

Analysis on the Development Trend and Influencing Factors of Intelligent Agriculture in Anhui Province

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Abstract: With the implementation of the "Internet +" strategy, the modern integration of information technology and agriculture has also entered the fast lane of development. A large number of high-tech equipment and technologies have been gradually integrated into agricultural production, greatly improving the efficiency of agriculture. Realizing agricultural intellectualization and modernization has become an important goal of China's agricultural and rural work at this stage. This paper establishes a model to analyze the current development trend and main influencing factors of smart agriculture in Anhui Province, so as to provide empirical reference for the development of smart agriculture. Firstly, the key factors affecting agricultural productivity in Anhui Province are the change of agricultural scale and agricultural productivity by using tobit-u model, and then the research results show that the change of agricultural productivity in Anhui Province is the key factor to improve agricultural productivity. The level of industrialization has a significant role in promoting the production efficiency of smart agriculture in Anhui Province, and the level of financial agricultural expenditure and urbanization rate have a significant negative effect.

Keywords: Smart agriculture, Production efficiency, Dea-bcc.

1. Introduction

"Agriculture, rural areas and farmers" has always been the focus of the state, but the high-quality development of agriculture in China lags behind. Developing smart agriculture can effectively improve agricultural production efficiency, promote industrial revitalization and drive rural revitalization. Therefore, this paper studies the production status of smart agriculture and measures the development level of smart agriculture, which has important guiding significance for agricultural development. Anhui Province is rich in agricultural resources and is a typical large agricultural province. In order to improve the production income of smart agriculture and promote rural revitalization, it is necessary to improve the total factor productivity of smart agriculture. Therefore, this paper studies the production efficiency of Intelligent Agriculture in Anhui Province, analyzes the factors affecting the production efficiency of Intelligent Agriculture in Anhui Province, and designs a more effective intelligent agricultural production scheme, which has important practical significance for the revitalization of rural industry in Anhui Province.

2. Data Sources and Modeling Methods

2.1. Construction of Index System

(1) Input output index selection

Smart agriculture is a kind of agricultural production mode, so some indicators used to measure agricultural production efficiency are also applicable to the calculation of smart agricultural production efficiency. At the same time, in smart agricultural production, producers can not leave traditional production factors, but also integrate technology into agricultural production through the allocation of production factors under the established technical conditions. On this basis, by referring to the existing relevant research, combined with the research purpose, the availability of data and the characteristics of agricultural production, human capital,

agricultural materials investment, agricultural mechanization level, irrigation investment, land investment and electricity investment are selected as the investment indicators. The specific index system is shown in Table 1, which reflects smart agriculture, including rural mobile communication investment, rural Internet investment. Scientific and technological innovation input is included in the input index system, and the total agricultural output value is selected as the output index.

(2) Selection of influencing factors

Labor productivity, financial support for agriculture, agricultural machinery density, agricultural scale level, planting structure, urbanization rate, industrialization level and location factors are selected as the influencing factors of intelligent agricultural production efficiency in Anhui Province. See Table 2 for specific variable selection and prediction results.

2.2. Modeling Method

(1) Data envelopment analysis (DEA)

DEA can be used to measure the effectiveness of DMU when there are multiple input variables and multiple output variables. Decision unit refers to the scheme of transforming a certain input into corresponding output. The principle of DEA is that it uses mathematical linear programming model to construct nonparametric piecewise surface, so as to compare the relative efficiency between decision units. In addition, DEA can also judge the scale stage of decision unit investment, And provide the target input scale, analyze whether there is redundancy in the existing input and output, so as to make the decision-making unit as effective as possible.

(2) Tobit model

Tobit model, also known as restricted dependent variable model, is a model in which the dependent variable meets certain constraints. The value range of efficiency value calculated by DEA method in this paper is between 0 and 1, which meets that the values at both ends of the explained variable are limited.

Table 1. Production efficiency index evaluation system of smart agriculture in Anhui Province

Primary index	Secondary index	Tertiary indicators
Input index	human capital	Number of employees in agriculture, forestry, animal husbandry and fishery (10000)
	Input of agricultural materials	Application amount of pesticide and chemical fertilizer (ton)
	Rural Internet investment	Number of rural Internet users (ten thousand people)
	Agricultural mechanization level	Total power of agricultural machinery (10000 kW)
	Irrigation input	Effective irrigation area (10000 hectares)
	Land input	Sown area of crops (10000 hectares)
	Power input	Power consumption of primary industry (10000 KWH)
	Science and innovation investment	Investment in primary industry (10000 yuan)
Output indicators	Total agricultural output value	Total output value of agriculture, forestry, animal husbandry and fishery (100 million yuan)

Table 2. Variable selection and prediction of influencing factors of smart agricultural production

Index	Characterization method	Effect prediction
Labour productivity	GDP of primary industry / Employees of primary industry	Forward direction
Financial agricultural expenditure level	Agricultural and forestry expenditure / Sown area of crops	Forward direction
Agricultural machinery density	Total power of agricultural machinery / Sown area of crops	Forward direction
Agricultural scale level	Farming area of rural households	Forward direction
Planting structure	Grain sown area / Total sown area of crops	Negative direction
Urbanization rate	Urban population / Total population	Negative direction
Industrialization level	Industrial added value / Regional GDP	Forward direction
Location variable	Southern, Central and Northern Anhui	Forward direction

3. Results and Analysis

3.1. Change Trend of Production Efficiency of Smart Agriculture

In order to study the changes of technical efficiency and

related composition of smart agricultural production, this paper uses the BCC model in DEA to study the overall changes and composition changes of smart agricultural production in Chinese provinces from 2010 to 2019. The calculation results are shown in Table 3.

Table 3. Changes in technical efficiency and composition of smart agricultural production in various provinces of China

Particular year	Comprehensive technical efficiency change	Technical progress	Pure technical efficiency change	Scale efficiency change	Total factor productivity
2010	0.732	0.922	0.843	0.985	0.895
2011	0.804	0.997	0.857	0.936	0.898
2012	0.832	0.975	0.859	0.921	0.897
2013	0.834	0.849	0.909	0.932	0.881
2014	0.856	0.892	0.911	1.023	0.921
2015	0.872	0.943	0.913	1.001	0.932
2016	0.913	1.034	0.916	0.995	0.965
2017	0.906	1.023	0.918	0.976	0.956
2018	0.912	0.994	0.919	0.899	0.931
2019	0.909	0.999	0.911	0.967	0.947
Mean value	0.857	0.973	0.896	0.964	0.922

The change of agricultural technology efficiency and the change of agricultural technology efficiency in Anhui Province in 2019 are calculated by using bcc-4 model. See table for the change of agricultural technology efficiency and the change of agricultural technology efficiency in 2019. It can be seen that the total factor productivity of smart agriculture in Anhui Province fluctuated continuously from

2010 to 2019, and the fluctuation range was large.

From 2010 to 2019, the total factor productivity of smart agriculture in Anhui province increased by an average of 5.2%, of which the comprehensive technical efficiency increased by 17.7% and the technological change increased by 7.7%. It can be seen from Figure 6 that the technological progress of smart agriculture in Anhui Province was basically

consistent with the change direction of total factor productivity during the research stage. It can be seen that the total factor productivity of Anhui Province was greatly affected by technological progress from 2010 to 2019, and the growth of total factor productivity mainly came from technological progress. It shows that with the continuous economic development and the investment of a large amount of national financial funds, advanced and excellent production technology has been widely popularized and applied, thus promoting technological progress.

From 2010 to 2019, the comprehensive technical efficiency of Maize in China increased by 1.77% annually, and the pure technical efficiency fluctuated around 0.9, indicating that in this historical process, the resources in all links of intelligent agricultural production in Anhui Province have been fully utilized, the input and output are in a better allocation, there is no serious waste of resources, and secondly, the scale efficiency remains stable. It can be seen from Figure 7 that from 2010 to 2019, Anhui Province is in the stage of increasing returns to scale of smart agricultural production.

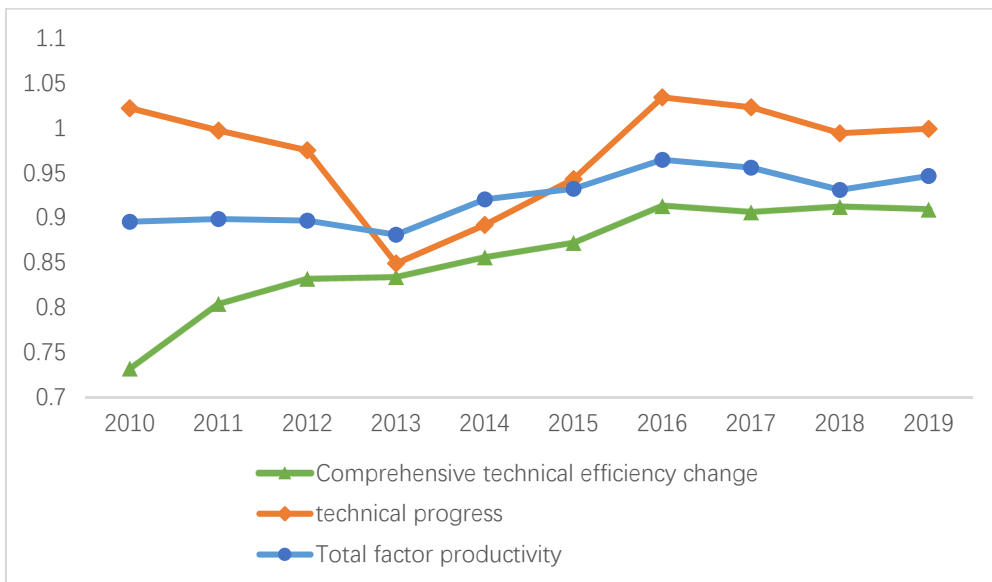


Figure 1. Changes in production efficiency and composition of smart agriculture in Anhui Province

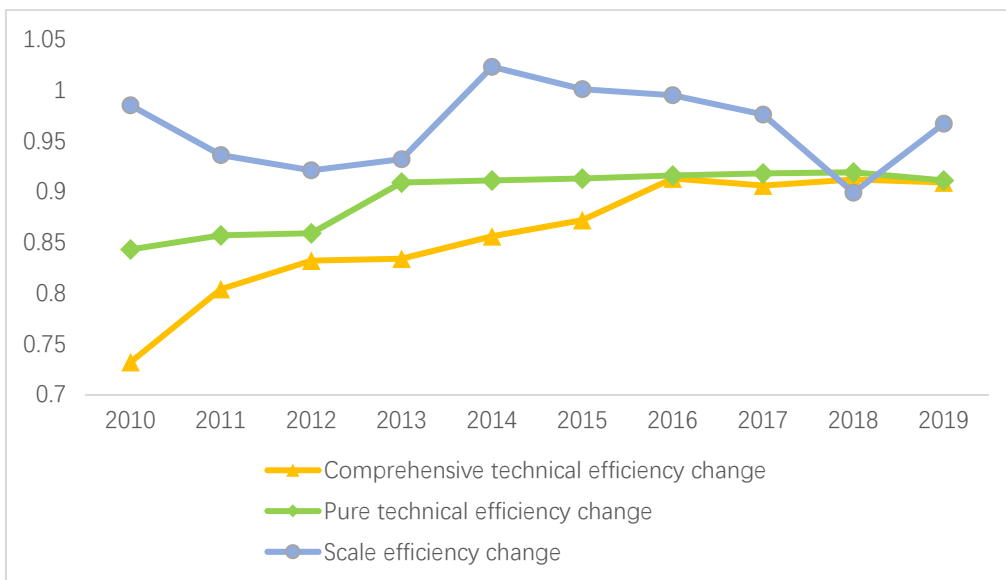


Figure 2. Changes in technical efficiency and composition of smart agriculture in Anhui Province

3.2. Analysis of Factors Affecting Production Efficiency

In this paper, the influencing factors of production

efficiency are estimated by Tobit regression through Stata software. The relevant parameter values are shown in Table 4.

Table 4. Analysis results of influencing factors of production efficiency of smart agriculture in Anhui Province

Index	Coef	Std.Err	t	P> t
Labour productivity	0.012	3.2E-07	0.011	0.011
Financial agricultural expenditure level	-1.51	1.2E-07	-0.67	0.010
Agricultural machinery density	0.017	1.4E-05	1.23	0.001
Agricultural scale level	0.012	1.17E-05	0.343	0.061
Planting structure	-0.027	1.2E-05	1.07	0.014
Urbanization rate	1.225	0.043	-2.21	0.003
Industrialization level	1.011	0.0312	0.21	0.018
Location variable	0.130	0.0899	0.89	0.017

The results show that there is a "positive U-shaped" curve relationship between labor productivity and intelligent agricultural production efficiency.

From the results, the level of financial support for agriculture is significant at the level of 10% and the impact is negative, mainly because the investment in supporting agricultural technology takes a long time to receive returns, and the effect is not obvious in the short term.

The density of agricultural machinery is significantly positive at the level of 10%, which shows that the density of agricultural machinery can significantly promote the production efficiency of intelligent agriculture. The planting structure is significantly negative at the 10% level, indicating that the change of planting structure will significantly reduce the production efficiency of intelligent agriculture.

The level of agricultural scale has passed the significance level test of the 10% level, and has a positive effect on the production efficiency of intelligent agriculture, which shows that the development of agricultural scale is conducive to the improvement of the production efficiency of Intelligent Agriculture in Anhui Province.

The urbanization rate is significantly positive at the level of 10%. The level of industrialization is significant at the level of 10%, and the impact on the production efficiency of smart agriculture is positive, indicating that the development of industrialization brings the improvement of scientific and technological level, drives the development of advanced agricultural technology, and promotes the improvement of agricultural production efficiency.

4. Conclusions and Suggestions

4.1. Conclusion

Based on the analysis of panel data related to smart agricultural production in 16 urban areas of Anhui Province from 2010 to 2019, this paper improves the use of BCC model and Tobit model in data envelopment analysis. This paper analyzes the overall development trend of China's smart agricultural production efficiency at this stage, and analyzes the influencing factors of smart agricultural production efficiency in Anhui Province. The results show that:

(1) From 2010 to 2019, the total factor productivity of China's smart agriculture fluctuated slightly around 0.9.

(2) On the whole, the smart agriculture in our province is in the stage of increasing returns to production scale and has good development prospects.

(3) The change trend of pure technical efficiency is consistent with that of comprehensive technical efficiency. It can be seen that the progress of Intelligent Agriculture in China is closely related to the innovation and progress of

science and technology.

(4) From the calculated production efficiency value of smart agriculture in 16 urban areas of Anhui Province, it can be found that the 16 urban areas of smart agriculture in Anhui Province are in good production state, but the development is still uneven.

4.2. Policy Suggestion

(1) Adjust policy guidance and introduce talents for urban and rural smart agricultural production. Contemporary young people tend to develop in big cities, which leads to China's obvious scientific and technological innovation and progress in smart agriculture, but in practical application, due to the limitation of professional knowledge, the use efficiency of mechanical equipment is low. The government can introduce more professional and technical talents for rural smart agricultural production by giving more welfare policies to college students who are willing to return to their hometown to work in agriculture, so as to promote industrial revitalization and further promote rural revitalization.

(2) Promote the synchronous development of smart agriculture and digital countryside. Strengthen the construction of rural digitization, add rural network service points, promote 5g construction, make rural areas realize "every household has access to the Internet and every family understands the Internet", regularly carry out compulsory lectures on Internet use publicity and education for farmers, enhance farmers' awareness of big data and Internet of things, promote farmers to advance with the times, better integrate with new technologies of smart agriculture, and create synchronous and intelligent agriculture and rural areas.

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