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Research on the Evaluation of Production Efficiency of Smart Agriculture based on DEA-malmquist Model

-- Taking Heilongjiang Province as an Example

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Abstract

Smart agriculture is the advanced stage of agricultural information development from digitalization to intelligence, which has milestone significance for agricultural growth and has become the trend of modern agricultural development in the world. Based on the agricultural data of Heilongjiang Province from 2009 to 2019, the DEA-Malmquist model is used to calculate the static and dynamic production efficiency of smart agriculture in Heilongjiang, and the redundancy of input elements is further explored. Through the analysis, it is found that in recent years, there have been many periods of non-optimal production efficiency of smart agriculture in Heilongjiang. Among them, improper investment scale is the main reason leading to ineffective production. The change of total factor productivity (TFP) in Heilongjiang Province is volatile, and one of the key factors to promote it is technical progress.

Keywords

Agricultural Productivity; Smart Agriculture; Data Envelopment Analysis (DEA); Malmquist Index.

1. Introduction

In recent years, "smart agriculture" is emerging in some developed countries. It is a new model of agricultural production and management that integrates traditional agriculture with industrial 4.0 technologies such as information and communication, big data and artificial intelligence. Smart agriculture has been successful in different agricultural development models in Europe, America, Japan and Korea since its birth. In 2018, the No.1 document of the central committee also points out that it is an inevitable choice for the future development of agriculture to promote the experimental demonstration of the Internet of Things and the application of remote sensing technology.

Heilongjiang Province, rich in natural resources and excellent ecological environment, is the most important major grain-producing area and commodity grain base in China. In recent years, Heilongjiang Province has actively promoted the application of big data in the field of agriculture, built application platforms, and accelerated the comprehensive utilization of agricultural and rural data. The above efforts in Heilongjiang Province not only consolidate the status of national food security as a ballast, but also provide the impetus for accelerating the high-quality development of modern agriculture and rural revitalization. Figure 1 shows that the gross output value of agriculture in Heilongjiang Province has continued to grow in recent 11 years, but the growth rate has slowed and fluctuated. To realize the development and upgrading of Heilongjiang agricultural industry, it is the key means and the only way to promote high-level smart agriculture. Among them, the calculation of production efficiency is helpful to find out the real development of smart agriculture in the province.

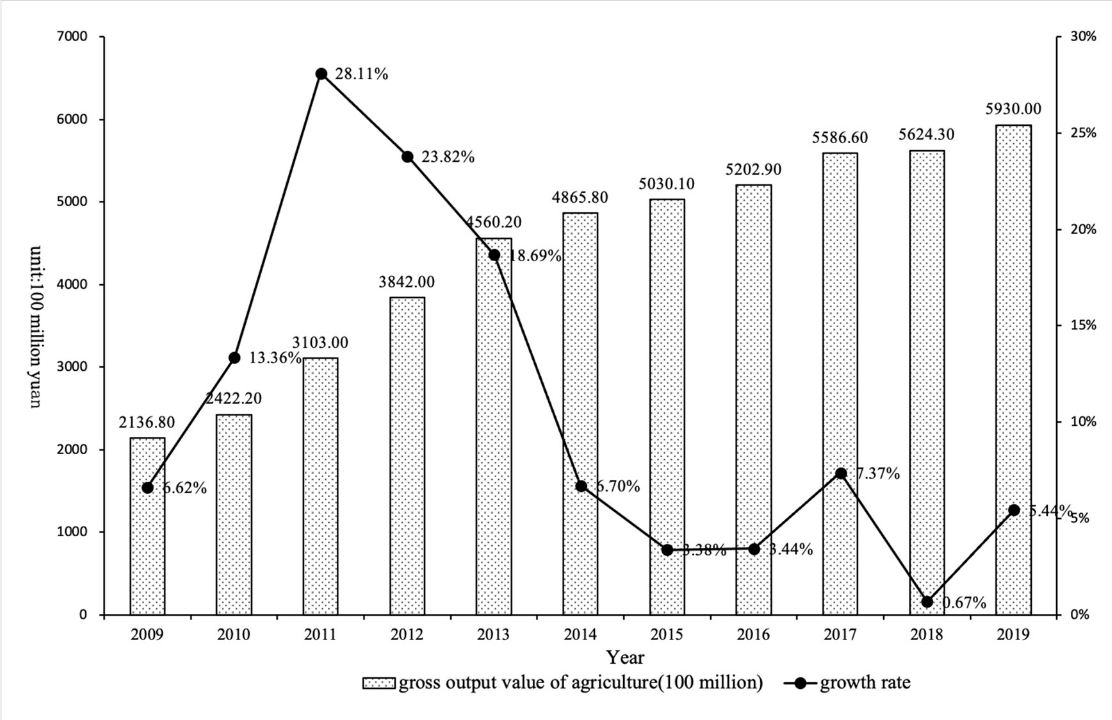

Figure 1. Trend of gross output value and growth rate of agriculture in Heilongjiang Province, 2009-2019

2. Review of Literature

At present, many scholars have studied the measurement of agricultural production efficiency in China, among which the Data Envelopment Analysis (DEA) model and its extensions are widely used. Taking Shaanxi Province in Northwest China as the research object, Feng[1] and Liu (2018) used the DEA model and the Malmquist index model to measure the static and dynamic agricultural production efficiency, and discovered that although the agricultural production efficiency of the province was not high, the development of each stage was generally stable and balanced. Li[2] et al. (2020) used the DEA model combined with the Malmquist index and the projection analysis method to empirically analyze the agricultural production efficiency of Jilin Province from 2004 to 2017. Based on the results, the development strategies of agricultural modernization, regionalization and high efficiency in Jilin Province were put forward. Since then, Zhou[3] and Zhang (2021), Liu[4] (2021) and Zhou[5] et al. (2022) also used the data envelopment analysis method to conduct studies related to the evaluation of agricultural production efficiency.

Only a few scholars have conducted quantitative studies related to smart agriculture in China. Zhang[6] and Yin (2018) measured the production efficiency of agricultural informatization in China by DEA method, and found that there were unbalanced and inadequate development characteristics of agricultural informatization in the east, middle, west and northeast regions of China. Zhang[7] and Bian (2019), on the other hand, used the analytical hierarchy process (AHP) method to assess the comprehensive benefits of smart agriculture in Heilongjiang Province. Jia[8] et al. (2021) included indicators reflecting the development of smart agriculture such as rural Internet inputs and R&D inputs in addition to traditional agricultural input indicators, and used the super-efficient SBM model to effectively measure the productivity of smart agriculture across Shandong Province from 2009 to 2019.

To sum up, most of the existing studies concerned about the measurement of traditional agricultural production efficiency, and only a few literature have carried out quantitative analysis related to smart agriculture. There is a lack of evaluation research on production efficiency of smart agriculture in Heilongjiang Province. Therefore, this paper uses DEA model and Malmquist index model to analyze the production efficiency of smart agriculture in Heilongjiang Province from 2009 to 2019 statically and dynamically, intuitively evaluates the development level of smart agriculture, and further excavate the redundancy of agricultural input elements, so as to provide targeted countermeasures and suggestions for improving the productivity of smart agriculture.

3. Research Methods and Data Sources

3.1. DEA-malmquist Model Construction

3.1.1. DEA Model Construction

The data envelopment analysis (DEA) method was put forward by Charnes[9], Cooper, and Rhodes in 1978. The principle of this method is to determine the relatively effective production frontier by keeping the inputs or outputs of the decision-making units (DMU) unchanged and projecting each DMU onto the production frontier of DEA with the help of mathematical programming and statistical data. Among them, the effective point will be located on the frontier surface with an efficiency value index of 1, and the ineffective point will be located outside the frontier surface with an efficiency value index between 0 and 1. The smart agriculture production efficiency measurement is of the input and output type, which fits with the DEA model and has good comparability.

Among the DEA methods applied, the most representative models are CCR model with constant returns to scale (CRS) and BCC model with variable returns to scale (VRS). Because of the different emphasis of research, DEA models can be further divided into input orientation and output orientation. Generally speaking, agricultural output is an uncontrollable variable, while input is a controllable one. Therefore, based on the input-oriented BCC (variable returns to scale) model, the production efficiency of smart agriculture in Heilongjiang Province was comprehensively evaluated. The formula is shown as follows:

$$s.t.\begin{cases} min\theta \\ \sum_{i=1}^{n}\lambda_i x_i + s^- = \theta x_0 \\ \sum_{i=1}^{n}\lambda_i y_i - s^+ = y_0 \\ \sum_{i=1}^{n}\lambda_i = 1 \\ \lambda_i \geq 0; i = 1,2,\dots,m; s^+ \geq 0, s^- \geq 0 \end{cases} \tag{1}$$

In the formula (1): We assume that the BCC model has multiple DMUs, where x_i and y_i denote input and output elements respectively, n is the number of DMUs, x_0 and y_0 are the original input and output indicators of the DMUs, respectively; λ_i is the coefficient of each DMU; s^- and $s^+$are the input and output slack variables, respectively; θ ($0 \leq \theta \leq 1$) is the decision variable, which is the production efficiency of the DMU, or called combined efficiency. When $\theta = 1$, the DMU is valid, and when $\theta < 1$, the DMU is invalid.

3.1.2. Malmquist Index Construction

Due to the incomparability of efficiency values in different years, it is impossible to simply carry out time series comparative analysis with annual efficiency results. Therefore, the traditional DEA model can only describe the static efficiency situation of DMU, and cannot reflect the dynamic changes of efficiency scores in different periods. So this paper combines the Malmquist index and establishes the DEA-Malmquist model. The output-based Malmquist index, proposed by Fare[10] et.al (1994), is an efficiency assessment method that defines efficiency through a distance function and is widely used to measure productivity changes. Under the CRS assumption, total factor productivity (TFP) can be divided into technical change (techch) and technical efficiency (effch), so it can be expressed as M = TFP = techch *effch . Taking the technology in period *t* as the base period, the expression of the Malmquist index from period *t* to *t+1* is as follows:

$$M_0(x_t,u_t,x_{t+1},u_{t+1}) = \left[\frac{D_0^t(x_{t+1},u_{t+1})}{D_0^t(x_t,u_t)} \bullet \frac{D_0^{t+1}(x_{t+1},u_{t+1})}{D_0^{t+1}(x_t,u_t)}\right]^{\frac{1}{2}} \tag{2}$$

Under the VRS assumption, the Malmquist index is the product of the technical change (techch), pure technical efficiency change (pech), and scale efficiency change (sech), so it can be expressed as *tfpch = techch • effch = techch • pech • sech*. The specific formula is as follows:

$$\begin{aligned} M_0(x_t,u_t,x_{t+1},u_{t+1}) = \frac{D_0^{t+1}(x^{t+1},u^{t+1}|\,VRS)}{D_0^t(x^t,u^t|\,VRS)} \bullet \left[\frac{D_0^t(x^t,u^t)}{D_0^{t+1}(x^t,u^t)} \bullet \frac{D_0^t(x^{t+1},u^{t+1})}{D_0^{t+1}(x^{t+1},u^{t+1})}\right]^{\frac{1}{2}} \\ \bullet \left[\frac{D_0^t(x^t,u^t)|\,VRS}{D_0^t(x^t,u^t)|\,CRS} \bullet \frac{D_0^{t+1}(x^{t+1},u^{t+1})|\,CRS}{D_0^{t+1}(x^{t+1},u^{t+1})|\,VRS}\right]^{\frac{1}{2}} \end{aligned} \tag{3}$$

When tfpch, effch, techch, pech and sech are all greater than 1, it shows that total factor productivity, technical efficiency, technical progress, pure technical efficiency and scale efficiency are all increasing; Otherwise, it will be decreased.

3.2. Indicator System Construction

Table 1. The index evaluation system

Index attribute	Specific indicator	Variables
Input Index	Labor input(X1)	Agricultural practitioners/10000 people
	Fertilizer input(X2)	Fertilizer application/ton
	Mechanical input(X3)	Agricultural machinery total power/1000 kilowatts
	Irrigation input(X4)	Effective irrigated land area/10000 hectares
	Land input(X5)	Sown area of major crop /10000 hectares
	Rural Internet input(X6)	Rural broadband access users/10000 households
	Innovation capital input(X7)	Comprehensive Agricultural Development Funds/10000 yuan (RMB)
Output Index	Agricultural output(Y)	Agricultural gross output value/100 million yuan (RMB)

As smart agriculture is a kind of agricultural production method, some indicators used to measure traditional agricultural production efficiency are also applicable to the measurement of production efficiency of smart agriculture. Therefore, this paper integrates traditional production factors and technical production factors, comprehensively considers the purpose of this paper and the difficulty of data collection, and constructs the evaluation system of smart agriculture production efficiency in Heilongjiang Province shown in Table 1.

The index system of evaluation is composed by seven input indexes and one output index. Among them, the five indexes of labor, fertilizer, machinery, irrigation and land input reflect the traditional agricultural production input, rural Internet investment and innovation investment are input indexes of smart agricultural production. The agricultural output value is the output index.

3.3. Data Sources

This paper takes Heilongjiang Province as the research objective, with 2009-2019 as the research interval. The relevant data of smart agricultural input and output economic indicators are mainly from the 2009-2019 *Heilongjiang Statistical Yearbook*, *China Statistical Yearbook*, *China Financial Yearbook*, *China Agricultural Yearbook*, *China Rural Statistical Yearbook*, *China Regional Economic Statistical Yearbook*, and provincial statistical bulletins. For original data see Table 2.

Table 2. Original data

Year	Y	X1	X2	X3	X4	X5	X6	X7
2009	2251.1	811.7	4802427	3401.27	340.6	1212.2	31.07	173023.31
2010	2536.3	798.6	5138394	3736.29	387.52	1244.5	36.68	261380.47
2011	3223.51	808.38	5419483	4097.76	433.27	1283.1	43.4	197767
2012	3952.3	789.98	5601697	4549.25	477.65	1321.2	48.96	285755.2
2013	4633.26	779.35	5789762	4848.69	534.21	1357.6	57.46	312662.69
2014	4894.8	768.6	5901989	5155.52	530.52	1396.8	59.43	369027.87
2015	5044.93	766	5930227	5442.73	553.09	1428.3	82.92	572161.37
2016	5197.75	758.2	5879446	5634.27	595.34	1420.2	89.58	341444.87
2017	5586.63	746.3	5861176	5813.76	603.1	1415.4	150.77	588281.44
2018	5624.29	736.5	5745010	6082.4	611.96	1421.5	241.13	630000
2019	5930	564.1	5293241	6359.08	617.76	1433.8	267.64	690000

4. Results and Analysis

4.1. Static Analysis of Production Efficiency of Smart Agriculture in Heilongjiang

Using DEAP 2.1 software, the production efficiency of smart agriculture in Heilongjiang Province from 2009 to 2019 was measured, including comprehensive technical efficiency (crste), pure technical efficiency (vrste) and scale efficiency (scale). "irs" indicates the increasing returns to scale of DMU, and "—" indicates that the return on scale of DMU is unchanged. The computing results are shown in Table 3.

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Table 3. The production efficiency value of smart agriculture in Heilongjiang province, 2009-2019

Year	crste	vrste	scale	rts	DEA validity
2009	0.895	1.000	0.895	irs	invalid
2010	0.840	1.000	0.840	irs	invalid
2011	1.000	1.000	1.000	–	valid
2012	0.990	1.000	0.990	irs	invalid
2013	1.000	1.000	1.000	–	valid
2014	1.000	1.000	1.000	–	valid
2015	0.989	0.989	1.000	–	invalid
2016	1.000	1.000	1.000	–	valid
2017	1.000	1.000	1.000	–	valid
2018	0.980	0.996	0.984	irs	invalid
2019	1.000	1.000	1.000	–	valid
Mean	0.972	0.999	0.978	–	–

As can be seen from the computing results in Table 3 that in the past 11 years in Heilongjiang Province, the input-output ratio of smart agricultural production is relatively general, and there are six years with complete DEA validity, accounting for 54.6 %. It can be seen from the row of average data in Table 3 that the average values of comprehensive technical efficiency, pure technical efficiency and scale efficiency are 0.972, 0.999 and 0.97, respectively, which indicates that Heilongjiang's smart agriculture has high production efficiency, and the input of modern factors such as technology has promoted its development to a certain extent. Compared with the above three efficiency averages, there are only two years below the average level of comprehensive technical efficiency and average scale efficiency, respectively in 2009 and 2010, accounting for only 18.2 % of the total number of years; there were also only two years below the average level of pure technical efficiency, 2015 and 2018, accounting for 18.2 percent of the total. It shows that the allocation efficiency of agricultural production resources in Heilongjiang is high, and the gap between each year is not large.

From the perspective of comprehensive technical efficiency, there are six years in which the comprehensive efficiency value of agricultural production is 1, namely, 2011, 2013, 2014, 2016, 2017 and 2019, indicating that the comprehensive technical efficiency of these six years reaches DEA effective, the factor inputs of smart agriculture are relatively reasonable, and there is no excess of factor inputs and insufficient outputs. The scale efficiency has also reached the highest value of 1 in 11 years, indicating that the development of smart agriculture has been regionalized and scaled, forming economies of scale. There are five years with comprehensive efficiency of agricultural production less than 1, including 2009, 2010, 2012, 2015 and 2018. It shows that the efficiency of smart agricultural production in these years is not optimal, and the utilization rate of production inputs is low. To some extent, it shows that the agricultural production structure in individual years is unreasonable.

By analyzing the pure technical efficiency and scale efficiency of each year, we can find the primary and secondary reasons that affect the comprehensive production efficiency. In terms of pure technical efficiency, two-fifths of the years in which the production inputs are invalid

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are caused by pure technical efficiency, accounting for 40% of the invalid production years. From the perspective of scale efficiency, among the five years of ineffective investment, the scale of improper investment in production factors is four years, accounting for 80 percent. So the inappropriate investment scale is the main reason for ineffective production, while the invalid pure technical efficiency is the second reason for ineffective production. Therefore, this paper will further discuss the redundancy of agricultural input.

Table 4 shows that the input redundancy in 2015 and 2018 is obvious. Taking the redundancy of agricultural industry inputs in 2018 as an example, 1.33 million more labor was invested, 0.39 million tons more fertilizer was applied, 0.13 million hectares more effective irrigation area was invested, 73.48 thousand more rural broadband access users were invested, and 37.39 million yuan more funds were invested in comprehensive agricultural development. All of these show that Heilongjiang Province has had insufficient productivity of smart agriculture in the past years, and cannot make the best use of each production input factor in the production process. Therefore, Heilongjiang should change the agriculture development pattern from resource input-based to technology input-based as soon as possible, and play the role of big data and artificial intelligence in promoting agriculture. At the same time, it is urgent to rationally utilize land and water resources, reduce agricultural pollution, authentically realize the scale of agricultural development and scientific management, improving agricultural production efficiency.

Table 4. Input slack variable for efficiency evaluation of smart agriculture in Heilongjiang Province from 2009 to 2019

Year	crste	Input slack variables						
		Labor	Fertilizer	Machinery	Irrigation	Land	Internet	Capital
2009	0.895	0	0	0	0	0	0	0
2010	0.84	0	0	0	0	0	0	0
2011	1.00	0	0	0	0	0	0	0
2012	0.99	0	0	0	0	0	0	0
2013	1.00	0	0	0	0	0	0	0
2014	1.00	0	0	0	0	0	0	0
2015	0.989	2.17	0	64.986	0	10.935	0	157045.9
2016	1.00	0	0	0	0	0	0	0
2017	1.00	0	0	0	0	0	0	0
2018	0.98	133.436	388515.4	0	13.002	0	7.348	3738.575
2019	1.00	0	0	0	0	0	0	0

4.2. Dynamic Analysis of Production Efficiency of Smart Agriculture in Heilongjiang

In order to more comprehensively and intuitively show the dynamic changes of the production efficiency of smart agriculture in Heilongjiang Province, this paper continues to apply the Malmquist index to analyze the dynamic efficiency of the output of smart agriculture in Heilongjiang. The results are shown in Table 5.

As can be seen from Table 5, the total factor productivity change (tfpch), pure technical efficiency change (pech), and scale efficiency change (sech) are all 1 and remain constant. Judging from technical progress change (techch), the phases of 2010-2011, 2011-2012, 2012-2013, 2015-2016 and 2018-2019 are positive growth, and the rest are negative growth, and the trend of technical change is consistent with total factor productivity, which shows that one of the key factors driving the variation of total factor productivity in Heilongjiang Province is the technical progress.

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The average total factor productivity is 1.010, and the positive and negative growth years accounted for 50% of the total period, which suggests that the dynamic efficiency of technology-led of Heilongjiang is not high, and the development of smart agriculture is insufficient. Overall, the change in total factor productivity of smart agriculture in Heilongjiang Province has fluctuated since 2009, which may be due to the imperfect development of technology and the inability to adapt to the modernization transformation.

Table 5. Total factor productivity decomposition of smart agriculture in Heilongjiang Province, 2009-2019

Period	effch	techch	pech	sech	tfpch
2009—2010	1.000	0.924	1.000	1.000	0.924
2010—2011	1.000	1.343	1.000	1.000	1.343
2011—2012	1.000	1.032	1.000	1.000	1.032
2012—2013	1.000	1.089	1.000	1.000	1.089
2013—2014	1.000	0.979	1.000	1.000	0.979
2014—2015	1.000	0.829	1.000	1.000	0.829
2015—2016	1.000	1.283	1.000	1.000	1.283
2016—2017	1.000	0.825	1.000	1.000	0.825
2017—2018	1.000	0.804	1.000	1.000	0.804
2018—2019	1.000	1.144	1.000	1.000	1.144
Mean	1.000	1.010	1.000	1.000	1.010

5. Conclusion

By constructing the DEA-Malmquist index model and using the data characteristics of agricultural production in Heilongjiang Province from 2009 to 2019, the thesis gives a quantitative analysis on efficiency in production and annual trend changes of smart agriculture from the static and dynamic aspects respectively, and draws the following conclusions:

From a static perspective, the average values of comprehensive technical efficiency, pure technical efficiency and scale efficiency in Heilongjiang Province in recent 11 years are 0.972, 0.999 and 0.978, which shows the high production efficiency of smart agriculture. However, there is still room for improvement, because only four years (2009, 2010, 2012 and 2018) have achieved an increase in returns to scale, for most of the province's overall returns to scale remain unchanged. Therefore, on the basis of consolidating agricultural production capacity, Heilongjiang Province should comprehensively implement the strategy of agricultural production modernization, such as promoting the construction of smart agriculture talent team and rural communication infrastructure.

1. The improper scale of production input is the principal cause of low efficiency of agricultural production in Heilongjiang in individual years, and the input redundancy in 2015 and 2018 is obvious. Pure technical ineffectiveness is the secondary cause of invalid production. Therefore, the agricultural department should optimize the scale of production and reasonably allocate agricultural resources, solving the redundancy problems in fertilizer application, agricultural machinery power, effective irrigation area, main crop planting area and so on.

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2. From the dynamic perspective, technical progress plays an active role in improving the production efficiency of smart agriculture, while technical efficiency has little effect on promotion. Since 2009, the technical progress rate of the whole province has been low, resulting in low total factor productivity, and the level of smart agricultural production technology has not achieved sustained and steady positive growth. Therefore, the government should strive for the breakthrough by increasing investment in agricultural high-tech R&D and achievement transformation, and actively building an innovative platform to realize the combination of talents and technical resources.

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