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Evaluation and Promotion Strategy of Intelligent Agricultural Production Efficiency based on DEA Model

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Abstract

Smart agriculture is a new agricultural development mode developed under the background of big data and combined with modern information technology means such as Internet of Things and electronic information. In this study, the data of 31 provinces and cities in 2019 were selected to analyze the calculated comprehensive technical efficiency by using deaf-BCC model, so as to analyze the overall production efficiency of smart agriculture. The results show that the development of smart agriculture is limited by regional economic conditions, and the smart agriculture in less developed areas is still in the enlightenment stage affected by economic level, and its main characteristics are late start, small scale and low level. Based on the research conclusions, some suggestions are put forward for regional smart agriculture construction.

Keywords

Smart Agriculture; DEA-BCC Model; Agricultural Production Efficiency; Rural Development.

1. Research Background

Agriculture, rural areas and farmers have always been the key work of the state. As a basic industry, agriculture is an important part of the national economy, and its development level is relatively lagging behind. Smart agriculture is a new way of agricultural development that integrates modern information technologies such as the Internet of Things and big data with agriculture. It is an important step in implementing the rural revitalization strategy and a booster for the transformation and upgrading of traditional agriculture in China. At present, China's smart agricultural technology has been applied to production testing, greenhouse plant planting, precision irrigation, agricultural product quality and safety traceability and many other fields. It is an effective way to promote agricultural production efficiency, agricultural economic growth and agricultural high-quality development by the development of smart agriculture.

"Smart agriculture" can improve agricultural production and operation efficiency to a large extent. For example, real-time monitoring technology can be used to accurately monitor the growth status of crops. The application of these technologies provides many reference elements for agricultural management development and upgrading. Intelligent mechanical alternative can solve the labor shortage of labor force and increasing the aging process, so as to realize the height of the agricultural scale, centralization, streamline management, make agriculture better able to cope with the extreme weather conditions such as external conditions, the agricultural production of low technology content is low to high level of modernization.

According to the classical economic growth theory, agricultural growth has two ways: increasing input factors and improving production efficiency. The increase of input factors only has short-term effects, while the improvement of agricultural production efficiency only has

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long-term effects. The development of smart agriculture must rely on the improvement of production efficiency. Therefore, the team evaluated the analysis efficiency of traditional DEA model for the development of smart agriculture by using original input and original output data to carry out initial production efficiency.

2. Research Scheme

2.1. Research Methods

Traditional economic growth theory holds that agriculture can develop in two ways, one is to increase input, the other is to improve productivity. Since the increase of input factors can only bring short-term effects, only by improving the efficiency of agriculture can it produce long-term effects. In order to develop intelligent agriculture, production efficiency needs to be improved. Therefore, based on the original input and output data, the research team in this paper evaluated the analytical efficiency of the traditional DEA-BCC model.

The method of DataEnvelopmentanalysis (DEA model) is proposed by three famous operational researchers in the United States a. charnes, e. fodes and w.w. Cooper, which is a new field of interdisciplinary application. They are operations research, management science and mathematical economics.

Although the traditional DEA model method has disadvantages, such as the non-parametric method, the significance test of the results cannot be carried out, and the results of this method are affected by the homogeneity of each decision-making unit, etc. However, it still has a strong advantage in measuring the efficiency value. Therefore, this paper adopts this method to study the input-output efficiency of smart agriculture in 31 provinces and cities of China. At the same time, DEA model is divided into input-oriented and output-oriented. Since this paper studies the input-output of intelligent agricultural production in 31 provinces of China based on 31 provinces, it is easier for policy makers to grasp R&D investment. Therefore, this paper adopts the input-oriented DEA model for analysis.

However, in actual production and application, not all decision making units are produced at the most appropriate scale, that is to say, returns to scale are changing, hence the BCC model proposed by b.D. Banker and other scholars based on the traditional DEA model. For any decision unit (DMU), the duality BCC model under input guidance can be expressed as:

$$min\,\theta_{j_0} - \varepsilon(\hat{e}^T s^- + e^T s^+)$$
$$s.t.\begin{cases} \sum_{j=1}^{n} X_j\lambda_j + s^- = \theta X_0 \\ \sum_{j=1}^{n} Y_j\lambda_j - s^+ = Y_0 \\ \lambda_j \geq 0,, s^-, s^+ \geq 0 \end{cases}$$

Where, "j=1,2, ⋯, " n represents n decision units, where the number is 31; X and Y are respectively the input and output vectors of intelligent agricultural production.

In this model, the calculated comprehensive technical efficiency (TE) is decomposed into scale efficiency (SE) and pure technical efficiency (PTE) under varying returns to scale, and the comprehensive technical efficiency (TE) = scale efficiency (SE) × pure technical efficiency (PTE) is satisfied. The closer the calculated TE, SE and PTE values are to 1, the better the production efficiency of smart agriculture in corresponding provinces and cities.

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2.2. Variable Selection

As a way of agricultural production, smart agriculture can also be used to measure agricultural production efficiency by some indicators. In addition, under the existing technical conditions of smart agricultural producers, the state of balance should be achieved through reasonable allocation of production factors. While taking into account traditional agriculture, new influencing factors brought by scientific and technological development should be taken into account. Based on this, the key requirement of this model is to select input-output indicators, comprehensively consider the availability of data, combine with reference to existing literature, At the same time, on the basis of meeting the data requirements of DEA-BCC model method (the inherent requirement of DEA method for decision units is that the number of decision units should be greater than or equal to twice of all input variables and output variables), a total of 8 input indicators and 1 output indicator are selected from 31 provinces and cities in China (except Hong Kong, Macao and Taiwan) in 2019. Including animal husbandry fishery output value as the only output index, number of ecological-economic practitioners appropriate amount, rural fertilizer and pesticide, mobile phone users, Internet users in rural areas, rural machinery total power, effective irrigation area, crop planting area, the first industrial electricity consumption and so on eight related indicators as input indicators. The selected indicators are as follows:

Table 1. Intelligent agricultural production efficiency input and output indicators

First-level indicators	Second-level indicators	third-level indicators
Input indicators	Human capital	Number of Persons employed in Agriculture, Forestry, Animal Husbandry and Fishery (ten thousand)
	Agricultural inputs	Pesticide and chemical fertilizer application amount (ton)
	Rural network information input	Rural Mobile Phone Subscribers (per 100 households)
		Rural Mobile Phone Subscribers (per 100 households)
	Level of rural mechanization	Total power of rural machinery (10,000 kW)
	Irrigation in	Effective irrigation Area (10 000 ha)
	Land investment	Sown area of crops (ten thousand ha)
	Power input	Primary industry electricity consumption (billion KWH)
Output indicators	Gross agricultural output	Gross output value of Agriculture, Forestry, Animal Husbandry and Fishery (100 million)

2.3. Data Sources

The 2019 data of 31 provinces and cities (except Hong Kong, Macao and Taiwan) were selected to calculate the production efficiency of smart agriculture and analyze the influencing factors. The data of the number of employees in the primary industry, the application amount of pesticides and fertilizers, the number of mobile phones, the number of Internet connections, the total power of rural machinery, the effective irrigated area, the sown area of crops, the power consumption of the primary industry and the gross output value of agriculture, forestry, animal husbandry and fishery were obtained from the Statistical Yearbook of China's Rural Areas in 2020 and the statistical yearbook of each province in 2020.

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3. Empirical Analysis

3.1. Analysis of deA-BCC Model Calculation Results

DEAP2.1 software is used to calculate the production efficiency of smart agriculture in 31 provinces and cities of China in 2019 (except Hong Kong, Macao and Taiwan). The results are shown in the table:

Table 2. Productivity evaluation of smart agriculture in 31 provinces and cities in China

Regional	comprehensive efficiency	pure technical efficiency	scale efficiency	type
Beijing	1.0000	1.0000	1.0000	Return to scale is constant
Tianjin	0.8200	1.0000	0.8200	Increasing returns to scale
Hebei	0.9850	1.0000	0.9850	Diminishing returns to scale
Shanxi	1.0000	1.0000	1.0000	Return to scale is constant
Inner Mongolia	0.6560	0.9160	0.7170	Increasing returns to scale
Liaoning	1.0000	1.0000	1.0000	Return to scale is constant
Ji Lin	0.9130	1.0000	0.9130	Increasing returns to scale
Heilongjiang	1.0000	1.0000	1.0000	Return to scale is constant
Shanghai	1.0000	1.0000	1.0000	Return to scale is constant
Jiangsu	0.9300	0.9330	0.9970	Diminishing returns to scale
Zhejiang	1.0000	1.0000	1.0000	Return to scale is constant
Anhui	0.7420	0.8830	0.8400	Increasing returns to scale
Fujian	1.0000	1.0000	1.0000	Return to scale is constant
Jiangxi	0.8120	0.9160	0.8860	Increasing returns to scale
Shandong	1.0000	1.0000	1.0000	Return to scale is constant
Henan	0.8710	0.8710	1.0000	Return to scale is constant
Hubei	1.0000	1.0000	1.0000	Return to scale is constant
Hunan	1.0000	1.0000	1.0000	Return to scale is constant
Guangdong	1.0000	1.0000	1.0000	Return to scale is constant
Guangxi	1.0000	1.0000	1.0000	Return to scale is constant
Hainan	1.0000	1.0000	1.0000	Return to scale is constant
Chongqing	1.0000	1.0000	1.0000	Return to scale is constant
Sichuan	1.0000	1.0000	1.0000	Return to scale is constant
Guizhou	1.0000	1.0000	1.0000	Return to scale is constant
Yunnan	0.9740	0.9790	0.9950	Diminishing returns to scale
Tibet	1.0000	1.0000	1.0000	Return to scale is constant
Shaanxi	0.9350	0.9790	0.9560	Increasing returns to scale
Gansu	0.6160	0.9020	0.6830	Increasing returns to scale
Qinghai	1.0000	1.0000	1.0000	Return to scale is constant
Ningxia	0.5100	0.8920	0.5720	Increasing returns to scale
Xinjiang	0.6840	0.7130	0.9600	Increasing returns to scale

Can be seen from the results in the table, the method through the DEA - BCC model, the wisdom of the whole agricultural production efficiency evaluation, the national 31 provinces and cities, with a total of nine provinces of China shows that the trend of increase efficiency, including tianjin, Inner Mongolia, jilin, anhui, jiangxi, shaanxi, gansu, ningxia and xinjiang, these cities are mostly distributed in the northern areas in China, It shows that smart agriculture has been applied in these cities and achieved good results, which has become an important factor for the rapid development of agriculture in these areas. In addition, 3 provinces and cities in the table show decreasing scale efficiency, while the remaining provinces and cities show constant scale efficiency. Overall, in 2019, the average production efficiency of smart agriculture in 31 provinces and cities was 0.908, which means that the actual output value of agricultural production accounted for 90.8% of the ideal output value. Moreover, only a few provinces and cities showed low production efficiency of smart agriculture, such as Ningxia, Xinjiang and Gansu, which was consistent with the actual situation. This reflects that in these provinces and regions, the development scale of smart agriculture is small, the penetration rate of smart agriculture is low and the value of agricultural output is not high. Relevant departments need to adopt effective policies to scientifically improve smart agriculture technology and gradually expand the scale of the industry.

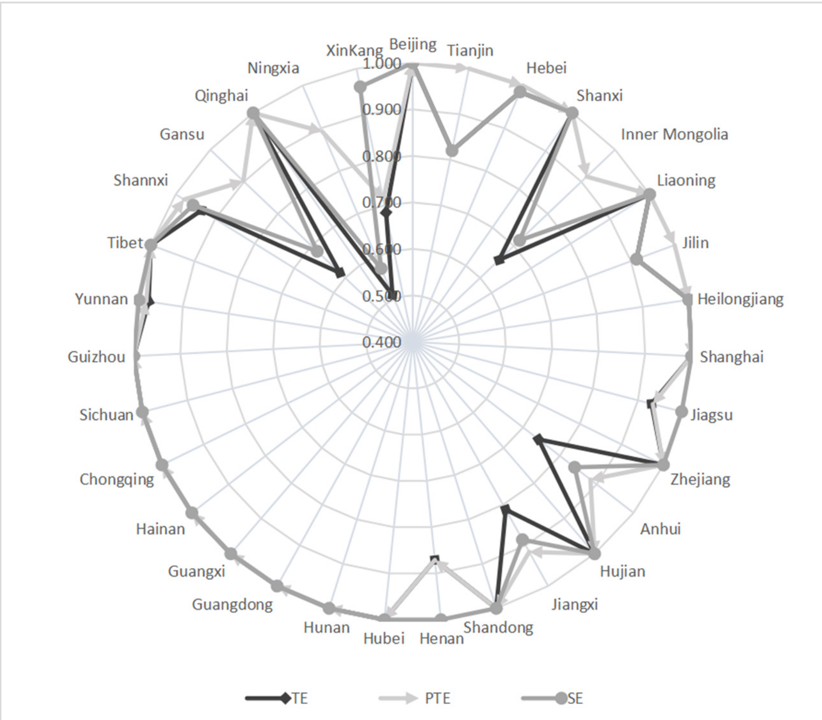

Figure 1. Radar map of intelligent agricultural production efficiency in 31 provinces and cities of China

3.2. Result Analysis

In general, the production efficiency of smart agriculture in rural China is still low, and there are significant spatial differences in the production efficiency of each region, showing the unbalanced regional development. By table 3 can be seen that the wisdom of the north China, east China and south China agricultural scale decision-making unit production efficiency is relatively high, the provinces and cities of rural agricultural production efficiency wisdom mainly have two obvious characteristics, development level is higher, the city itself to rural wisdom drives the positive effect of regional agricultural development, such as Beijing, zhejiang and Shanghai; The city itself lags behind in economic development, but it has strong resource advantages, such as Heilongjiang, Hainan and so on. At the same time, there is a certain gap between the production efficiency of intelligent agriculture in each region and the local economic development degree. For example, the development degree of Jiangsu and Anhui is higher than that of Jiangsu and Anhui, but the efficiency of rural ecological environment management in Xizang and Hainan is higher than that in Sichuan and Yunnan. It can be seen that areas with higher level of economic development have greater input and output in rural smart agriculture production, but they also face difficulties in governance, resulting in the mismatch between agricultural input and output.

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4. Conclusions and Suggestions

4.1. Conclusion

DAE method was used to analyze the overall production efficiency of smart agriculture in China, and the original input value and target input of 31 provinces and cities were used to study the production status of smart agriculture in all provinces and cities. The following conclusions were drawn:

(1) Regional economic conditions restrict the development of smart agriculture.

In the construction of agricultural informatization, the low level of science and technology, especially the low level of informatization, directly restricts the development of agricultural informatization. Under different terrain and climate conditions, the optimum growth conditions of the same crop are not the same, so it is necessary to carry out experimental research by scientists. Due to the cooperation with agricultural research units, most of the agricultural data obtained are shoddily made, and the lack of complete data on the growth process of crops makes the construction of production management model a castle in the air, so we have to set the RESEARCH and development center in Shanghai and other developed cities, which also increases the intermediate cost.

(2) The intelligent agricultural scientific research system is not perfect, and the ability of agricultural science and technology promotion is insufficient.

China's current agricultural scientific research system is not perfect. The ability of scientific research results in productivity is not strong, which leads to the slow progress of agricultural research. It is difficult to for the construction and development of smart agriculture.

First of all, China has not established a systematic top-level organization of agricultural research institutions, many agricultural research institutions have not formed a unified system, lack of scientific division of labor, cooperative guidance and communication channels.Many small scientific research institutions repeat research projects, breakthrough large-scale research projects are difficult to complete.

Secondly, due to the lack of unified guidance and support for agricultural scientific research institutions, the operating indicators of many agricultural science and technology systems cannot be determined based on a large number of production data, and many scientific research achievements lack application testing, leading to the lack of accuracy of some intelligent agricultural scientific research achievement systems and too frequent operation fluctuations.

(3) The infrastructure of smart agriculture is backward and the modernization of mechanical equipment is low.

At present, most of our country's agricultural infrastructure is still very backward, lack of large-scale modern agricultural machinery. Most farmland roads are badly damaged, narrow, potholed, and muddy on rainy days. The infrastructure of most livestock and poultry houses is limited to lighting and heating, with little modern feeding equipment; Agricultural irrigation equipment in most places of China is simple canal, which can only take the traditional way of flood irrigation, while efficient water-saving sprinkler irrigation, drip irrigation and other pipelines are only built in a few places, resulting in a large amount of waste of water resources, soil compaction, nutrient loss. In addition, due to the low market input, high price and low national subsidies of domestic agricultural machinery and equipment, small and scattered small-scale agricultural producers are unable to buy, and many modern agricultural machinery cannot enter the farmland.

4.2. Advice

Based on the data analysis and existing conclusions, suggestions for comprehensively improving the development level of smart agriculture are as follows:

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(1) Accelerate the construction of backward areas, help the establishment of agricultural infrastructure. On the one hand, the government should strengthen its support for regions with relatively lagging development of smart agriculture, optimize them through policies and special funds, reduce equipment purchase costs and encourage farmers to take the initiative to purchase advanced agricultural machinery and tools through financial subsidies. At the same time, the construction of rural informatization should be strengthened to lay a foundation for the development of smart agriculture in all regions.

(2) Develop characteristic agriculture according to local conditions. China has complex regions and changeable climate, and agricultural development in different regions has different basic conditions. Therefore, in the development of smart agriculture, local natural conditions should be fully considered, measures taken in accordance with local conditions should be developed to meet local characteristics, intensive management should be carried out, and agricultural production efficiency and development quality should be improved as a whole.

(3) Strengthen investment in scientific and technological research and promote the transformation of scientific research results. According to this study, intelligent agriculture is an effective way to improve the quality of agricultural products. To improve the efficiency of agricultural production, scientific and technological research and development should be strengthened to promote the transformation of agriculture into a scientific and intelligent type. At the same time, we should strengthen the connection between scientific research departments and production bases, attach importance to the development status of smart agricultural production bases as the "first frontier", transform scientific research achievements into actual production capacity, and improve the wisdom of agricultural production.

(4) Train professional talents and fully tap the potential of young talents. In any industry, talent is the first priority. It is suggested that we first promulgate policies for talent introduction, introduce high-level and high-level talents in a scientific way, fully tap talent potential, cultivate young people's skills, and expand professional talent teams.

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