Research Article

Efficiency Analysis of the Crop Production in China in 2019 and 2020: Role of Uncertainty Perceptions in COVID-19

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This paper employs data envelopment analysis (DEA) to determine crop production efficiency in 15 major provinces of China during 2019–2020. The total power of agricultural machinery, the application amount of chemical fertilizer, the irrigation area of cultivated land, the area of grain sowing, and the total capacity of reservoirs in each province are defined as the input items. The production of food, production of oil plants, and production of fruits are considered output items. According to the findings from the DEA, the most efficient crop production is observed in Shandong and Xinjiang provinces. We also discuss the role of farmers’ uncertainty perceptions in COVID-19. By cluster analysis, the provinces with large grain sown area and high grain yield are Henan and Heilongjiang, the provinces with moderate grain production in the grain sown area are Hunan, Hubei, Jiangxi, Guizhou, and Yunnan, and Xinjiang, Shandong, Hebei, Anhui, Sichuan, Jiangsu, Inner Mongolia, and Jilin are the provinces with low grain production.

1. Introduction

China is a large developing agricultural country, and its total crop output ranks among the top in the world. Every year, China exports a large number of crops. With the increase of our country’s population, the demands for all kinds of agricultural products increase rapidly. However, economic growth has also brought many environmental problems and ecological crises, such as climate change, land desertification, water pollution, the spread of acid rain, and so on. All these issues will lead to a decrease in crop yield in our country. The increasing demand for agricultural products and the decreasing supply are bound to affect people’s living standards. Therefore, it is of great significance to analyze the yield efficiency of the major crop-producing provinces in China in the past three years and explore how to improve the resource utilization rate, so as to improve the crop production efficiency and expand China’s crop yield.

Currently, most people use the DEA model to study agricultural production efficiency. Farrell [1] first put forward the prototype of DEA, and then Charnes et al. [2] formally proposed the DEA model. Vollrath [3] and Restuccia et al. [4] studied the agricultural production efficiency of many countries with the help of this model. For instance, Jiang et al. [5] studied the utilization efficiency of agricultural resources in 16 sample areas of prefecture-level cities in Anhui Province using the super-efficiency-DEA model. Dong et al. [6] adopted DEA efficiency to evaluate the agricultural production of Zhejiang Province and put forward the corresponding countermeasures. They found an overall low level of agricultural production efficiency in Zhejiang Province. The poor efficiency of resource utilization and the improper scale of input was the main elements affecting the agricultural efficiency, and the production technology level is the secondary one. Based on the C2R model of DEA, Mingyue [7] evaluated the grain production efficiency of 13 major grain-producing provinces in 2018, including Heilongjiang, Henan, Shandong, Jilin, Jiangsu, Anhui, Sichuan, Hebei, Hunan, Inner Mongolia, Hubei, Jiangxi, and Liaoning. Based on the previous research, our paper takes the crop yield of 15 provinces in 2019 and 2020 as the research object. It takes the total power of agricultural machinery, fertilizer application amount, cultivated land irrigation area, grain sowing area, and total reservoir.
2. Research Methods

2.1. Super-Efficiency-DEA Model. In calculating the efficiency value of the CCR model, there are often multiple effective decision units (efficiency value is one), making it impossible to compare and analyze between effective decision units. In order to achieve the order of decision-making units, Anderson and Pearson [8] eliminated the evaluated decision-making units from the efficiency boundary and utilized the remaining decision-making units to form a new efficiency boundary, thus calculating the distance between the eliminated decision-making units and the new efficiency boundary. Since the efficiency boundary does not surround the excluded decision-making units, the new efficiency value calculated by the excluded decision-making units is bigger than one for the effective decision-making units. In contrast, for the invalid decision-making units, the efficiency value obtained by the excluded decision-making units remains unchanged. It is still less than one so that all decision-making units can be sorted completely. Since the effective decision unit efficiency is greater than one, the concept of super-efficiency is invented.

Super-Efficiency Master Mold. When evaluating the efficiency of the decision-making unit, the fractional programming model is

$$\text{max} \ h_j = \frac{u^TY_j}{u^TX_j}$$

s.t. $$h_j = \frac{u^TY_j}{v^TX_j} \leq 1 \ (j = 1, 2, \ldots, n; j \neq j_0)$$

In this formula, the variables of the model are $v$ and $u$. It can be transformed into a linear programming problem model.

$$\text{max} \ h_{j_0} = \mu^T Y_{j_0}$$

s.t. $$\omega^T X_j - u^T Y_j \geq 0 \ (j = 1, 2, \ldots, n; j \neq j_0)$$

Its dual linear rule can be expressed as

$$\text{min} \ \theta - \epsilon \left( \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^- \right)$$

s.t. $$\sum_{j=1}^{n} X_j \lambda_j + s^- = \theta X_j \sum_{j=1}^{n} Y_j \lambda_j + s^- = Y_j \lambda_j \geq 0 \ (j = 1, 2, \ldots, n) s^+ \geq 0, s^- \geq 0$$

In this model, $\theta$ represents the super-efficiency value of the $j_0$th decision unit, $\epsilon$ is the non-Archimedean infinitesimal quantity, $n$ is the number of DMUs, each DMU includes $m$ input variables and $s$ output variables, $s_i^-$ are $s_r^-$ are input and output slack variables, respectively, $X_j$ represents the value of the $j$th decision-making unit on the $i$th input indicator, $Y_j$ represents the value of the $j$th decision-making unit on the $r$th output (output) indicator, $\lambda_j$ is the weight coefficient of input and output indicators, and $\theta$, $\lambda_j$, $s_i^-$, $s_r^-$ represent unknown parameters, which the model can solve. Assume that the optimal solutions of the model equation of the planning problem are as follows:

1. If $\theta \geq 1$ and $s^0 = s^+ = j_0$th DM $U_0$ represents that DEA is efficient.
2. If $\theta \geq 1$ and $s_i^- \neq 0$ or $s_r^- \neq 0$, $j_0$th DM $U_0$ represents that DEA is weakly efficient.
3. If $\theta \geq 1$ and $s_i^- \neq 0$ or $s_r^- \neq 0$, $j_0$th DM $U_0$ represents that DEA is invalid.

2.2. Cluster Analysis. Clustering analysis is based on the principle of similarity. The training data with high similarity are included in the same cluster, and those with a high difference are divided into different clusters. K-means
clustering algorithm is unsupervised learning and a classical algorithm in clustering analysis. K-means algorithm takes distance as the standard of similarity measurement between training data. This means that the smaller the gap between the training data is, the higher the similarity is, and the more likely the training data is to be included in the same cluster. K-means algorithm usually uses the Euclidean distance to calculate the distance between training data.

The mapping method of Sammon [9] is used to find N points in q-dimensional space, where the original data come from higher N-dimensional space.

The measured \( d_{ij} = d(x_i, x_j) \) point distance in N-dimensional space is similar to \( \hat{d}_{ij} = (d^*(y_i, y_j)) \).

Corresponding q-dimensional space: this evidence is achieved by minimizing the error standard E, also called the Sammon pressure.

\[
E = \frac{1}{N} \sum_{i,j=1}^{N} \frac{(d_{ij} - \hat{d}_{ij})^2}{d_{ij}} \tag{4}
\]

where \( \lambda = \sum_{i,j} d_{ij} = \sum_{j=1}^{N} \sum_{i=1}^{N} d_{ij} \), and it is not necessary to maintain \( \lambda \) to successfully solve the optimization problem because, as a constant, it will not change the optimization problem.

3. Empirical Analysis

3.1. Sample Data and Variables. This part analyzes the yield efficiency evaluation of 15 major agricultural production provinces in China in 2019 and 2020. In this paper, the total power of agricultural machinery, the application amount of chemical fertilizer, the irrigated area of cultivated land, the sown area of grain, and the total reservoir capacity are taken as input items, and grain, oil plant, and fruit output are output items. The data are selected from China Statistical Yearbook. The specific index data are shown in Table 1.

The output indicators of super-efficiency-DEA are described as follows. Technical efficiency (TE) reflects the effective degree of existing technology utilization in production, that is, the ability of the evaluated object to obtain the maximum output under the given input. Scale effect (SE) reflects the effectiveness of production scale, that is, whether each decision unit is operating under the most appropriate investment scale. Synthesis technical efficiency (STE) includes technical efficiency and scale efficiency, also called scale technical efficiency. When the observed decision-making unit achieves technical efficiency and scale efficiency, it is called scale technical efficiency.

STE Effectiveness. CCR model evaluates both scale effectiveness and technical efficiency, namely, total efficiency. The total efficiency value satisfies \( 0 \leq \theta \leq 1 \) when the efficiency value \( \theta = 1 \), and the evaluated decision-making unit is scale technology effective. Otherwise, it is scale technology invalid.

TE effectiveness is the BCC model used to evaluate the technical effectiveness of decision-making units. Technical efficiency satisfies \( 0 \leq \theta \leq 1 \). When \( \theta = 1 \), the evaluated object is in a state of technical effectiveness. Otherwise, it is technically invalid.

SE effectiveness is determined by total efficiency and technical efficiency, and its formula is \( SE = TE/TE \).

Super-Efficiency-DEA Effectiveness. The efficiency value \( \theta \) is no longer limited in the range of \( 0 \sim 1 \) but allows an efficiency value of more than 1. If \( \theta \geq 1 \), the scale is more technical. Otherwise, it is invalid in scale or technology. This method can be used to compare and sort each decision-making unit effectively. Using the \( \lambda j \) CCR model, the returns to scale of the decision unit \( DM Uj \) can be analyzed. When \( \sum_{j=1}^{N} \lambda^{j_0} = 1 \), \( DM Uj \) is economies of scale not changed, when \( \sum_{j=1}^{N} \lambda^{j_0} < 1 \), \( DM Uj \) is economies of scale increased, when \( \sum_{j=1}^{N} \lambda^{j_0} > 1 \), \( DM Uj \) is economies of scale reduced.

3.2. Findings of Super-Efficiency-DEA. When the DEA method is used to measure performance, the effectiveness of the results largely depends on the input and output indicators used in the evaluation process. The calculation results of grain production efficiency of major grain-producing provinces in China in 2019 and 2020 are shown in Tables 2 and 3.

From Table 2, we can get that among the 15 major crop-producing provinces in 2019, Shandong, Henan, Hunan, Heilongjiang, Sichuan, Jiangsu, Hubei, Inner Mongolia, Jilin, Jiangxi, Yunnan, and Xinjiang are 12 provinces with effective output, and the remaining provinces are not. The output efficiency of 15 provinces is statistically analyzed. The minimum value is 0.8606, and the average value is 0.9755. The output efficiency of Hebei, Anhui, and Guizhou did not reach the average value. Shandong, Henan, Hunan, Heilongjiang, Sichuan, Jiangsu, Hubei, Inner Mongolia, Jilin, Jiangxi, Yunnan, and Xinjiang are effective. In addition to the above provinces, Guizhou is still effective in technical efficiency. Except that the returns to scale of provinces with STE effectiveness remain unchanged, the returns to scale of other provinces increase. By sorting the super-efficiency-DEA value, it can be found that the benefit rankings of Henan, Hebei, Sichuan, and Jiangxi are greatly decreased, and the benefit ranking of Xinjiang is unchanged.

Table 3 shows the results in 2020. Effective output is Shandong, Henan, Hunan, Heilongjiang, Sichuan, Jiangsu, Hubei, Inner Mongolia, Jilin, Jiangxi, Yunnan, and Xinjiang twelve provinces; the remaining provinces have not reached the maximum output. The output efficiency of the 15 provinces is statistically analyzed. The minimum value is 0.8791, and the average value is 0.9789. The output efficiency of Hebei, Anhui, and Guizhou does not reach the average value. Shandong, Henan, Hunan, Heilongjiang, Sichuan, Jiangsu, Hubei, Inner Mongolia, Jilin, Jiangxi, Yunnan, and Xinjiang are effective. In addition to the above provinces, Guizhou is still effective in technical efficiency. Except that the returns to scale of provinces with STE effectiveness remain unchanged, the returns to scale of other provinces increase. By sorting the super-efficiency-DEA value, it can be seen that the benefit rankings of Sichuan, Jiangsu, Hubei, Jiangxi, and Yunnan are greatly decreased, and the benefit ranking of Xinjiang is unchanged. In summary, those
provinces need to make more efficient use of the resources to improve the output because of the output efficiency differences and uneven distribution of resources.

3.3. Results of Cluster Analysis. The K-means algorithm clusters the grain production and grain-planting area of the main grain-producing provinces in China in 2020. According to the actual situation, the provinces are divided into three grades: large grain production of grain-planting area, medium grain production of grain-planting area, and small grain production of grain-planting area. The distinction between the three grades is obvious. The clustering analysis results of grain production evaluation grades in 2020 are shown in Table 4, and the clustering graph of each province is shown in Figure 1.

The provinces with high grain yield in large grain-planting areas are Henan and Heilongjiang, accounting for 13.33%. The provinces with moderate grain yield in medium grain-planting areas are Hunan, Hubei, Jiangxi, Guizhou, Yunnan, and Xinjiang, each accounting for approximately 10%. The provinces with low grain yield in small grain-planting areas are Inner Mongolia, Jilin, Guizhou, and Xinjiang, each accounting for less than 10%.
Yunnan, and Xinjiang, accounting for 40%. The provinces with low small grain yield in small grain-planting areas are Shandong, Hebei, Anhui, Sichuan, Jiangsu, Inner Mongolia, and Jilin, accounting for 46.67%. The large grain yield in large grain-planting areas will also increase. These 15 provinces are major grain-producing provinces in China. However, the proportion of provinces with low small grain yield in small grain-planting areas reaches 46.67%. Therefore, expanding grain-planting areas is of great significance to improve grain yield.

4. Conclusions

In this paper, the super-efficiency-DEA method is employed to study the crop yields of 15 provinces in 2019 and 2020, which includes Shandong, Henan, Hebei, Anhui, Hunan, Heilongjiang, Sichuan, Jiangsu, Hebei, Inner Mongolia, Jilin, Jiangxi, Guizhou, Yunnan, and Xinjiang. The total power of agricultural machinery, the amount of chemical fertilizer application, the irrigation area of cultivated land, the grain sowing area, and each province’s total reservoir capacity are used as input items. The grain output, oil output, and fruit output are taken as output items to analyze the output efficiency of the main crop-producing provinces in China. The empirical analysis results show that compared with other provinces and cities, Shandong, Henan, Heilongjiang, Sichuan, Jiangsu, Hebei, Inner Mongolia, Jilin, Jiangxi, Guizhou, Yunnan, and Xinjiang are always in the forefront of grain output in 2019 and 2020. They should lead other provinces to improve the level of crop production. In the ranking of super-efficiency-DEA values in 2019 and 2020, Henan and Hebei are declining for two consecutive years. In the ranking of super-efficiency-DEA values in 2019-2020, Sichuan and Jiangxi are also declining. Overall, the ranking of most provinces fluctuates year by year.

We should fully understand the importance and urgency of preventing cultivated land from “non-grain” to stabilize...
grain production and improve and mend a series of laws and regulations related to cultivated land. Sufficient grain production is an important guarantee for national food security. Insufficient grain sowing area will lead to a sharp decline in China’s grain production. At present, because of the ecological damage, China’s cultivated land area is being reduced, and the cultivated land area in China is decreasing. If this situation continues, it will affect China’s food security. Therefore, a series of laws and regulations related to cultivated land should be improved, and laws and regulations should be strictly implemented to prevent the “non-grain” of cultivated land.

It is also necessary to adhere to arable land resources’ scientific and rational use and clear priority of arable land use. Cultivated land is the foundation of grain production, but the area of cultivated land is limited. To take full advantage of the existing cultivated land resources, under the premise of preventing the “non-grain” of cultivated land, we should adhere to the scientific and rational use of cultivated land resources and properly deal with the relationship between the development of grain production and the development of comparative benefits. We should not simply determine the use of cultivated land by economic benefits but implement strict cultivated land protection measures, strictly control the conversion of cultivated land to forest land, garden land and other types of agricultural land, and ensure sufficient food production to ensure people’s daily life needs and reserves.

This paper compares the crop production efficiency in 15 major provinces of China during 2019-2020. We found a significant decline in crop production efficiency in 2020 compared to 2019. We suggest that this difference comes from the risk perceptions in COVID-19. Most small businesses and producers have been shut down due to COVID-19, and the uncertainty has risen in the markets. Therefore, we suggest that producers, especially small-size farmers, should be strengthened by grain-planting incentive mechanisms. It is necessary to implement the reward policy of grain-producing across provinces and give grain growers certain subsidies every year to mobilize farmers’ enthusiasm to plant food. We should vigorously promote mechanized production to improve grain-planting scale efficiency. Food-planting professionals can be sent to the countryside to give farmers technical support to help them solve some technical bottlenecks, thereby increasing food production. Through cluster analysis, we can know that expanding grain-planting area is of great significance to improving grain output.

Data Availability

The data used to support the findings of this study are obtained from http://www.stats.gov.cn/tjsj/ndsj/2021/indexch.htm.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References