Study on the Impact Path of Digital Inclusive Finance on Agricultural Eco-Efficiency

Jinyuan Li *, Xiaochen Shi *, Mingzi Li*

School of Statistics, Chengdu University of Information Technology, Chengdu 610103, China.
***These authors contributed equally to this work.**

Abstract: Theoretical research shows that digital financial inclusion can promote the growth of rural digital economy by reducing transaction costs. Therefore, in the context of digital China, it has practical significance to discuss the current situation of agricultural eco-efficiency, the influence path of digital financial inclusion on agricultural eco-efficiency. First, this paper constructed an input-output index system of agricultural ecological efficiency. Secondly, based on the super-efficiency SBM model, the national agroecological efficiency index was calculated, and the development level and differentiation of the eastern, middle and western regions were analyzed. Finally, based on the panel threshold model, the impact path of digital financial inclusion on agricultural eco-efficiency was explored and visualized. The results showed as follows: 1. The average value of agricultural eco-efficiency in China was basically at a medium level, and the regional level was high in eastern China, low in western China and similar in central China. 2. The development level of digital inclusive finance has a significant positive impact on agro-ecological efficiency, and the effect becomes stronger from weak. Therefore, we advocate promoting regional ecological agriculture cooperation and strengthening the construction of digital infrastructure in rural areas, and increasing policy support for digital inclusive finance.

Keywords: Digital Inclusive Finance; Agroecological Efficiency; Super Efficiency SBM Model; Panel Threshold Model

1. Introduction

1.1 Research background

Agricultural power is the basic force of socialist modern power and the key to rural revitalization. At present, China's agricultural field is transforming to green ecological agriculture, but there are still problems such as uneven regional development of agricultural ecological efficiency and long-term low agricultural ecological efficiency. At the same time, the development of modern agriculture is inseparable from the input of agricultural science and technology. Therefore, digital inclusive finance, as a new financial form based on big data, artificial intelligence, blockchain and other technologies, can reduce service costs, reach more rural customers, solve the problem of information asymmetry and no collateral, and effectively solve the financing difficulties in the development of digital agriculture. So as to promote the growth of rural digital economy and promote the development of modern agriculture.

1.2 Literature review

In this paper, literature was collected from high-quality journals such as Peking University Core and CSCD in CNKI, and analyzed from both qualitative and quantitative perspectives. Cite Space 6.22 was used to draw the co-occurrence network map and clustering map of the collected literature keywords, and simplified the complex literature and its relationship into a viewable view (as shown in Figure 1).Regarding the study of agricultural eco-efficiency, Wang Chenxuan et al. (2021) analyzed the spatial effects of agricultural eco-efficiency from the perspective of agricultural science and technology input. Han Songyan et al. (2021) explored the impact of agricultural pollution on the development level and efficiency of eco-agriculture. Most literatures only considered agricultural carbon emission at the level of non-expected output, ignoring agricultural pollution factors such as fertilizer loss, pesticide loss and agricultural film residue. As for the research on digital inclusive finance, Zhang Yongqi (2022) explored the impact and mechanism of digital inclusive finance on rural land transfer. Wang Sen et al. (2022) constructed an evaluation system for high-quality agricultural development and explored the intermediary and threshold effects of digital financial inclusion on agricultural development.

2. Index system construction and data source

2.1 Construction of input-output index system of agricultural ecological efficiency

Thirty provincial-level administrative regions (municipalities directly under the Central Government and autonomous regions) were selected in this paper. Due to the large amount of missing data in Tibet Autonomous Region and the differences in the statistical caliber of data in Hong Kong, Macao and Taiwan, Hong Kong, Macao and Tibet were excluded from the study area. Since carbon emission and other indicators are only updated to 2019, this paper selects data from 2011 to 2019 to construct agro-ecological efficiency indicators from two perspectives of input and output, and selects mechanical power, land, labor, irrigation, fertilizer, pesticide, agricultural film and energy as input indicators. The total output value of agriculture was selected as the expected output index. Agricultural carbon emission and agricultural pollution were selected as non-expected output indicators. Based on the level of non-expected output and considering the negative externalities of agricultural production, the absorption rate of chemical fertilizer, utilization rate of pesticide and residual rate of agricultural film were set as 0.35, 0.5 and 0.1 respectively according to the Pollution Coefficient Manual based on relevant literature under the condition that the annual use amount of pesticide, fertilizer and agricultural film was known. Therefore, the corresponding average level of fertilizer loss, pesticide loss and agricultural film residue can be calculated. Agricultural carbon emissions are measured by the total carbon emissions of chemical fertilizers, pesticides, agricultural film, agricultural diesel, agricultural irrigation and agricultural farming. The required agricultural carbon emissions are calculated using the emission factor method. The final agricultural eco-efficiency input-output index system is shown in Table 1.

Table 1: Input-output index system of agricultural ecological efficiency

Input-output dimension	Index name	Concrete variable	unit	Instructions
Input level	Mechanical input	Total power of agricultural machinery	megawatt	
	Land input	Crop sown area	Square kilometer	
	Labor input	Number of people employed in agriculture	Thousands of people	Number of people employed in agriculture = People employed in primary industry *(total output value of agriculture/total output value of agriculture, forestry, husbandry and fishery)
	Irrigation input	Effective irrigated area	Ten thousand tons	
	Fertilizer input	Conversion amount of fertilizer applied	Ten thousand tons	
	Pesticide input	Pesticide use	Ten thousand tons	
	Agricultural film input	Agricultural film usage	Ten thousand tons	
	Energy input	Agricultural diesel use	Ten thousand tons	
Expected output level	Agricultural output	Gross agricultural output value	Hundred million yuan	
Undesired output level	Agricultural pollution	Fertilizer loss	Ten thousand tons	According to “National Pollution Coefficient Manual”, “Agricultural Fertilizer Loss Manual”, “Pesticide manual” and related literature
		Amount of pesticide loss	Ten thousand tons	
		Agricultural film residue	Ten thousand tons	
	Carbon emission	Agricultural carbon emission	Ten thousand tons	Total carbon emissions of fertilizers, pesticides, agricultural film, agricultural diesel, agricultural irrigation and agricultural farming

2.2 Data source

2.2.1Agroecological efficiency

The data used in this paper come from China Statistical Yearbook, China Rural Statistical Yearbook and statistical yearbooks of various provinces from 2012 to 2020. The missing individual values are supplemented by interpolation method, and the nine-year provincial panel data of 30 provinces are obtained through data processing.

2.2.2 Digital Financial Inclusion Index

This paper quotes the "Peking University Digital Financial Inclusion Index" compiled by the joint research group of Peking University Digital Financial Research Center and Ant Technology Group Research Institute. The digital Financial inclusion index of 30 provinces from 2011 to 2019 is selected.

3. The analysis of agricultural ecological efficiency in our country

3.1 National agroecological efficiency assessment based on Super-SBM model

This paper uses MATLAB software and Super-SBM model to measure and analyze the agro-ecological efficiency of 30 regions except Tibet Autonomous Region from 2011 to 2019 (see appendix).According to the economic region division method proposed by China in the 1980s, 30 regions are divided into east, middle and west. With reference to relevant literature, the agro-ecological efficiency level was divided into low level 0~0.6, medium level 0.6~0.8, medium high level 0.8~1, and high level >1.

In the whole country, the average agricultural eco-efficiency from 2011 to 2019 was basically at a medium level, showing a stable fluctuation state, and the agricultural eco-efficiency fluctuated between 0.68 and 0.8. The agricultural eco-efficiency in 2014, 2017 and 2019 was relatively low, and the other years were relatively high. According to the coincidence degree of Figure 1, the agricultural eco-efficiency in the central region is closer to the national level of agricultural eco-efficiency, while the agricultural eco-efficiency in the eastern region is higher than the national level, and the agricultural eco-efficiency in the western region is lower than the national level.

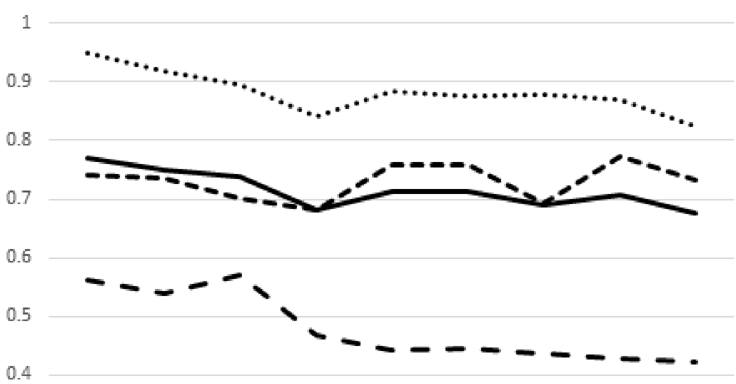

Figure 1: Fluctuation of agroecological efficiency from 2011 to 2019

3.2 Regional comparison of inter-provincial agroecological efficiency based on three economic zones

The spatial differentiation of agro-ecological efficiency levels in the eastern and western central regions was summarized (as shown in Table 2).

Table 2: Distribution of mean agroecological efficiency in eastern, central and western regions

	The east	Middle part	west
High level	A surname Guangdong and Fujian		Guizhou, Shaanxi and Qing
Medium-high level	Su and Zhe Guangxi and Shanghai		Sichuan
Medium level	Tianjin and Liao	Hunan and Hubei	Ning and Yu
Low level	Lu and Ji	Gan, Hei and Henan Mongolia, Anhui, Jin and Ji	Cloud, new, sweet

4. An empirical study on the influence path of digital inclusive finance on agricultural ecological efficiency

4.1 The setting of threshold model

Threshold model is a model that observes whether other variables will suddenly turn to other development situations when one variable reaches a certain value in a group of panel data.

This paper argues that the impact of digital inclusive finance on agricultural eco-efficiency may be influenced by its own value range. In order to verify this hypothesis, this paper further constructed panel threshold data and took digital financial inclusion index (zs) as threshold variable to study its impact on agricultural eco-efficiency.

At the same time, in order to achieve a unified value and facilitate calculation, this paper carried out a logarithmic operation on the data, set the digital inclusive financial index (zs) as the core explanatory variable and threshold variable, set the agricultural ecological efficiency y as the explained variable, and took the input-output indicators of agricultural ecological efficiency as the control variable.

4.2 The test of threshold model

In this paper, single-threshold, double-threshold and three-threshold tests were conducted on the data in the sample. The test results are shown in Table 3.According to the results of the threshold effect test, when zs (Digital Financial Inclusion Index) is taken as the threshold variable, the single threshold effect passes the significance test at the confidence level, while neither the double threshold nor the triple threshold pass the test, confirming that within the scope of this study, there is a specific correlation between the impact of digital financial inclusion on agricultural ecological efficiency, that is, there is a threshold effect. And a single threshold model can be constructed for estimation.

Table 3: Test results of threshold model

Threshold number	f-number	p-value	Threshold		
			1%	5%	10%
Single threshold	23.3	0.0400	19.5638	22.3465	32.5748
Double threshold	12.99	0.3700	22.9399	27.9985	34.0133
Triple threshold	16.78	0.1700	26.6622	36.2854	43.3900

4.3 Estimation of threshold model

As shown in Table 4 of the threshold estimates, the single threshold estimate with zs (Digital Financial Inclusion Index) as the threshold variable is 5.6535 and is significant at the confidence level. Accordingly, this paper divides the impact of digital inclusive finance on agricultural ecological efficiency into two different intervals according to the inclusive finance index, namely, the samples with $lnzs \leq 5.6535$ and the samples with $lnzs > 5.6535$.

Table 4 Single threshold estimates

	Estimated value	p-value	95% confidence interval
Single Threshold (zs)	5.6535	0.0500	(5.642,5.6573)

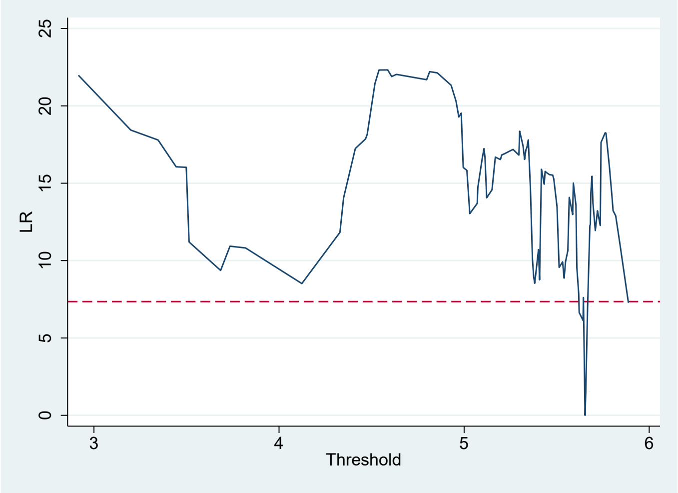

Figure 2 Threshold likelihood ratio function diagram.

As can be seen from FIG. 2, under the 95% confidence interval, when the LR value of the likelihood ratio function approaches 0, the lnLQ value is about 5.6535, which corresponds to the threshold estimate in Table 4. Therefore, the threshold estimate mentioned above is reliable.

4.4 Regression analysis of threshold model

Table 5 Regression coefficient of single threshold model

Variable name	Nonlinear single threshold panel model			
	coefficient	T-value	[95% Conf.	Interval]
LNZS (LNZS 5.6535 or less)	0.06269066	0.0186997	0.163752	0.0900612
LNZS (LNZS > 5.6535)	0.0860963	0.0188884	0.1833136	0.1088791
lnzs	--	--	--	--
lnzdl	0.165665	0.0470032	0.2779828	0.0533471
lnbzmj	0.35057377	0.0259974	0.0574752	0.5540002
lncyrys	0.2515933	0.0591702	0.3681808	0.1350057
lnggmj	3.040885	3.016039	8.983619	2.901849
lnnysy	0.1164234	0.0115506	0.3362201	0.1033734
lnnmsy	0.0620919	0.0109448	0.2777458	0.1535621
lncysy	0.2319603	0.0476903	0.3259282	0.1379924
lnzcz	0.5134007	0.0494341	0.3371817	0.6896197
lntpf	2.805215	0.0319336	3.48691	9.097339
_cons	1.165345	3.334918	7.736391	5.405701

In order to more intuitively show the impact of digital financial inclusion index on each input-output index of agricultural ecological efficiency, this paper uses Gephi 10.0 software to visualize the correlation, and the blue color of the results in Figure 3 represents a negative correlation. Red means positive correlation; The larger the arrow, the larger the absolute value of the regression coefficient, indicating the stronger the correlation between the digital financial inclusion index and the indicator.

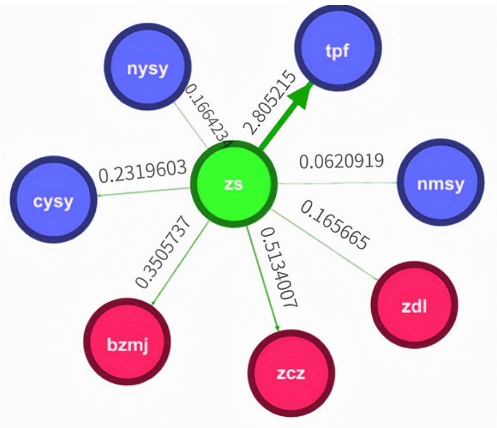

Figure 3: Correlation influence path visualization

5. Conclusion and suggestion

5.1 Research conclusion

This paper establishes an agricultural ecological efficiency input-output index system based on the panel data of 30 provincial-level administrative regions (municipalities directly under the Central government and autonomous regions) in China from 2011 to 2019, and calculates the index levels of the country, eastern region, central region and western region through the super-efficiency SBM model. Then, the digital inclusive financial index is introduced. The influence path and synergistic effect on agricultural eco-efficiency were explored, and the following conclusions were reached:

The average value of agricultural ecological efficiency in China is basically medium level

Regional level characteristics: "high in the east, low in the west, similar in the middle"

Digital financial inclusion has a significant positive impact on agro-ecological efficiency

There is a positive spatial aggregation relationship of agricultural ecological efficiency in China

5.2 Relevant suggestion

Digital inclusive finance has played an important role in promoting China's modernization drive. To this end, the following recommendations are made:

We will promote regional cooperation on ecological agriculture and improve agricultural ecological efficiency in the central and western regions.

Strengthen the construction of digital infrastructure in rural areas, and increase policy support for digital finance to promote the sustainable development of green agriculture.

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