, on the other hand, shows an undulating form of evolution, with declines in 2014 and 2019 and increases of varying degrees in all other years, and scale efficiency and pure technical efficiency show a more similar pattern of movement, which indicates that there are problems in the current development of food production, such as the instability of output. Therefore, the government should focus on technical efficiency to promote the conversion of available resources and ensure stable food output, thereby improving TFP efficiency values.

6 Conclusions

This paper provides an overall assessment of the efficiency of grain production in China's 31 provinces in 2020 through DEA static analysis, and the specific conclusions of this study are as follows: China's grain production development has good geographical advantages and production conditions, but due to the failure of some provinces and municipalities to effectively conversion pure technical efficiency or scale efficiency, there may be a situation where inputs and outputs are not equal, gradually pulling down the overall efficiency. This paper uses the Malmquist index method to conduct a dynamic analysis of the TFP value of grain production in China's 31 provinces from 2011 to 2020, from which it is concluded that the TFP values of grain production in China's 31 provinces are all greater than 1, with an increase of 6.3%, indicating that China's grain production is better overall. In terms of the trend of efficiency evolution, the core factor driving the rise in the TFP value of grain production is the efficiency of technological progress, while the key factor restricting the development of grain production in China is technical efficiency. Therefore, technical efficiency is the core of the efficiency improvement of China's grain production, and the investment in technology should be increased in the later development process.

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