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Research on the Relationship between Agricultural Supply Chain Optimization and Farmers' Income Increase Based on PLS Algorithm

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Abstract With the implementation of rural revitalization strategy, the development of agricultural supply chain is of great significance in promoting rural economic development and farmers' income growth. Starting from the two directions of both definitions and influencing factors, the evaluation index system of both is determined, followed by proposing the use of entropy weighting method to analyze the evaluation indexes in terms of weighting and measurement. The results are set as explanatory variables, explanatory variables, in addition to supplementing the corresponding control variables, on the basis of which the partial least squares method is used to complete the construction of the regression model. Setting the data source of this research, with the help of this paper's model to explore the mechanism of action between the two in depth. The regression coefficients of the explanatory variables and the explained variables are 0.419, 0.157, 0.216 respectively, while both of them have a positive and significant correlation at the 1% level, i.e., there is a positive correlation between the optimization of supply chain of agricultural products and the increase of farmers' income.

Index Terms entropy weight method, partial least squares method, regression model, supply chain optimization

I. Introduction

Traditional agriculture is accelerating the transition to a new type of modern agriculture, the biggest obstacle to the sustainable and healthy development of agriculture is not only the quality of agricultural products, but also the circulation problem has become a key factor [1], [2]. Agricultural supply chain as a connection between production, circulation and sales of the core link, its operational efficiency and management level directly affects the agricultural producers, processing enterprises, wholesalers and retailers and other aspects of the main body's personal interests [3]-[5]. With the accelerated process of agricultural modernization, the traditional agricultural supply chain model has been difficult to adapt to the new period of agricultural development needs. Traditional supply chain information asymmetry, high logistics costs, poor production and marketing interface and other issues, seriously restricting the farmers' income space [6], [7]. The digital supply chain has a powerful force of change, which can completely break the limitations inherent in the traditional agricultural product circulation model, thus realizing the rapid circulation and efficient supply of agricultural products [8], [9].

However, in the context of the current digital economy, the optimization of the agricultural supply chain faces many challenges and opportunities. On the one hand, the application of digital technology provides the possibility of transparent and intelligent management of the agricultural supply chain, which helps to reduce operating costs, improve response speed, and enhance market competitiveness [10]-[12]. On the other hand, how to effectively integrate the resources of all parties, realize the close synergy of all links in the supply chain, as well as how to enhance the flexibility and resilience of the supply chain while guaranteeing the quality and safety of agricultural products have become urgent issues [13]-[15]. Therefore, exploring the optimization path of agricultural supply chain supported by intelligent algorithms has important theoretical value and practical significance for promoting the quality and efficiency of agriculture and realizing the sustainable income of farmers.

The construction and management of digital supply chain is not only an indispensable key path to promote the modernization of agriculture, but also an important engine to realize the efficient, green and sustainable development of agriculture, for this reason, a large number of scholars take advantage of the advanced digital technology to help the supply chain management of agricultural products towards a brand new stage of intelligence, automation and refinement. Tao, Q., et al. investigated the scheduling optimization of the supply chain of agricultural products under the environment of big data. method, proposing a data mining-based management architecture that incorporates evolutionary algorithms to solve large-scale complex structure supply chain scheduling optimization problems in order to enhance the effectiveness of agricultural product supply chain design and management [16]. Shen, L. et al. established a fresh agricultural product inventory optimization model with the goal of maximizing the overall profit of the agricultural product supply chain, and used genetic optimization algorithms to solve this optimization problem for the supply and replenishment strategy of agricultural products under the supply chain [17]. Banasik, A. et al. constructed a multi-objective mixed-integer linear programming model with economic and chemical context as the indicators to optimize the logistic structure in the agricultural products supply chain in order to realize the supply chain closure, so as to further improve the profitability of the supply chain [18]. Gharye Mirzaei, M. et al. developed a mixed integer linear programming (MILP) model for uncertainty problems in agricultural supply chain networks, which fully considered the effects of factors such as weather conditions and economic fluctuations, combined with optimization algorithms to optimize the supply chain of agricultural products, and provided practical suggestions for supply chain management [19]. Liu, L. et al. analyzed the logistics and distribution paths in the supply chain of agricultural products, and introduced the ant colony algorithm to Liu, L. et al. analyzed the logistics and distribution paths in the agricultural supply chain and introduced the ant colony algorithm to construct a soluble solids maturity model for agricultural products, which can fully guarantee the delivery time of agricultural products to reduce the logistic loss and improve the income of the agricultural supply chain [20]. Zhang, J. et al. showed that there is still a serious problem of “chain breakage” in the logistics of the fresh agricultural products in the cold chain, and according to this, they combined the fault tree model and Bayesian network to evaluate the reliability of the cold chain distribution system affecting the agricultural products. Accordingly, they combined the fault tree model and Bayesian network to assess the key factors affecting the reliability of the cold chain distribution system for agricultural products, and proposed an optimization method to improve the reliability of the agricultural supply chain [21].

This paper first collects the influencing factors of agricultural supply chain optimization and farmers' income level, and then formulates the evaluation index system about them respectively. From an objective point of view, the entropy weight method is used to calculate the weights of the indicators and the comprehensive evaluation results. The above results are used as the research variables of the subsequent study, after which the partial least squares method is combined to realize the task of constructing the regression model. Due to the existence of regional differences between the two, for this reason, the spatial Durbin model was designed. The Agricultural Statistical Yearbook is used as the data source of this study, and the model of this paper is integrated to carry out empirical research and analysis on the mechanism of the role of agricultural supply chain optimization and the level of farmers' income increase.

II. Theoretical explanations of agricultural supply chains and farmers' income growth

II. A. Connotation and characteristics of agricultural supply chains

Agricultural supply chain is a complex system covering the whole process of agricultural products from production to consumption, including production, harvesting, primary processing, packaging, transportation, warehousing and distribution [22]. As the core composition of the agricultural industry chain, the agricultural supply chain has significant differentiation characteristics [23]. From the perspective of product attributes, agricultural products are highly perishable, have a short shelf-life and large fluctuations in quality, which put forward strict requirements on the timeliness and environmental control of the supply chain. From the point of view of production characteristics, agricultural production has seasonal and regional characteristics, yield and quality are susceptible to natural conditions, increasing the difficulty of supply chain management. From the perspective of market characteristics, agricultural products have greater demand elasticity, frequent price fluctuations, and prominent market information asymmetry. From the viewpoint of participating subjects, the agricultural supply chain involves farmers, cooperatives, processing enterprises, logistics companies, retailers and other diversified participants, with significant differences in the interests of all parties, making synergy more difficult. From the perspective of operation mode, the agricultural supply chain shows the trend of integration of production, supply and marketing, and the relationship between upstream and downstream subjects is becoming increasingly close, which still requires the establishment of a long-term cooperation mechanism. From the perspective of value chain, the optimization potential of agricultural supply chain is huge, and by improving the supply chain efficiency and service quality, it can effectively reduce the circulation cost and improve the added value of products.

II. B. Major supply chain constraints to farmers' income growth

The development of the agricultural supply chain faces many constraints, which affect the room for farmers to increase their income. At the infrastructure level, the lack of cold-chain logistics facilities and the insufficient capacity for pre-cooling and refrigerated transportation at the place of origin have led to a high rate of loss of agricultural products, which has reduced the actual income. At the level of technology application, the low level of digitalization and intelligence in the supply chain makes it difficult to realize accurate production and efficient distribution, thus restricting the release of income-generating potential. At the level of organizational model, small farmers are not well connected with modern agricultural development, and the docking of production and marketing information is insufficient, which affects the bargaining power of agricultural products. At the level of benefit distribution, farmers are in a weak position in the supply chain, and the value-added benefits of the industrial chain are difficult to be effectively transmitted to farmers. At the level of standard system, the quality standard and brand construction of agricultural products are lagging behind, and the homogenization of products is serious, making it difficult to obtain brand premium. At the level of financial services, the development of supply chain finance is imperfect, and the problems of difficult and expensive financing for farmers are prominent, affecting the industrialized operation. At the talent support level, there is a lack of rural talents, a shortage of supply chain professionals, and the management and operation level needs to be improved.

III. Study design

III. A. Measuring the level of optimization of agricultural supply chains

Agricultural supply chain optimization is the explanatory variable of this paper, and its scientific measurement is a complex and important task, which requires full consideration of the influencing factors of each link and the construction of a comprehensive evaluation index system in order to better assess the optimization level of the agricultural supply chain.

Table 1 Evaluation indicators of agricultural product supply chain

Target layer	Criterion :layer	Symbol	Indicator layer	Symbol	Unit	Attribute
Optimization of the agricultural product supply chain	Economic sustainability	X1	Gross agricultural production value	X11	Billion yuan	Positive
			The total sown area of crops	X12	Thousands of hectares	Positive
			Total power of agricultural machinery	X13	Thousands of hectares	Positive
			Output of major agricultural products	X14	Ten thousand kilowatts	Positive
			Cargo turnover volume	X15	Billions of ton-kilometers	Positive
			Per capita disposable income of rural residents	X16	Yuan	Positive
	Social sustainability	X2	Rural labor force	X21	Thousands of people	Positive
			The number of comprehensive agricultural product markets with an annual revenue of over 100 million yuan	X22	Number	Positive
			The number of employees in the transportation industry	X23	People	Positive
			The number of civilian cargo vehicles owned	X24	Ten thousand vehicles ·	Positive
			Per capita urban road area	X25	Square meter	Positive
			Residents' expenditure on food consumption	X26	Yuan	Positive
	Environmental sustainability	X3	Effective irrigated area	X31	Thousands of hectares	Positive
			The application amount of agricultural chemical fertilizers	X32	Ten thousand tons	Negative
			Pesticide usage amount	X33	Ton	Negative
			Carbon emissions from agricultural product logistics	X34	One million tons	Negative
			Daily urban sewage treatment capacity	X35	Ten thousand cubic meters	Positive
			The harmless treatment rate of domestic waste	X36	%	Positive

III. A. 1) Extraction of Impact Factors

The supply chain of agricultural products involves the production and circulation of agricultural products, and the concept of sustainable development emphasizes the coordinated development of nature, science and technology, economy and society. In order to carry out in-depth research on agricultural supply chain and adapt to the long-term and efficient development of agricultural supply chain, this paper adopts the literature analysis method to select the influencing factors, and through screening domestic and foreign literature, it selects the indicators and determines their nature according to the research and conclusions of relevant scholars, and then obtains the main indicators of optimization of agricultural supply chain.

III. A. 2) Construction of the indicator system

The evaluation indexes of agricultural supply chain optimization level are shown in Table 1. Based on the above extracted influencing factors, relying on the theory of sustainable development, this paper measures the sustainable development level of the agricultural supply chain in each region from the three dimensions of economy, environment and society, starting from the three links of supply chain production, circulation and consumption, and finally forming 3 guideline layers and 18 indicators.

III. B. Measuring the level of farmers' income growth

III. B. 1) Impact factor settings

According to the existing research results of the indicator evaluation system of farmers' income increasing level and the actual situation of the development of farmers' income increasing level in a province, to set the factors affecting farmers' income increasing level. It helps to distinguish the advantages and disadvantages, gains and losses of farmers' income-generating work under different conditions of economic and social development, and is of great theoretical and practical significance for the promotion of urban-rural integration and development, as well as an important reference value for other regions.

III. B. 2) Construction of the evaluation indicator system

Based on the principles and influencing factors of the relevant evaluation indexes, the task of constructing the evaluation index system of farmers' income increase is completed, and the evaluation index system of farmers' income increase is shown in Table 2. Farmers' ability to increase income refers to the space and difficulty of increasing farmers' disposable income. According to the source of income, farmers' income can be divided into 4 aspects: wage income, operating income, property income and transfer income. Therefore, the above 4 aspects of income-raising factors are selected as level 1 indicators. Taking into account the data availability, general comparability and quantifiable indicators, 4 secondary indicators totaling 16 indicators are selected from each level 1 indicator to construct the evaluation system of farmers' ability to increase income. Among them, five indicators, namely, the ratio of rural labor, the ratio of primary industry, the coverage rate of low-income insurance, the degree of economic primacy, and the density of villages, are negative indicators, and the larger the value of these indicators, the weaker the ability of farmers to increase income. The rest of the indicators are positive indicators, with the larger the value of the indicator, the stronger the ability of farmers to increase their income.

Table 2: Evaluation index system for increasing farmers income

Target layer	Criterion layer	Symbol	Indicator layer	Symbol	Unit	Attribute
Farmers income increase	Wage income	Y1	The proportion of rural labor force	Y11	%	Negative
			Proportion of non-agricultural operations	Y12	%	Positive
			The current enterprise density	Y13	Individuals/ten thousand people	Positive
			Social employment rate	Y14	%	Positive
	Operating income	Y2	Per capita sown area of grain	Y21	Hm2/ ten thousand people	Positive
			The proportion of the primary industry	Y22	%	Negative
			Per capita consumption capacity	Y23	Ten thousand yuan	Positive
			Per capita gross national product	Y24	Ten thousand yuan	Positive
	Property income	Y3	Economic density	Y31	100 million yuan per kilometer	Positive
			Fiscal density	Y32	100 million yuan per kilometer	Positive
			Housing price-to-income ratio	Y33	Yuan /m2	Positive
			Rural car ownership rate	Y34	%	Positive
	Transfer income	Y4	Minimum living allowance coverage rate	Y41	%	Negative
			Economic primacy	Y42	%	Negative
			Population density	Y43	100 people per kilometer	Positive
			Village density	Y44	Number	Negative

III. C. Indicator weighting and measurement of results

III. C. 1) Entropy weight method

Indicator empowerment method is divided into subjective empowerment method and objective empowerment method, in which subjective empowerment method includes expert scoring method and hierarchical analysis method, etc., and objective empowerment method mainly includes entropy value method, CRITIC method and principal component analysis method. Through the related research on the measurement of agricultural supply chain and farmers' income increase, we found that entropy value method is one of the most adopted methods by scholars. At the same time, in order to test the robustness of the model, the entropy value method is also used to measure. Entropy value method is mainly based on the degree of disorder of the indicator, that is, the size of the entropy of the indicator to indicate the degree of differentiation of each indicator on the evaluation object, that is, the smaller the entropy value of a certain indicator indicates that the indicator data is more organized, the greater the degree of difference between the sample data, the greater the reflective capacity of the evaluation object, and the greater the weight of the weight [24]. The entropy value is calculated and then normalized to obtain the weight of the indicator. The entropy value method has the advantages of stronger objectivity, simpler calculation process and wider scope of application.

III. C. 2) Calculation process

(1) Calculate the p value:

$$p_{ij}=\frac{X_{ij}^{*}}{\sum_{i=1}^{n}X_{ij}^{*}} \tag{1}$$

(2) Calculate the information entropy:

$$e_j=-k\sum_{i=1}^{n}(p_{ij}\ln p_{ij}) \tag{2}$$

$$k=\frac{1}{\ln(n)} \tag{3}$$

(3) Calculating redundancy:

$$d_j=1-e_j \tag{4}$$

(4) Calculate w to get the variable weights:

$$w_j=\frac{d_j}{\sum_{j=1}^{n}d_j} \tag{5}$$

(5) Calculation of comprehensive evaluation indicators:

$$Score=\sum_{j=1}^{n}(w_j * X_{ij}^{*}) \tag{6}$$

III. D. Regression model based on PLS algorithm

III. D. 1) Variable settings

(1) Explanatory variables

The level of farmers' income increase (Y) as an explanatory variable, taking the value from the composite score obtained by applying the entropy weight method measured above.

(2) Explanatory variables

The agricultural supply chain (X) consists of three hierarchical indicators of economic sustainability (X1), social sustainability (X2) and environmental sustainability (X3), in which X serves as the explanatory variable of the baseline regression model based on the PLS algorithm, and (X1), (X2) and (X3) serve as the explanatory variables of the three hierarchical models, and the values are taken from the results of the measurement above.

(3) Control variables

In this paper, government macro-control (GM), agricultural market demand (AMR), provincial economic development level (ED) and agricultural infrastructure construction (AID) are selected as control variables, in which government macro-control (GM) is expressed by local fiscal science and technology expenditure (billion yuan), agricultural market demand (AMR) is expressed by the total index of production price of agricultural products, and provincial economic development level (ED) is expressed by per capita GDP (million yuan), and agricultural infrastructure development (AID) is expressed by total fixed asset investment in rural farm households (billion yuan). The control variables are taken from the National Bureau of Statistics, EPS Macroeconomic Database and China Agriculture and Forestry Database.

III. D. 2) PLS algorithm (partial least squares)

Suppose there are p independent variables (denoted by x) and q dependent variables (denoted by y). After fully observing n sample points, data tables for the independent and dependent variables $X=\left(y_1,y_2,\cdots,y_q\right)_{n\times p}$ and $Y=(y_1,y_2,\cdots,y_q)_{n\times q}$. After that, the PLS method is used to extract from the table the linear combinations t_1 and u_1 about $x_1,x_2,\cdots,x_p$ and $y_1,y_2,\cdots,y_q$, respectively, and make the correlation degree of t_1 and u_1 is maximized and carries as much as possible the information about the variation in the data table. variation information in the data table. This shows that the linear combinations t_1 and u_1 not only represent the data information in the respective tables, but also t_1 has a strong explanatory power for u_1. After the 1st round of extraction of t_1 and u_1, the PLS model is utilized to perform the regression of X and Y on t_1, respectively, and then continue to utilize the residual information of X and Y after being explained by t_1 for the 2nd round of constituent extraction until a satisfactory precision is reached, and the regression of $k=1,2,\cdots,q$ on $t_1,t_2,\cdots,t_m$ is performed using the PLS method, which is the principle of partial least squares regression model. Therefore, this paper adopts the partial least squares regression analysis method that can simultaneously deal with the information of explanatory variables and multiple explanatory variables, effectively eliminates the multicollinearity between variables, and establishes a regression model that contains all the information of the data, so as to ensure the full utilization of the data information and ensure the stability of the model.

Partial least squares regression analysis (PLS) is a method used to solve the problem of interference of multiple correlations of variables on systematic regression modeling, which opens up an effective technical way and has unique advantages in dealing with the problems of small sample sizes, a large number of explanatory variables, and the existence of serious multiple correlations between variables [25]. Partial least squares regression analysis allows for regression modeling, data structure simplification, and correlation analysis between two sets of variables. Before deciding whether or not to use PLS method for modeling, the first preparatory analysis should be carried out to determine whether or not there are multiple correlations in the independent variables (dependent variables), and to determine whether or not there are correlations between the independent variables and the dependent variables, which is calculated as follows: for the matrix $Z=(X,Y)$, notate that $F_0=(e_{ij})_{n\times p}=Y$, and $E_0=(f_{ij})_{n\times q}=X$. The construction steps of the partial least squares regression analysis model are as follows:

(1) Normalize the original data

The standardized data matrices $E_0=(f_{ij})_{n\times q}$ (i.e., X) and $F_0=(e_{ij})_{n\times p}$ (i.e., Y), where:

$$e_{ij}=(x_{ij}-\overline{xj})/sx_j,\quad i=1,2,\cdots,n;j=1,2,\cdots,n \tag{7}$$

$$f_{ij}=(y_{ij}-\overline{yj})/sy_j,\quad i=1,2,\cdots,n;j=1,2,\cdots,n \tag{8}$$

In Eqs. (7) and (8), $\overline{xj}$ and $\overline{yj}$ are the mean of the j th column of data of matrices X and Y, respectively, and sx_j and sy_j are the standard deviation of the j th column of data of matrices X and Y.

(2) Extraction of the 1st component t_1

Find the unit eigenvector W_1 corresponding to the largest eigenvalue of matrix $E_{0T}F_0F_{0T}E_0$ to get the first principal component t_1 of the independent variable X:

$$t_1=E_0W_1 \tag{9}$$

where W_1 is the first axis of E_0, called the effect weights of the model, and $\|W1\|=1$.

Find the unit eigenvector C_1 corresponding to the largest eigenvalue of the matrix $F_{0T}E_0E_{0T}F_0$ to obtain the first principal component u_1 of the independent variable Y:

$$u_1=F_0C_1 \tag{10}$$

where C_1 is the first axis of F_0, called the dependent variable weight of the model, and $\|C1\|=1$.

Here it is required that t_1 and u_1 can express the information of the data in X and Y well respectively, and t_1 has a strong ability to explain u_1. After that, the residual matrix E_1 and F_1 are solved: $E_1=E_0-t_1p_{1T}$, $F_1=F_0-t_1r_{1T}$, where $p_1=E_{0T}t_1/\|t1\|^2$, $r_1=F_{0T}t_1/\|t1\|^2$. This leads to the regression equation of F_0 and E_0 on t_1:

$$E_0=E_1+t_1p_{1T} \tag{11}$$

$$F_0=F_1+t_1r_{1T} \tag{12}$$

(3) Extraction of the 2nd component t_2

Let $E_0=E_1$, $F_0=F_1$, go back to step (3) above, carry out a new round of component extraction and regression analysis on the residual matrix, and repeat the extraction step of the 1st component t_1, and finally get the regression equations of F_1 and E_1 on t_2:

$$E_1 = E_2 + t_2 p_{2T} \tag{13}$$

$$F_1 = F_2 + t_2 r_{2T} \tag{14}$$

The h th component t_h is extracted in the same way.

(4) Construct partial least squares regression model

Based on the above analysis, we construct the partial least squares regression model as follows:

$$Y = XWR' + F_2 \tag{15}$$

where $W = [W_1, W_2, \cdots, W_h]$, $R = [r_1, r_2, \cdots, r_h]$ and F_2 is the residual matrix.

III. E. Space benefits

III. E. 1) Spatial correlation tests

In this paper, global Moran's (Moran's I) is used to test the spatial correlation of the relationship between agricultural supply chain and farmers' income increase. The value range of global Moran's index is (-1<Moran's I<1), the larger the absolute value, the stronger the spatial correlation. If the global Moran's index is positive, it indicates positive spatial correlation; if the global Moran's index is negative, it indicates negative spatial correlation. The calculation method is as follows:

$$Moran's\ I = \frac{\sum_{i=1}^{n} \sum_{j=i}^{n} (x_i - \overline{x})(x_j - \overline{x})}{s^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{16}$$

where $s^2 = \frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n}$ is the sample difference.

III. E. 2) Spatial Durbin Model

The appropriate spatial econometric model is selected using LR and Wald tests, and the spatial Durbin model is constructed based on the test results. Using the calculation results of the extreme entropy weighting method, the impact of economic sustainability (X1), social sustainability (X2), and environmental sustainability (X3) of agricultural supply chain optimization on farmers' ability to increase their income is investigated.

$$Y_{it} = \alpha + \beta_1 \ln X1_{it} + \beta_2 \ln X2_{it} + \beta_3 \ln X3_{it} + \beta_4 Z_{it} + \varepsilon \tag{17}$$

In the above equation, $\mu_{it} = \lambda W_{ij} Y_{it} + \varepsilon$, $\varepsilon \sim N(\sigma^2 I)$, W_{ij} stands for the spatial judgment matrix, λ stands for the coefficient of spatial error, and σ stands for normal distribution standard deviation of the normal distribution, I is the unit matrix; $W_{ij} Y_{it}$ is the spatial lag term of the explanatory variables; ρ is the correlation coefficient, which represents the degree of linkage between the sample observations of the explanatory variables across regions; $W_{ij} \ln C_{jt}$ is the spatial lag term of the core explanatory variable, the level of integration of the rural industries; β_7, β_8 represent the corresponding regression coefficients, respectively. Spatial neighbor weight matrix and geographic weight matrix are used as the spatial weight matrix. For the spatial neighbor matrix, the rules for the value of each element w_{ij} are shown below:

$$w_{ij} = \begin{cases} 1, When\ i\ and\ j\ are\ adjacent,\ there\ is\ spatial\ correlation \\ 0, When\ i\ and\ j\ are\ not\ adjacent, \\ there\ is\ no\ spatial\ correlation \end{cases} \tag{18}$$

For the geographic weight matrix, the rules for taking the values of the elements are:

$$w_{ij} = \begin{cases} \frac{1}{d^2}, i \neq j \\ 0, i = j \end{cases} \tag{19}$$

where d is the spherical distance between the different regions.

IV. Analysis of empirical studies

IV. A. Data sources

All the data in this paper come from the Rural Statistics Yearbook, the Annual Report of Business Management Statistics, the Annual Report of Rural Cooperative Economy Statistics, the Agricultural Yearbook, and local statistical yearbooks, etc., to provide solid data support for the following research work.

IV. B. Level measurement analysis

IV. B. 1) Measurement and analysis of the level of optimization of agricultural supply chains

(1) Descriptive statistics of raw each indicator variable

Before the entropy weight method and spatial measurement, the first descriptive statistics of the data characteristics, the software used is Matlab 17.0, in order to accurately assess the degree of dispersion of the indicators in each region, the following data are the original data that have not yet been normalized, and the results are shown in Table 3. Due to the existence of different scales between the indicators, at this time the comparison of the standard deviation alone can not measure the degree of dispersion of the data, as can be seen from the table, the number of observations of the indicators is consistent, there are no missing values, and the overall comparison is relatively smooth, but there is a certain gap between the various regions.

Table 3: Descriptive statistics of the original index variables

Index	Number of observations	Mean	Standard deviation	Min	Max
X11	500	7.978	0.605	1	10
X12	500	8.249	0.662	1	10
X13	500	9.069	0.481	1	10
X14	500	7.745	0.766	1	10
X15	500	5.324	0.708	1	10
X16	500	8.183	0.706	1	10
X21	500	5.661	0.589	1	10
X22	500	5.347	0.384	1	10
X23	500	9.561	0.334	1	10
X24	500	9.941	0.335	1	10
X25	500	6.723	0.381	1	10
X26	500	5.584	0.784	1	10
X31	500	5.599	0.553	1	10
X32	500	9.599	0.542	1	10
X33	500	5.683	0.608	1	10
X34	500	5.782	0.539	1	10
X35	500	8.558	0.338	1	10
X36	500	6.652	0.578	1	10

Table 4: Summary of the calculation results of the entropy weight method

Target layer	Criterion layer	Indicator layer	Weight
Optimization of the agricultural product supply chain	X1	X11	0.0608
		X12	0.0629
		X13	0.0691
		X14	0.0590
		X15	0.0406
		X16	0.0624
	X2	X21	0.0431
		X22	0.0407
		X23	0.0729
		X24	0.0757
		X25	0.0512
		X26	0.0425
	X3	X31	0.0427
		X32	0.0731
		X33	0.0433
		X34	0.0441
		X35	0.0652
		X36	0.0507

(2) Summary of calculation results of entropy weight method

After calculating the above indicators according to the formula, the weight of each indicator in measuring the optimization level of agricultural supply chain is obtained as shown in Table 4. From the table, we can learn that a total of 18 indicators to measure the level of optimization of the agricultural supply chain, there are some differences in the weight of the indicators, the weight distribution of each indicator ranges from 0.04 to 0.08, in addition to this, the weight of the indicators under the guideline layer is summed up, respectively, 0.3547, 0.3263, 0.3191, the distribution is more average, and it is very good from the three aspects of the current measure of agricultural products supply chain optimization level.

(3) Comprehensive evaluation results

On the basis of the weights of the above indicators, multiplying the corresponding indicators with the weights and accumulating them, the comprehensive score of the optimization level of agricultural supply chain is obtained. It is used to measure the level of agricultural industrialization:

$$S(X)=\sum_{k=1}^{n} W_k \cdot mms\_X_k \tag{20}$$

Through relevant calculations, the comprehensive score of the optimization level of agricultural supply chain is derived, and the results of the comprehensive score are shown in Table 5. From the perspective of the optimization level of agricultural supply chain, from 0.261 in 2014 to 0.354 in 2023, the optimization level of agricultural supply chain in the East, Central and West regions has maintained a steady growth. However, there is an imbalance in the development of the East, Central and West regions, in terms of the development level, the East, Central and West show a sequentially decreasing spatial distribution, but in terms of the development speed, the East, Central and West show a sequentially increasing spatial distribution.

Table 5: Comprehensive score result

Name	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
East	0.261	0.268	0.269	0.272	0.289	0.304	0.305	0.327	0.332	0.354
Middle	0.108	0.108	0.145	0.151	0.168	0.173	0.175	0.187	0.195	0.213
West	0.062	0.068	0.073	0.108	0.108	0.128	0.141	0.145	0.165	0.179

IV. B. 2) Measurement and analysis of farmers' income levels

(1) Descriptive statistics of the original each indicator variable

Through the research data sources set above, the original data of each index variable of farmers' income increase can be derived, and the results of the original data are shown in Table 6. Through the data in the table, it can be seen that the distribution range of the mean value of the original index variables of farmers' income increase is 5~10, and the corresponding standard deviation is 0.3~0.8, which shows that there is a great dispersion in the data of the indexes, which is due to the fact that the unit scale of the indexes is not uniform.

Table 6: Original data result

Index	Number of observations	Mean	Standard deviation	Min	Max
Y11	500	8.129	0.636	1	10
Y12	500	5.913	0.784	1	10
Y13	500	7.911	0.445	1	10
Y14	500	8.731	0.795	1	10
Y15	500	9.757	0.499	1	10
Y16	500	6.686	0.633	1	10
Y21	500	7.696	0.393	1	10
Y22	500	7.284	0.605	1	10
Y23	500	8.603	0.726	1	10
Y24	500	5.329	0.638	1	10
Y25	500	6.637	0.302	1	10
Y26	500	5.181	0.474	1	10
Y31	500	5.917	0.534	1	10
Y32	500	8.797	0.596	1	10
Y33	500	6.488	0.481	1	10
Y34	500	6.331	0.661	1	10

(2) Summary of calculation results of entropy weight method

After collecting relevant data, the entropy weight method is used to calculate the weights of the evaluation indicators of farmers' income increase, and the results of the weights of the indicators are shown in Table 7. According to the data in the table, it can be seen that the weight values of 16 secondary indicators are in the interval of 0.04~0.08, of which the weight values of the four primary indicators are 0.2659, 0.2723, 0.2232, 0.2386, which indicates that the weight distribution of the four indicators is more uniform.

Table 7: The results of the weights of each indicator

Target layer	Criterion layer	Indicator layer	Weight
Farmers income increase	Y1	Y11	0.0704
		Y12	0.0512
		Y13	0.0686
		Y14	0.0757
	Y2	Y21	0.0846
		Y22	0.0579
		Y23	0.0667
		Y24	0.0631
	Y3	Y31	0.0746
		Y32	0.0462
		Y33	0.0575
		Y34	0.0449
	Y4	Y41	0.0513
		Y42	0.0762
		Y43	0.0562
		Y44	0.0549

(3) Comprehensive evaluation results

Based on the relevant calculation formula and data analysis software, the comprehensive evaluation and analysis of the farmers' income increase level from 2014 to 2023 is carried out, and the comprehensive evaluation results are shown in Table 8. From 2013 to 2023, the level of farmers' income increase has experienced significant growth, a change that reflects the progress in agricultural modernization.In 2014, the level of farmers' income increase in the eastern region was 0.301, and it grew to 0.396 in 2023, presenting a growth rate of 23.99%. This growth is attributed to the government's policy push and financial investment. In addition, the central region and the western region also show the same trend of growth, the difference is that the growth level of the central region and the western region is not as good as that of the eastern region. The entropy weight method is used to calculate its comprehensive score, which lays the foundation for further quantitative research on the relationship between agricultural supply chain and farmers' growth.

Table 8: Comprehensive evaluation result

Name	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
East	0.301	0.302	0.308	0.321	0.334	0.338	0.355	0.387	0.388	0.396
Middle	0.145	0.153	0.158	0.171	0.183	0.205	0.205	0.216	0.232	0.252
West	0.093	0.096	0.112	0.127	0.124	0.149	0.154	0.168	0.182	0.197

IV. C. Descriptive statistical analysis

The descriptive statistics of the variables involved in the paper are shown in Table 9. The minimum values of the explanatory variables of the three dimensions are 0.046, 0.043, 0.082, the maximum values are 0.457, 0.371, 0.583, and the mean values are 0.158, 0.134, 0.167, which infers that there is a large difference in the level of optimization of the supply chain of agricultural products in different regions. The minimum value of the explanatory variables is 0.117, the maximum value is 0.709, and the mean value is 0.341, which indicates that there are large differences in the level of farmers' income in different regions. In addition, among the control variables, the minimum, maximum and mean values of government macro-control (GM), agricultural market demand (AMR), provincial and regional economic development level (ED) and agricultural infrastructure construction (AID) differ greatly, which means that there is a large difference between different regions, and also reflects the existence of spatial effects in both.

Table 9: Variable descriptive statistics

Variable		Observation quantity	Mean value	Standard deviation	Min	Max
Explained variable	Y	500	0.341	0.0335	0.117	0.709
Interpretation variable	X1	500	0.158	0.0372	0.046	0.457
	X2	500	0.134	0.0243	0.043	0.371
	X3	500	0.167	0.0394	0.082	0.583
Control variable	GM	500	0.084	0.0351	0.017	0.092
	AMR	500	0.075	0.0244	0.024	0.146
	ED	500	0.091	0.0348	0.031	0.111
	AID	500	0.068	0.0266	0.009	0.092

IV. D. Regression modeling and spatial effects analysis

IV. D. 1) Regression model analysis

Using the model of this paper, the relationship between the supply chain of agricultural products and farmers' income is regressed and analyzed, and the results of the regression analysis are shown in Table 10. On the whole, the regression coefficient of agricultural supply chain is significantly positive at the 1% probability level, indicating that the optimization of agricultural supply chain has a significant positive impact on farmers' income increase, that is, the optimization of agricultural supply chain is conducive to the improvement of farmers' income increase, and in addition, the regression coefficients of economic sustainability, social sustainability and environmental sustainability are 0.419, 0.157 and 0.216, respectively, which are significantly positive at the 1% probability level, indicating that economic sustainability, social sustainability, Environmental sustainability has a positive effect on farmers' income, and the regression coefficient of economic sustainability is significantly greater than that of social sustainability and environmental sustainability, indicating that the economic sustainability of the agricultural product supply chain at this stage is constantly exerting force and promoting the current level of farmers' income increase.

Table 10: Regression analysis results

Variable	(1)Y	(2)Y	Y(3)
X1	0.419** (4.358)		
X2		0.157** (3.208)	
X3			0.216*** (4.934)
GM	0.016*** (2.848)	0.022** (2.026)	0.024** (2.318)
AMR	0.605*** (4.941)	0.675** (5.319)	0.748*** (5.934)
ED	0.024* (1.734)	0.028*** (2.655)	0.021 (2.116)
AID	0.049*** (3.924)	0.036*** (2.726)	0.037*** (0.012)
_Cons	0.018 (1.429)	0.016 (1.279)	0.012 (1.532)
Province/year	Yes	Yes	Yes
N	500	500	500
R2	0.416	0.408	0.426

IV. D. 2) Analysis of spatial effects

(1) Global autocorrelation analysis

In this paper, the common Moran's I index method is selected to test whether there is spatial correlation between different regions in terms of farmers' income increase, the original hypothesis is that there is no spatial autocorrelation between the research objects, while the alternative hypothesis is that there is spatial autocorrelation, whose index value is usually in the range of -1-1. If the Moran index is less than 0, it indicates negative spatial correlation, and if the Moran index is greater than 0, it indicates positive spatial correlation, and when the Moran index tends to 0, it means that the spatial autocorrelation is extremely weak, and it can even be said that there is no spatial autocorrelation, and the model is no longer applicable in this case, and the results of the global autocorrelation analysis are shown in Table 11.In 2014-2023, the Moran indexes of the increase in farmers' income in different regions are all greater than 0, while the vast majority of years passed the significance test, that is, farmers' income increase in different regions shows a significant spatial correlation, and farmers' income increase in different regions of a region is related to both the economic variables of the region and those of the neighboring regions, which means that the regions with higher farmers' income increase in different regions are spatially clustered, and vice versa, that is, the overall presentation of This also means that different regions with higher farmers' income are spatially clustered together, and vice versa, i.e. the overall distribution is characterized by “high and high clustering” and “low and low clustering”. Meanwhile, the Moran index rises from 0.129 in 2014 to 0.258 in 2024, with an overall folding upward trend, which also indicates that the spatial agglomeration of farmers' income increase in different regions is gradually increasing. Therefore, it is reasonable to introduce the spatial Dubin model to analyze the impact of agricultural supply chain optimization on farmers' income increase.

Table 11: Global autocorrelation analysis

Year	I	E(I)	Sd(I)	Z	P-value
2014	0.129	-0.027	0.108	1.479	0.129
2015	0.167	-0.027	0.109	1.765	0.068
2016	0.184	-0.027	0.110	1.888	0.049
2017	0.196	-0.027	0.111	1.958	0.044
2018	0.207	-0.027	0.110	2.064	0.029
2019	0.238	-0.027	0.110	2.349	0.009
2020	0.228	-0.027	0.109	2.468	0.006
2021	0.237	-0.027	0.110	2.306	0.016
2022	0.216	-0.027	0.109	2.379	0.009
2023	0.258	-0.027	0.110	2.337	0.015

Table 12: Analysis of the overall Result of Spatial effect

Variable	Short-term effect			Long-term effect		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ln X1	0.106*** (4.415)	0.206*** (6.805)	0.312*** (8.451)	0.937*** (7.234)	0.327*** (1.425)	1.264*** (4.415)
ln X2	0.099*** (4.211)	0.105*** (6.402)	0.204*** (8.451)	0.781*** (7.234)	0.157*** (1.425)	0.938*** (4.415)
ln X3	0.121*** (4.007)	0.301*** (6.222)	0.422*** (7.451)	0.073*** (5.142)	0.086*** (1.127)	0.159*** (2.125)
GM	0.0713** (1.511)	0.0926** (1.535)	0.1639** (1.272)	0.459** (1.591)	0.238** (1.511)	0.697** (1.581)
ln AMR	0.053*** (5.735)	0.054*** (5.601)	0.107*** (5.121)	0.071*** (0.923)	0.062*** (0.886)	0.133*** (5.735)
ln ED	0.036*** (4.733)	0.038*** (4.711)	0.074*** (4.992)	0.025*** (0.128)	0.036*** (0.237)	0.061*** (4.733)
ln AID	0.049*** (4.742)	0.051*** (4.217)	0.010*** (4.087)	0.075*** (2.475)	0.032*** (1.813)	0.107*** (4.742)

(2) Analysis of total results of spatial effects

The total effect indicates the total impact of the optimization of agricultural supply chain in a certain region on the increase of farmers' income in all regions, the direct effect indicates the impact of the optimization of agricultural supply chain in the region on the increase of farmers' income in the region, and the indirect effect, i.e., spatial spillover effect, indicates the impact of the optimization of agricultural supply chain in the region on the increase of farmers in the neighboring regions, and the analysis of the total spatial effect results is shown in Table 12. Regardless of the short-term effect or the long-term effect, the optimization of the agricultural supply chain has a significant positive impact on the income increase of local farmers at the level of 1%, and a significant positive impact on the income increase of farmers in neighboring areas at the level of at least 10%, which indicates that the estimation results of the model are still robust without the impact of the "feedback effect". Comparing the long-term effect with the short-term effect, it can be seen that the regression coefficients of the short-term effect are generally lower than those of the long-term effect, which indicates that the impact of the agricultural supply chain on the farmers' income increase is long-term, and this impact can be gradually enhanced, probably because the agricultural supply chain, after a long period of development, has become more mature in its ability to research, develop and adopt new technologies, and at the same time, it is able to form a certain scale efficiency, which can have more significant impact on the farmers' income increase. The effect on farmers' income increase is more significant. Comparing the direct effect with the indirect effect, it is found that among the long-term effects, the coefficient of the direct effect affecting the local area is larger, which also confirms that the spillovers of the agricultural supply chain usually need to involve a larger number of departments and personnel, which is difficult, and thus the agricultural supply chain has a greater impact on the farmers' income increase in the region than in the neighboring regions. Regarding the control variables, their role is mainly to reduce endogeneity and the estimation bias of the core explanatory variables.

V. Conclusion

In this paper, on the relevant definitional features, we obtain the factors related to the theme, and compose them into the evaluation index system of the relationship between agricultural supply chain and farmers' income increase. The entropy weight method is utilized to assign and measure the evaluation indexes. Setting relevant variables, based on the method of least squares, constructing a regression model for the optimization of agricultural supply chain and farmers' income increase, and using the model to explore and analyze the relationship between the two in an instance. From the three dimensions of agricultural supply chain, the regression coefficients are 0.419, 0.157, 0.216, and there is a significant relationship at the level of 1.0%, which indicates that the two have a positive and significant influence.

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