Research on the Relationship Between Agricultural Mechanisation and Economic Development Based on Big Data Analysis

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Abstract. The law of agricultural economic development is inevitably the gradual replacement of traditional agriculture by modern agriculture, and agricultural mechanisation as the core of agricultural modernisation plays an important role in the whole transformation process. This paper firstly analyses the history of the development of agricultural mechanisation in China and discusses the characteristics of the development of agricultural mechanisation in different processes. Secondly, we use big data technology to obtain data on the development of agricultural economy and agricultural mechanisation in recent years, and use quantitative analysis to measure the index of transformation of agricultural economic development and the index of agricultural mechanisation development, and incorporate them into the evaluation system of transformation of agricultural economic development in China. Finally, the impact and role of agricultural mechanisation development on the transformation of agricultural economic development mode is summarised. The study is conducive to promoting the improvement of agricultural science and technology, and has a significant role to play in improving labour productivity, the commodity rate of agricultural products and the effective utilisation rate of resources.

Keywords: Agricultural Economy · Mechanization · Big Data Analytics · Development Goals

1 Introduction

The similarities and differences between agricultural economic growth and agricultural economic development. In terms of their respective objectives, economic growth in agriculture is the pursuit of growth as a goal and an increase in the target quantity. At the same time, Harrod-Doma argues that it is the inputs of the factors of production that bring about the output of the economy [1]. From the perspective of agricultural development, the driving force of the agricultural economy is the input of capital and agricultural labour, the input of physical and human capital, a kind of economic growth driven by the input factors [2]. In this context, scholars such as Romon put forward the

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new economic growth theory, which is based on a modification of Harold's economic growth theory, arguing that the output of total social product is not only determined by two factors, capital and labour, but also non-productive factors play a great role in the development of agricultural economy, and that with the increasing role of market mechanism in resource allocation, productive factor inputs will not be able to meet the limited resource allocation [3]. Therefore, in the agricultural economic system, it is important to consider not only the contribution of production factors to the economy, but also to focus on the analysis of the role as non-production factors to the economy as a whole [4]. Agricultural mechanisation has a natural link with the agricultural economy. At present, China has proposed to accelerate the transformation of the agricultural economy and the development of agricultural mechanization strategy, and as the country further increases the support of the policy of agricultural mechanization [9], how to scientifically identify the relationship between the development of agricultural mechanization and the transformation of the agricultural economy during this critical development period, and explore the effective and sustainable development direction of agricultural mechanization, is the top priority of agricultural development. Therefore, this section makes use of non-production factors to drive the growth of the economy to indicate the change in the way the agricultural economy is developed, in order to exclude the factors of traditional production factors.

2 Measurement of the Agricultural Economic Transformation Index

2.1 Research on the Agricultural Economic Development Mode Change Index Model Based on C-D Model

The C-D production function is a simpler form of studying the relationship between production inputs and output based on the assumptions of a constant capital-output ratio and capital saving rate in the Harrod-Doma model by Charles Cobb and Paul Dauglas [8]. The original expression of the C-D production function divides factor inputs into two categories: capital inputs and labour inputs. The basic form of the C-D function is then expressed as:

$$Y = AL^{\alpha}K^{\beta} \tag{1}$$

Therefore, in the agricultural economic system, it is necessary to consider not only the contribution of production factors to the economy, but also to focus on the analysis of the role as non-production factors to the whole economy. In this paper, we introduce the agricultural economic development mode transformation index1ln Y as a reflection of the pull of non-production factors to the economy [5], which is actually the logarithm of the difference between the total agricultural output value and the output value driven by production factors, and its model is:

$$lnY_1 = lnY - \alpha lnL - \beta lnK - \varepsilon \tag{2}$$

where Y represents total agricultural output, ln Y_1 represents the agricultural economic development transformation index, L represents labour input and K represents capital input. α and β represent labour and capital elasticities respectively.

Table 1. ADF unit root test results for variables.

Variables	Inspection forms	ADF statistics	Threshold values			Conclusion
			10%	5%	1%	
LNY	(C,T,0)	−1.61	−4.47	−3.64	−3.26	Unstable
D(LNY)	(C,0,0)	−4.46	−3.80	−3.02	−2.65	Stable
LNL	(C,T,1)	−1.47	−4.49	−3.65	−3.26	Unstable
D(LNL)	(0,0,0)	−3.68	−2.69	−1.96	−1.60	Stable
LNK	(C,T,0)	−4.83	−4.46	−3.64	−3.26	Unstable
D(LNK)	(C,0,0)	−6.50	−3.80	−3.02	−2.65	Stable

2.2 Testing Process and Estimation Results of the Model for Measuring the Agricultural Economic Development Mode Change Index

Testing for smoothness of variables: As time series data are used, to avoid pseudo-regressions, economic variables need to be tested for smoothness prior to regression analysis. The ADF (Augmented Dickey-Fuller) unit root test was used to determine the stationarity of the variables. After iterative debugging, the final test results are shown in Table 1. From the test results in Table 1, we can see that the ADF values of LnK, LnL and LnY are all greater than the critical value at the 5% confidence level, showing non-stationarity; however, the ADF of their respective first-order difference sequences LnK, LnL and LnY are all less than the critical value at the 1% confidence level, showing the characteristics of stationarity, i.e. LnK, LnL and LnY are all first-order single-integer processes. Therefore, instead of using the traditional Ordinary Least Squares (OLS) regression analysis to construct a C-D production function model, cointegration theory should be used to investigate the long-run equilibrium relationship between the variables.

Cointegration test and analysis of results: This paper uses Johansen's maximum likelihood estimation method to test the cointegration of variables. Johansen's cointegration test starts from vector autoregression (VAR), determines a reasonable number of lags, and then tests the number of cointegrating vectors r by Johansen's likelihood ratio statistic, starting from the null hypothesis (H0) that there is no cointegration relationship (r = 0), if H0 is accepted if the null hypothesis of no cointegration (r = 0) is accepted, indicating no cointegration; if H0 is rejected, the number of cointegrating vectors is r0 if H0 is rejected at r = r0–1 and accepted at r = r0.

The results of the Johansen cointegration test: Since the lag order chosen for the Johansen cointegration test is equal to the optimal lag order of the unconstrained VAR model minus 1, the optimal lag order for the cointegration test is 2–1 = 1. Through the joint test of model selection, the model with a linear trend in the observed series and only an intercept in the cointegration equation was identified as the most appropriate cointegration test model. The cointegration tests were performed step by step starting from the null hypothesis and the results are shown in Table 2.

Table 2. Johansen co-integration test results for the variables.

Null hypothesis H_0	Alternative hypothesis H_1	Eigenvalue	Trace test statistic	5% critical value
$r = 0$	$r \geq 1$	0.752211	44.15028	42.91525
$r \leq 1$	$r \geq 2$	0.395431	16.24672	25.87211
$r \leq 2$	$r = 3$	0.265890	6.181930	12.51798

3 Agricultural Mechanisation Development Index Measurement

3.1 Measurement Models and Variable Selection

Choice of model: In this paper, an attempt is made to use multivariate statistical methods to conduct principal component analysis on the three variables reflecting the degree of development of agricultural mechanisation and synthesise them into one indicator [10]. As there is a certain correlation between the selected indicators, the principal component indicator is used to indicate the agricultural mechanisation development index.

Variable selection and processing: The analysis of the indicators affecting agricultural mechanisation has been carried out above, and the indicators of the level of agricultural mechanisation equipment and the level of agricultural mechanisation operations were directly selected, and the data were obtained from the Compilation of Statistical Information of the Six Decades of New China, spanning the period from 1998 to 2020.

3.2 The Analysis Process of the Principal Component Analysis Method

In terms of the method itself, the main reason is that these variable factors reflect or embody, to some extent, certain information about the subject under study, and therefore the contribution of various indicators can be determined using this method [8]. Because the first variable has the largest variance, it is considered the first principal component; the second variable is not correlated with the first variable and is considered the second principal component when the variance value is the next highest [6]; a system containing i variables will form i principal components. Suppose there are n objects to be evaluated, and the objects correspond to p variables respectively, these can be represented by a p*n dimensional matrix.

$$\begin{vmatrix} X_{11} & X_{12} & \dots & X_{1p} \\ X_{21} & X_{22} & \dots & X_{2p} \\ \dots & \dots & \dots & X_{3p} \\ X_{n1} & X_{n2} & \dots & X_{np} \end{vmatrix} \tag{3}$$

3.3 Agricultural Mechanisation Development Index Measurement Model Estimation Results

Modeling of the index measurement: The results of the KMO and Bartlett's spherical tests were first performed before the principal component analysis and are shown in

Table 3. KMO and Bartlett's spherical test results.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.772
Bartlett's Test of Sphericity	Approx. Chi-Square	441.479
	df	45
	Sig	0.0

Table 4. Descompunerea varianței componentelor principale.

Component	Initial Eigenvalues			Extraction of sum of squares loaded		
	Root	Variance %	Cumulative %	Root	Variance%	Cumulative %
1	2.729	90.979	90.979	2.729	90.979	90.979
2	0.246	8.198	99.177	0.246	8.198	99.177
3	0.025	0.823	100.000	0.025	0.823	100.000

Table 3. From the data in the table, the value of the KMO statistic was $0.646 > 0.5$ and the value of the chi-squared statistic for the spherical test was 78.583, with a one-sided P-value of $0.000 < 0.01$, indicating that the data were suitable for principal component analysis.

As can be seen from Table 4, the cumulative variance contribution of the first previous principal component reaches 90.979%, which shows that there is one principal component in these three variables and it explains more than 90% of the variance. Based on the factor loading matrix, it can be seen that the previous principal component we have chosen basically covers all the observed variables. Therefore, it is entirely possible to use this one principal component to represent the four original indicator variables mentioned above for the next step of the analysis.

Analysis of estimation results: In the period 1998–2020, the level of development of agricultural mechanisation in China can be roughly divided into three stages, the first stage from 1998 to 1998, this stage of China's agricultural mechanisation level, although there is a certain development in the development, but the degree of development is not significant [13]. From 1998 to 2012, it can be seen that the development level of agricultural mechanisation is growing at a fast pace. From 2012 to 2020, the level of development of agricultural mechanisation in China has increased the most, from the original 60.66 to 91.12 in 2020, an increase of 30%. From this, we can also analyse that the development level of agricultural mechanisation has been steadily increasing in the past 22 years, and we can also see that there is still great momentum for the development level of agricultural mechanisation to increase.

Table 5. Evaluation system for the transformation of the agricultural economy.

Primary Indicators	Secondary indicators
Input power indicators	Degree of agricultural policy support
	Original value of fixed assets owned by households at the end of the year
	Rural Engel coefficient
Technical level indicators	Level of urbanisation
	Agricultural mechanisation development index
	Effective irrigation rate
Intensification efficiency indicators	Land production capacity
	Intensive efficiency indicators
Environmental indicators of agricultural resources	Fertilizer use intensity
	Effective utilization coefficient of electric energy

4 Evaluation System for the Transformation of the Agricultural Economy

4.1 Framework Construction and Analysis of the Indicator System

In accordance with the principles of constructing an evaluation system of indicators, a system of indicators for the transformation of China's agricultural development mode is constructed, including four components, namely input dynamics, technology level, intensive efficiency and agricultural resources, with a total of 10 specific indicators set up under each level. The evaluation draws on the relevant elements or indicators in the evaluation systems of modern agriculture, two types of agriculture and agricultural sustainability, and includes agricultural mechanisation, which takes into account the purpose of elevating agricultural mechanisation to a strategic level and can also objectively reflect the process of transformation of the agricultural economic development mode. The specific indicators are as Table 5.

4.2 Empirical Analysis

Principal component regression method for variables: The core idea of principal component analysis (PCA) is to concentrate information scattered over a set of variables onto a few composite indicators (principal components) by dimensionality reduction [15], while minimising the extent to which the indicator system explains the dependent variable. The KMO statistic had a value of $0.772 > 0.5$, the spherical test chi-square statistic had a value of 441.479 and the one-sided P-value was $0.000 < 0.01$, indicating the suitability of the data for principal component analysis.

Table 6. Johansen co-integration test results for the variables.

Null hypothesis H0	Alternative hypothesis H1	Eigenvalue	Trace test statistic	5% critical value	Prob.**
$r = 0$	$r \geq 1$	0.604547	39.18006	35.19275	0.0176
$r \leq 1$	$r \geq 2$	0.517350	19.69787	20.26184	0.0596
$r \leq 2$	$r = 3$	0.189035	4.400146	9.164546	0.3558

Principal components extracted using the factor analysis module that comes with SPSS software were analysed. In general, principal components were extracted using the principle that the cumulative variance contribution was greater than 85% and the eigenvalue was greater than 1. When two principal components were extracted, the contribution of the first and second principal components were 73.487% and 13.501% respectively [14], with a cumulative contribution of 86.988%; the eigenvalues were 7.349 and 1.350 respectively, in line with the principles of cumulative variance contribution greater than 85% and eigenvalue greater than 1. This shows that there are 2 principal components in these 10 variables and they explain more than 86% of the variance.

Cointegration analysis: The Johansen cointegration test is based on the analytical framework of the VAR model, which is sensitive to the choice of lags, and uses a combination of LR, FPE, AIC, SC, HQ and other judgement criteria to determine the optimal lag order [11], with the criterion being the order that satisfies the most criteria. The test results show that all judgement values point to the selection of the 1st order lag order, indicating that the VAR(1) model is the most reasonable, implying that the established VAR(1) model is also stable. Since the cointegration test is a constraint test on the lags of the first-order difference variables of the unconstrained VAR model, the optimal lag order for the cointegration test is 0. The results of the test are shown in Table 6.

The trace test shows that the original hypothesis of no co-integration is rejected at 5% confidence level and the original hypothesis of at least one co-integration is accepted. The original hypothesis of no co-integration is rejected at 5% confidence level and the original hypothesis of at least one co-integration relationship is accepted, indicating that there is a co-integration relationship between the variables that is stable and balanced over time. The estimated values of the co-integration vector are (1.000, 4.2781, 3.7059) The economic significance of the coefficients of each variable is reasonable.

Analysis of the empirical results: By analysing the data for the period 1998–2020, it was possible to obtain the correlation coefficients for each of the indicators influencing the transformation of China's agricultural economic development [12]. The correlation coefficients for each of the influencing factors in the transformation of the agricultural economy were obtained [7]. The results of the study show that the degree of intensification has the greatest impact on the transformation of the agricultural economy, with an impact of 15.85%. The degree of influence of the development of agricultural mechanisation is 8.423% (for every 1% increase in the index of development of agricultural mechanisation, the index of change in the mode of development of the agricultural economy increases by 8.423%). The impact of fixed asset input, Engel's coefficient,

urbanisation level and agricultural policy support on the transformation of the agricultural economy exceeded 1%. Less influential are the effective utilisation rate of fertiliser, the effective utilisation of electricity and the production capacity of land.

5 Conclusions

Based on the C-D production function and the new economic growth theory, this paper constructs a model of the agricultural economic development index and measures the agricultural economic development index using the co-integration equation, pointing out that the transformation of China's agricultural economic development mode is a fluctuating upward state, and although there are periods of fluctuation and decline in the whole process, the overall is in the upward period, which also indicates that the transformation of China's agricultural development mode is still in the overall good direction It also shows that the transformation of China's agricultural development mode is still developing in a good direction. It can be seen from the development history of China's agricultural mechanisation in the past 20 years that after 2012, China's agricultural mechanisation development entered a golden period, during which China's.

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