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Calculation and Analysis of Agricultural Trade and Influencing Factors between China and SCO Based on Network Perspective

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Abstract Based on the social network analysis method SNA and expanding gravity model, this study explores the network structure characteristics and influencing factors of agricultural trade between China and SCO member countries in the Shanghai Cooperation Organization (SCO) from the perspective of international trade networks. Through the construction of the global agricultural trade network, it is found that from 2008 to 2024, the density of SCO regional trade network increased from 0.4834 to 0.6294, indicating that the trade links between member countries were significantly enhanced, and the intermediate central potential index decreased from 35.23% to 27.42%, reflecting the evolution of the trade network from "single-core" to "multi-core" structure. The regression results of the extended gravity model show that China's economic scale β=0.384 and the economic level of SCO countries β=0.378 have a significant positive effect on agricultural exports, while geographic distance β=-0.843 shows an inhibitory effect, and institutional factors such as common language also play a potential role. The endogeneity test and spatial correlation analysis further verify the robustness of the model. The article's study of agricultural trade in the SCO is beneficial to China's food production storage in order to dynamically regulate the national strategy of balancing food supply and demand, and to ensure the quality and safety of agricultural products and security of supply.

Index Terms Shanghai Cooperation Organization (SCO), agricultural trade, social network analysis, extended gravity model

I. Introduction

In the context of the world's unprecedented changes superimposed on the global epidemic, many international organizations have begun to decline, while the Shanghai Cooperation Organization (SCO) is growing [1]. Established out of the maintenance of regional security, the SCO organization has now become a multidisciplinary cooperation organization, which is a model of new international relations, especially in agricultural cooperation, due to the obvious differences in natural resources and strong complementarities in economy, technology, and market, the trade of agricultural products between member countries has a greater advantage of cooperation [2].

With the rapid development of trade between the member countries of the SCO organization, the economic and trade cooperation between countries has been strengthened, and the source of growth of trade between countries has become today's academic community. Traditional trade theory, that countries according to comparative advantage in the international division of labor and specialization of production, a country's export growth mainly from the increase in the number of products exported [3]. The new neo-trade theory represented by Sampson, T proposed the theory of heterogeneous firms, which argues that the complementarity between productivity selection and technology diffusion generates endogenous growth, while trade integration enhances long-run growth due to dynamic selection effects [4]. Subsequently, Scholars such as Burkholz R further explored the theories in the field of trade networks, which suggests that Bilateral trade is shaped not only by economic attributes and geographic proximity but also by the interactions within the broader trade network [5]. In the theoretical framework of international trade networks, it also provides a new perspective for us to study China's agricultural trade with the SCO.

Studies on China's agricultural product trade network have mainly focused on the characterization of trade connections between China and particular countries or an economic organization [6]. For example, Chen, W et al. demonstrated that the Belt and Road Initiative has substantially facilitated the evolution of transnational grain trade networks across participating nations, with India, Russia, and Ukraine constituting pivotal nodal economies that dominate the hierarchical core-periphery architecture of this system, thereby manifesting systemic supply-demand asymmetries within global agricultural markets [7]. Chong, Z et al. adopted the network analysis method to explore the determinants of trade relations and found that spatial proximity, cultural differences, trade agreements, economic distance and trade facilitation have significant influences on the formation of the Belt and Road trade network [8]. Hu Q et al. combined the impact of COVID-19 with the agricultural product import trade network of the countries along the "Belt and Road", constructed a risk supply model of agricultural products, and found that under the influence of the epidemic, the spatial correlation structure of agricultural product trade became increasingly sparse, and the network connectivity and density also declined. But it also provides an opportunity to break the predicament of excessive reliance on external markets in agricultural product trade [9]. Hao, X et al. found that the social network analysis of renewable energy product flows revealed a tightly integrated, centralized network structure wherein enhanced trade intensity and nodal centrality positively correlated with Sustainable Development Goals (SDG) Index performance while concomitantly stimulating renewable energy infrastructure expansion [10]. Zhu, N et al. introduced the complex network theory into the analysis of the RCEP regional trade pattern and the research on the formation mechanism of trade relations, and explored the characteristics of nodes and networks by combining indicators such as centrality, density, reciprocity and distance [11]. In terms of studies on factors influencing regional agricultural trade, Abula, K et al. found that factors such as customs environment, finance and e-commerce, security management, trust, institutions, logistics development and market environment, information, and resource sharing would have an impact on China-Central Asia agricultural trade [12]. Zhou, L et al. argued that economic scale, farmers' agricultural input, labor productivity, land productivity and trade openness have positive impacts on agricultural product trade between China and the countries along the "Belt and Road", while land resources and the conditions of government agricultural input have negative impacts [13].From the above literature, it can be seen that there are relatively rich theoretical studies on both trade networks and influencing factors, but the literature on combining the two to explore the characteristics of the agricultural product trade network between China and SCO member countries, and its influencing factors is not yet complete.

This study aims to systematically elaborate the research methodology of influencing factors of agricultural trade between China and SCO member countries of the Shanghai Cooperation Organization (SCO). This chapter adopts a research framework that combines the social network analysis method SNA with the extended gravity model to reveal the network structure characteristics of agricultural trade and its key driving factors from a multidimensional perspective. The social network analysis method analyzes the strength of trade links among nodes, overall network characteristics such as density, clustering coefficient, central potential index and node attributes such as degree centrality and intermediate centrality by constructing a global agricultural trade network in order to quantify the core position and control capacity of each country in the trade network. In addition, the community discovery method further divides the trade associations and reveals the grouping characteristics of regional trade, which provides a structured perspective for understanding China's trade interactions with SCO member countries. Then based on the extended analysis of the gravity model, the article introduces variables such as economic size, geographical distance, population, exchange rate, etc., and combines institutional and environmental factors to construct a panel data model in order to empirically test the direction and intensity of the influence of each factor on agricultural trade flows.

II. Methodology for the analysis of factors affecting trade in agricultural products between China and the SCO

II. A. Analysis of Factors Influencing Agricultural Trade Cooperation between China and SCO Member States

Current national and regional bilateral trade is not only affected by basic factors such as production factors and labor force, but also by multiple factors such as internal development strategies and external environment, etc. Factors such as the size of the agricultural population, GDP per capita, trade freedom, institutional environment, and agricultural technological progress all have an important impact on agricultural trade. Drawing on the above studies, this chapter introduces other influencing factors that can represent agricultural trade, such as arable land resource endowment, agricultural value-added, labor force and other indicators to examine the extent of their influence on agricultural trade between China and SCO member countries from four aspects: political, economic, agricultural resources, and social conditions.

II. B. Social network analysis

This paper focuses on the Shanghai Cooperation Organization SCO region, firstly adopts the social network analysis method to portray the pattern of the agricultural trade network in the SCO region and clarify the characteristics of the agricultural trade network in the SCO region, and on this basis adopts the extended gravity model to clarify the influencing factors of the agricultural trade.

II. B. 1) Agricultural trade networking

Take the agricultural trade countries (regions) as nodes, and take the agricultural trade links between nodes as edges to build a global agricultural trade network G:

$$G = (V, E, W, W', T) \tag{1}$$

where: V represents the set of all nodes; E is the set of all edges; W and W' denote the set of all node attributes (number of trade links) and the set of all edge attributes (trade amount), respectively; and T is the set of all agricultural products trade network years.

In this paper, network characteristics and node characteristics indicators are used to analyze the overall characteristics of agricultural trade networks and changes in the trade status of each node, and the community discovery method is used to classify the agricultural trade network clusters.

II. B. 2) Network characterization indicators

The overall characteristics of the network reveal the connections among the node members in the network from different dimensions, which are usually represented by the network density (M), the average clustering coefficient (S), the average path length (L), and the median central potential index (C_B). Network density is the ratio of actual node connections to possible node connections in the network, reflecting the closeness of the global agricultural trade network, and the larger the value, the closer the countries are connected. Clustering coefficient reflects the possibility of the existence of trade relations between nodes, and the average clustering coefficient is the average of the clustering coefficients of all nodes, reflecting the degree of aggregation of countries in the agricultural trade network. The average path length refers to the average shortest distance between nodes, reflecting the agricultural trade accessibility of each node and the connectivity of the network. The intermediate centrality potential index measures the dependence of countries in the network on the core countries by the difference in intermediate centrality between each node and the core node, and the larger the value, the stronger the dependence of nodes in the agricultural trade network on the core countries. The network characteristic index expression is:

$$\begin{gathered} M = \frac{r}{n(n-1)}; S = \frac{2r_i}{n_i(n_i-1)}; L = \frac{2}{n(n-1)}\sum_{i \geq j}^{n} d_{ij} \\ C_B = \frac{\sum_{i=1}^{n}\left(BC_{\max} - BC_i\right)}{n-1} \end{gathered} \tag{2}$$

where: r_i and r denote the number of links (bars) that actually exist in each node and in the network, respectively; n_i and n denote the number of nodes in the network (nos.); d_{ij} is the shortest path between a point i and a point j; $BC_{\max}$ denotes the intermediate centrality of the highest node of intermediate centrality; and BC_i denotes node i intermediate centrality.

II. B. 3) Community discovery method

The community discovery method can divide the global agricultural trade community into different communities composed of densely connected nodes, so as to reveal the group structure characteristics of the global agricultural trade network. The modularity index Q reflects the quality of agricultural trade community division, and its value range is $[-1,1]$, and the closer the modularity is to 1, the higher the quality of network community division. Its calculation formula is:

$$Q = \frac{1}{2m}\sum_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta\left(c_j, c_j\right) \tag{3}$$

where: Q is the modularity degree, the higher value of Q means the better the result of group division; m denotes the sum of trade flows of the whole network; A_{ij} is the weight of the edges between point i and point j; k_i, k_j denote the sum of all the trade flows connected with point i, point j respectively; $\delta\left(c_i, c_j\right)$ denotes whether point i, point j are in the same neighborhood (take 1 if they are the same, 0 otherwise).

II. B. 4) Node Characterization Indicators

Node characteristic index can reflect the node's central position and control ability in the network, mainly including degree centrality D, middle centrality (BC), proximity centrality (CC) and eigenvector centrality $[P(g)]$.

Degree centrality (D) is the number of countries with which a country has trade transactions in agricultural products, consisting of point out degree D^{out} and point in degree D^{in}, reflecting the vastness of a country's agricultural product export market and import sources. Weighted degree (WD) is based on the degree of the amount of agricultural trade as the weight to form a weighted network, reflecting the scale of agricultural trade between countries. Its calculation formula is:

$$D^{out}(i) = \sum_{j=1}^{n} a_{ij}; D^{in}(i) = \sum_{j=1}^{n} a_{ji}; WD(i) = \sum_{j=1}^{n} a_{ij} W_{ij} \tag{4}$$

where: $D(i)$ denotes the number of node edges, i.e., the number of nodes with trade relations (pcs); the point out degree D^{out} is the number of nodes with export relations (pcs) for node i; the point in degree D^{in} is the number of nodes with import relations for node i (pcs); a_{ij} and a_{ji} denote the trade relations between two countries; W_{ij} represents the trade flow between point i and point j (in billions of dollars); $WD(i)$ denotes the size of agricultural trade of node i (in billions of dollars).

The intermediate centrality (BC) refers to a country's ability to control the trade links between non-neighboring countries, and a higher intermediate centrality indicates that the country is at the core of the agricultural trade network and has a stronger control over other nodes. The calculation formula is:

$$BC(i) = \sum_{j}^{n}\sum_{k}^{n} b_{jk}(i) = \sum_{j}^{n}\sum_{k}^{n} \frac{g_{jk}(i)}{g_{jk}} \tag{5}$$

where: $g_{jk}(i)$ is the number of shortest paths between country j and country k through the fixed point country i (one); g_{jk} is the total number of shortest paths between country j and country k (one).

The degree of proximity to the center (CC) can measure the degree of closeness of a node to the center of the network, and the higher the degree of proximity to the center, the closer the node is to the center of the network, and the higher its position in the network. Its calculation formula is as follows:

$$CC(i) = \frac{n-1}{\sum_{j=1}^{n} d_{ij}} \tag{6}$$

Eigenvector centrality $[P(g)]$ measures a country's trade network status in terms of the influence of neighboring nodes, the higher the value, the stronger the influence of the country's partners in the agricultural trade network, i.e., the higher the status, which is computed by the formula:

$$P_i^K(g) = \sum_{j \neq i} g_{ij} \frac{P_j^K(g)}{D_j(g)} \tag{7}$$

where: $P_i^K(g)$ and $P_j^K(g)$ denote the eigenvector centrality of node i and node j, respectively; $D_j(g)$ denotes the degree centrality of node j; and g_{ij} is 1 when node i has a trade link with node j for agricultural products.

II. C.Model Setting and Variable Selection

II. C. 1) Model setup

The trade gravity model is a widely used model in the study of international trade issues, dating back to Newton's theorem of universal gravitation. Measurements of bilateral trade flows have led to the conclusion that the volume of trade between two countries is positively proportional to their level of economic development and inversely proportional to the geographical distance between them. A basic gravitational model is developed for this:

$$EXP_i = \frac{GDP_{ci} \times GDP_{si}}{DIS_{cr}} A \tag{8}$$

where EXP_i denotes the trade export value of China to SCO countries in year i, A is a constant term, GDP_{ci} and GDP_{si} denote the economic development level of China and SCO countries in year i, respectively, and are expressed in terms of the gross domestic product, GDP; and DIS_{cr} is the geographic distance between China and SCO countries, and is expressed in terms of the geographic distance between the capitals of the Chinese provinces and the The geographic distance between the capitals of SCO countries is expressed as the geographic distance between the provincial capitals of China and the capitals of SCO countries.

By logarithmizing both sides of the basic gravity model at the same time, the absolute value of the data can be reduced without affecting the nature of the data and interrelationships, and the effect of heteroskedasticity on the model can be attenuated to a certain extent, so the linear formula of the basic gravity model is derived:

$$\ln EXP_i = \alpha + \beta_1 \ln GDP_{ci} + \beta_2 \ln GDP_{si} + \beta_3 \ln DIS_{cr} + \varepsilon \tag{9}$$

where α is the constant term; β_1, β_2, β_3 are the regression coefficients, reflecting the degree of change of the corresponding explanatory variables; the error not considered by the model but actually exists is represented by ε.

The study selects China's agricultural exports to SCO countries as the explanatory variables, and the data come from the statistics of China's General Administration of Customs. Based on the information and literature found, the level of economic development, geographic distance between the two regions, population size, exchange rate fluctuations, the existence of a common border and the existence of a common language are selected as explanatory variables. Finally, the expanded gravity model is established as follows:

$$\begin{aligned} \ln EXP_i = \alpha &+ \beta_1 \ln GDP_{ci} + \beta_2 \ln GDP_{si} + \beta_3 \ln DIS_{cr} \\ &+ \beta_4 \ln POP_{ci} + \beta_5 \ln POP_{si} + \beta_6 \ln RATE_i \\ &+ \beta_7 \ln BOR + \beta_8 \ln LANG + \varepsilon \end{aligned} \tag{10}$$

II. C. 2) Data Sources and Interpretation of Variables

The study selects panel data for the years 2008 to 2024 and identifies nine countries and regions of the Shanghai Cooperation Organization (SCO), i.e., Russia, Kazakhstan, Kirghizia, Tajikistan, Uzbekistan, India, Pakistan, Iran, and Belarus, as the sample for the study. Table 1 shows the data sources and explanation of variables.

Table 1: Data source and variable interpretation

Variable	Variable meaning	Anticipatory symbol	Data source
EXP_i	China's agricultural trade exports to trading countries in Year i	+	General Administration of Customs of China
GDP_{Ci}	Gross domestic product of China in year i	+	National Bureau of Statistics
GDP_{Si}	GDP of SCO countries in Year i	+	World Bank database
DIS_{Cr}	The geographical distance between the capital of China and the capital of SCO countries	-	GoogleEarth
POP_{Ci}	The population of China in year i	+/-	National Bureau of Statistics
POP_{Si}	Population of SCO countries in year i	+/-	World Bank database
$RATE_i$	Year i RMB Exchange rate (Direct quotation method)	-	World Bank database
BOR	Is there a common border between China and SCO	+	CEPII Database
$LANG$	Is there a common language between China and SCO countries	+	CEPII Database

III. Empirical analysis of the characteristics and influencing factors of the agricultural trade network between China and the Shanghai Cooperation Organization (SCO)

Based on the social network analysis framework and the expanded gravity model constructed in the previous section, this chapter will quantitatively analyze the characteristics of the agricultural trade network between China and the SCO member countries, and empirically test the specific influence mechanisms of economic scale, geographic distance, institutional environment, and other factors on the trade flows, in order to reveal the dynamic evolution law of regional agricultural trade and its driving factors.

III. A. Analysis of agricultural trade network indicators

III. A. 1) Overall network characterization

Table 2 reveals the network density and central potential index of agricultural trade of SCO member countries in 2008-2024.

Table 2: Characteristics of the overall network of agricultural trade of SCO countries

Year	Di	De	Be
2008	0.4834	35.23%	14.61%
2009	0.4986	37.20%	12.99%
2010	0.5194	35.08%	15.30%
2011	0.5296	34.95%	10.27%
2012	0.5236	34.18%	11.69%
2013	0.5374	34.08%	10.16%
2014	0.5475	33.88%	7.03%
2015	0.5549	33.30%	11.76%
2016	0.5697	33.22%	9.28%
2017	0.5756	33.14%	8.69%
2018	0.5844	31.43%	6.92%
2019	0.5907	31.14%	8.83%
2020	0.6018	30.70%	13.46%
2021	0.6179	29.73%	12.47%
2022	0.6294	28.42%	9.69%
2023	0.6256	27.76%	8.06%
2024	0.6294	27.42%	9.53%

From Table 2, it can be found that (1) from the overall trade network density. 2008-2024, the SCO member countries agricultural trade network density overall growth trend, in 2008, the overall trade network density of agricultural products in the SCO region is only 0.4834, and by 2024, the overall trade network density of agricultural products in the SCO region amounted to 0.6294, the growth is more obvious, which can be seen that the SCO countries are increasingly close trade in agricultural products, the degree of contact is also higher. (2) From the point centrality indicator, from 2008 to 2024, the change of point centrality indicator fluctuates a lot, but the overall trend is decreasing, from 35.23% in 2008 to 27.42% in 2024, which indicates that the agricultural trade between SCO member countries is becoming more and more decentralized, and is no longer concentrated within certain countries. (3) Starting from the intermediate centrality potential indicator, the intermediate centrality potential fluctuates greatly from 2008 to 2024, with the highest in 2010 at 15.30% and the lowest in 2018 at a low of 6.92%. Overall, the intermediate centrality potential indicator shows a decreasing trend, from 13.46% in 2020 to 9.53% in 2024, indicating that the dependence of non-core countries on core countries in the agricultural trade network of SCO member countries has decreased.

III. A. 2) Analysis of centrality indicators

This paper first explores the trade status of countries in the trade network in terms of their centrality indicators, and then elaborates on China's trade in agricultural products and its position within the SCO region. There are 10 official member countries of the SCO, including Russia, Kazakhstan, Kyrgyzstan, Tajikistan, Uzbekistan, India, Pakistan, Iran, and Belarus in addition to China. Table 3 reveals the individual network characteristics of SCO member countries in the trade network for the three nodal years 2008, 2016 and 2024.

Table 3: Centrality of agricultural trade networks in 2008, 2016 and 2024

Nation	2008				2016			
	D	BC	CC	P(g)	D	BC	CC	P(g)
Russia	0.872	0.145	0.785	0.923	0.891	0.132	0.802	0.935
Kazakhstan	0.765	0.098	0.721	0.847	0.783	0.105	0.734	0.862
Kyrgyzstan	0.432	0.024	0.512	0.542	0.458	0.028	0.528	0.567
Tajikistan	0.398	0.018	0.487	0.501	0.417	0.021	0.503	0.524
Uzbekistan	0.521	0.035	0.604	0.621	0.543	0.041	0.617	0.645
India	0.689	0.082	0.673	0.754	0.703	0.076	0.691	0.772
Pakistan	0.623	0.057	0.642	0.698	0.641	0.063	0.658	0.715
Iran	0.587	0.044	0.615	0.664	0.602	0.049	0.628	0.681
Belarus	0.354	0.015	0.456	0.478	0.369	0.017	0.468	0.492
Nation	2024							
	D	BC	CC	P(g)				
Russia	0.905	0.121	0.815	0.942				
Kazakhstan	0.801	0.091	0.749	0.878				
Kyrgyzstan	0.476	0.031	0.539	0.583				
Tajikistan	0.431	0.025	0.514	0.539				
Uzbekistan	0.562	0.037	0.629	0.662				
India	0.725	0.068	0.703	0.789				
Pakistan	0.659	0.055	0.671	0.731				
Iran	0.618	0.042	0.639	0.697				
Belarus	0.382	0.019	0.477	0.503				

Degree of centrality (D): Russia always occupies a central position, with its D value growing steadily from 0.872 in 2008 to 0.905 in 2024, reflecting its establishment of trade links with more member countries; Kazakhstan and India's D values grow from 0.765 and 0.689 to 0.801 and 0.725, respectively, indicating that both countries are gradually expanding the market for their agricultural exports and the sources of imports; small countries such as Kyrgyzstan and Tajikistan have lower D values, but show a slow growth trend, which may be related to regional economic integration policies. Smaller countries such as Kyrgyzstan and Tajikistan have lower D-values, all below 0.500, but show a slow growth trend, which may be related to regional economic integration policies.

Degree of intermediate centrality (BC): Russia's BC value declined from 0.145 to 0.121, showing that its control over trade among non-neighboring countries has weakened, and the trade network has tended to be multi-polarized; India's BC value declined from 0.082 to 0.068, indicating that its role as an intermediate hub has weakened, and Kazakhstan's fluctuating BC value, 0.098→0.105→0.091. may be affected by geopolitics; and Pakistan's BC decreases from 0.057 to 0.055, reflecting its relatively stable but limited role in Central Asian trade corridors.

Proximity to the center (CC): Russia's CC value rises from 0.785 to 0.815, indicating that its distance from the center of the network continues to shrink and its core position is solid; India's and Iran's CC values increase from 0.673 and 0.615 to 0.703 and 0.639, respectively, indicating that the two countries are gradually integrating into the regional trade network; Belarus has always had the lowest CC (0.477 in 2024), and its geographic remoteness limits its role in the Central Asian trade corridor, which is relatively stable but limited.), and its geographic remoteness limits its trade accessibility.

Eigenvector centrality (P(g)): Russia's P(g) value rises from 0.923 to 0.942, indicating the increasing influence of its trading partners; Kazakhstan's P(g) increases from 0.847 to 0.878, reflecting the deepening of its cooperation with high-influence countries; and Pakistan's P(g) rises from 0.698 to 0.731, possibly benefiting from the impetus of the China-Pakistan Economic Corridor.

Taken together, the network shows multipolarity, with the BC value of Russia decreasing and the D and CC values of other countries generally increasing, indicating that the SCO agricultural trade network has evolved from a “single-core” to a “multi-core” structure. At the same time, there is regional integration, and the indicators for small and medium-sized countries (e.g., Kyrgyzstan and Uzbekistan) are slowly increasing, reflecting the gradual effectiveness of regional cooperation policies. At the same time, due to geo-economic influences, the growth of indicators in India and Iran is closely related to their strategy of expanding regional trade, while Belarus, due to its geographic location, shows the smallest increase.

III. B. Empirical study of factors affecting regional agricultural export trade

After systematically analyzing the overall characteristics and node centrality of the agricultural trade network, this section further explores the influencing factors of China's agricultural export trade with SCO member countries from a multidimensional perspective based on the panel data model, in order to reveal the differential effects of economic, geographic and institutional variables on the trade flows.

The research data selected for this paper is panel data with a time span of 17 years, 9 countries in each time section, and a sample capacity of 162 observations, so this paper will use the econometric analysis software SPSS29.0 to further analyze the selected panel data.

III. B. 1) Descriptive analysis

In order to arrive at accurate empirical results, descriptive statistical analysis of the selected variable data sets is conducted prior to the econometric analysis, and this session is aimed at systematically revealing the basic characteristics and distribution of the data for each variable. Table 4 shows the results of descriptive statistics for each variable of the model.

Table 4: Descriptive statistical results for each variable

Variable	Min	Max	Mean	Standard Deviation	Median	Dispersion Coefficient
EXP_i	12.345	956.782	284.619	198.743	265.43	0.698
GDP_{Ci}	31.405	156.892	92.157	36.829	88.346	0.423
GDP_{Si}	0.532	3.876	1.854	0.973	1.792	0.525
DIS_{Cr}	1205.34	5892.67	3256.48	1324.56	3120.15	0.407
POP_{Ci}	1324.57	1412.35	1375.62	25.893	1378.9	0.019
POP_{Si}	8.745	1432.56	287.341	402.156	154.678	1.422
$RATE_i$	6.123	7.845	6.984	0.543	6.945	0.078
BOR	0	1	0.222	0.417	0	1.879
$LANG$	0	1	0.111	0.315	0	2.838

Table 4 reflects the status of descriptive statistics for each variable indicator, and the analysis of descriptive statistics results usually involves the examination of the central tendency, the degree of dispersion, and the distribution pattern of the data, so this study chooses to describe the degree of dispersion of the data. The degree of dispersion in descriptive statistics is usually expressed by the value of the dispersion coefficient, which is equal to the ratio of the standard deviation to the mean, and the larger the value of the coefficient of dispersion in descriptive statistics, the greater the degree of fluctuation of the data. Based on my observation of the coefficient of dispersion values in the above table, most of the coefficients of dispersion of the variables are less than 20%, therefore, the degree of fluctuation of the data is relatively small.

Specific analyses about each variable are as follows: the mean value of EXP agricultural exports is 28.4619 billion dollars, the standard deviation is 198.743, and the CV of the coefficient of dispersion is 0.698, which indicates that the fluctuation of the export value is large, and it may be significantly affected by the market demand and policies; the mean value of China's GDP is 92.157 trillion dollars, with a standard deviation of 36.829, and a CV=0.423, which shows that China's economy is steady growth, but there are differences in the growth rate in different years; the average value of GDP of SCO countries is 1.854 trillion U.S. dollars, CV=0.525, reflecting significant differences in the economic scale among the member countries; DIS China's geographic distance from the SCO member countries is an average of 3,256.48 kilometers, with a standard deviation of 1,324.56 and a CV=0.407, which indicates that the distribution of geographic distances between capitals of the countries and China is wider, e.g. Belarus is closer and Iran is farther away. China's population has a mean value of 1.375 billion, CV=0.019, with a highly stable population size. SCO countries have a mean value of 287 million, CV=1.422, with great differences in population size. RATE exchange rate has a mean value of 6.984, CV=0.078, with small exchange rate fluctuations and obvious policy regulation. BOR common border has a mean value of 0.222, with only 22.2% of the countries in the sample bordering with China, such as Russia, Kazakhstan, and the United States. BOR countries have a common border with China. China, such as Russia and Kazakhstan. LANG common language mean value 0.111, fewer countries with common language.

III. B. 2) Correlation analysis

When exploring the interrelationships between data variables, the strength of the correlation can be measured by the absolute value of the calculated correlation coefficient, and the direction of the correlation is determined by the sign of the coefficient (positive or negative). When the independent variables on the right-hand side show statistically significant correlations with the dependent variable, this helps us to gain insight into the underlying structure of the link between the selected variables, although this is not directly equivalent to the conclusions of the regression analysis. For the independent variable level, it is expected that they do not show excessive linear correlation with each other during the model construction period because excessive correlation may lead to the problem of multicollinearity, which can negatively affect the stability and accuracy of the model output. Therefore, this study first proceeds with a preliminary correlation exploration of each variable. Figure 1 shows the correlation analysis of the variables.

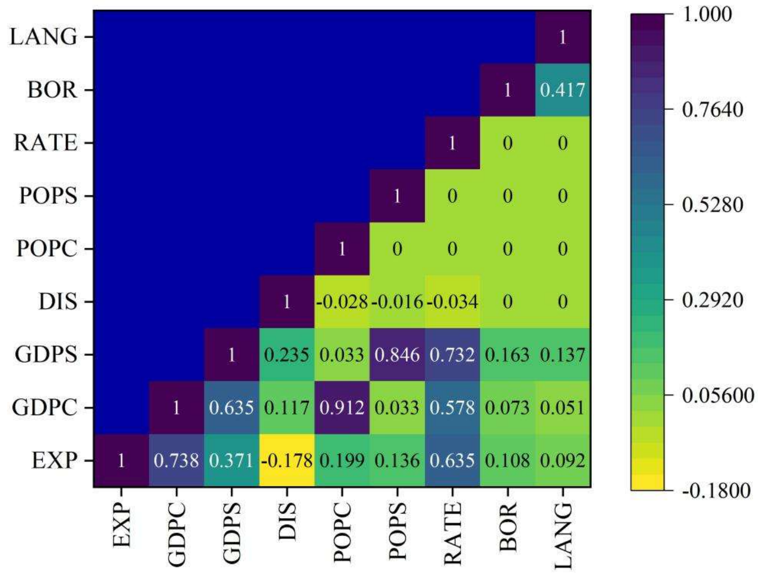

Figure 1: Correlation analysis of each variable

As shown in Figure 1, the correlation coefficient between EXP and GDP_C is 0.738, a strong positive correlation, China's expanding economy significantly promotes the export of agricultural products; the correlation coefficient between EXP and GDP_S is 0.371, a medium positive correlation, the economic level of the SCO countries to improve the demand for imports; the correlation coefficient between EXP and DIS is -0.178, a weak negative correlation, the increase in geographic distance slightly inhibit The correlation coefficient between GDP_C and POP_C is 0.912, a very strong positive correlation, population size and GDP growth are highly synchronized; the correlation coefficient between GDP_S and POP_S of the same SOC member countries is 0.846, a strong positive correlation, and the large populated countries (e.g., India) have a larger economy; the correlation coefficient between BOR and LANG is 0.417, a medium positive correlation, and the neighboring countries are more likely to share languages due to historical ties. Are more likely to share languages due to historical ties. Overall economic size GDP and exchange rate RATE are the core drivers of agricultural exports. Geographical distance DIS has a weak effect, but the dummy variables BOR and LANG show that geographic and cultural factors cannot be ignored. The risk of multicollinearity is low (correlation coefficients between independent variables are generally <0.8) and the model stability is good.

III. C. Model regression analysis

Stepwise regression method is used to analyze the model, i.e., first regress the EXP of China and SCO countries on the three core variables of the trading countries' agricultural trade exports, GDP_C and GDP_S to get model 1; then gradually introduce the three variables of geographic distance DIS, population size POP_C and POP_S for regression to get model 2; and then finally add the exchange rate RATE, the border BOR and the voice LANG three dummy variables for regression, to get model 3.The regression results of the factors affecting agricultural trade between China and SCO countries are shown in Table 5.

Table 5: Regression results of influencing factors of agricultural trade

Variable	Model 1	Model 2	Model 3
GDP_{Ci}	0.348*** (0.0311)	0.322*** (0.0456)	0.384*** (0.0508)
GDP_{Si}	0.326*** (0.0327)	0.356*** (0.0416)	0.378*** (0.0452)
DIS_{Cr}		-0.989*** (0.360)	-0.843*** (0.478)
POP_{Ci}		0.624*** (0.0877)	0.742*** (0.0842)
POP_{Si}		0.615*** (0.0921)	0.688*** (0.899)
$RATE_i$			0.409*** (0.0562)
BOR			0.477(0.424)
$LANG$			0.804*** (0.976)
Constant term	-17.23** (4.072)	-25.38*** (4.729)	-28.17*** (5.711)
Observed value	802	802	802
R-squared	0.6817	0.7531	0.7942

*, ** and *** represent 10%, 5% and 1% levels of statistical significance, respectively.

Table 5 demonstrates the stepwise regression results of the factors influencing agricultural trade between China and SCO member countries of the Shanghai Cooperation Organization. Model 1 contains only the core variables, and the results show that the coefficients of China's GDP and SCO member countries' GDP are 0.348 and 0.326, respectively, and are significant at the 1% level, indicating that the expansion of the economic scale of the two sides has a significant positive impact on agricultural exports. Model 2 introduces geographic distance DIS, China's population POPC and SCO countries' population POPS, and the coefficient of geographic distance is -0.989, which is in line with the expectation that an increase in geographic distance inhibits trade; the coefficients of the population variables are all significant and positive, indicating that population growth promotes trade through demand expansion. Model 3 further adds dummy variables such as exchange rate RATE, common border BOR and common language LANG, at which time the coefficient of China's GDP increases to 0.384, and the coefficient of SCO countries' GDP rises to 0.378, indicating that the impact of economic scale is further enhanced. The negative effect of geographic distance diminishes to -0.843, but is still significant. It is worth noting that the coefficient of common border BOR is 0.477, but fails the significance test, probably because only a few countries in the sample share a border with China; while the coefficient of common language LANG is as high as 0.804, but with a large standard deviation of 0.976, suggesting that its effect is unstable. The overall explanatory power of the model gradually increases, and the R-squared increases from 0.6817 in Model 1 to 0.7942 in Model 3, indicating that the model fit is significantly optimized after introducing more variables.

III. D. Spatial correlation test

Spatial autocorrelation can determine the degree of correlation of attribute values located in adjacent spatial units, and if there is spatial correlation between the research variables, it indicates that it is more appropriate to establish a spatial econometric model to estimate the variables. In order to analyze whether there is spatial autocorrelation in agricultural exports between China and SCO member countries, this paper will examine the local spatial autocorrelation perspective.

Local spatial autocorrelation can depict the similarity of agricultural exports between a country and its neighbors, and reflect the law of spatial correlation with location. Moran's scatter plot presents the local spatial aggregation with intuitive two-dimensional images, showing the degree and significance of the difference between the observed values of one country and the observed values of neighboring countries, and can directly distinguish the relationship between the agricultural exports of a certain country and its neighboring countries. Moreover, Moran's scatter plot corresponds to four different local spatial relationships with four quadrants: the first quadrant represents the phenomenon of "high aggregation" around which the surrounding units are also high-value; The second quadrant represents the phenomenon of "low-high clustering", which is surrounded by high-value units; The third quadrant represents the phenomenon of "low-low aggregation" around which are also low-value units; Finally, the fourth quadrant represents the phenomenon of "high-low clustering" surrounded by low-value cells.

In this paper, we use Stata16.0 software to conduct regression analysis based on the panel data of China's agricultural exports to SCO member countries during the period of 2008-2024, and draw a Moran scatter plot of China's agricultural export trade volume to SCO member countries as shown in Fig. 2.

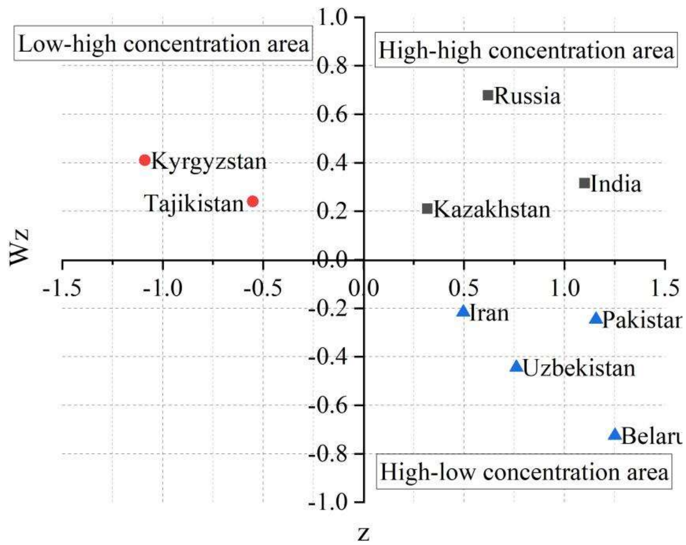

Figure 2: Moran scatter of China's agricultural export efficiency to SCO countries

Taking the above figure as a whole, three countries, including Russia, Kazakhstan and India, are located in the “high agglomeration” zone in the first quadrant, suggesting that the above countries with high levels of export trade are surrounded by countries with similarly high levels of trade, which is characterized by a positive spatial correlation; Two countries, including Kyrgyzstan and Tajikistan, are located in the “low-high agglomeration” zone in the second quadrant, indicating that a country with a low level of export trade development is surrounded by countries with a high level of export trade development, and that spatial trade has a tendency to be differentiated, with spatial negative correlation characteristics; Four countries, Uzbekistan, Pakistan, Iran and Belarus, are located in the “high and low agglomeration” zone in the fourth quadrant, indicating that a country with a high level of export trade development is surrounded by countries with a low level of export trade development, which is characterized by negative spatial correlation.

In summary, this paper takes China's agricultural export trade volume to SCO member countries as a test index, and according to Moran's scatter plot, it can be seen that most countries are located in the second and fourth quadrants of "low-high agglomeration" and "high-low agglomeration", that is, countries with higher (lower) imports of Chinese agricultural products tend to be adjacent to countries with lower (higher) imports of Chinese agricultural products geographically, showing an obvious spatial negative correlation effect.

IV. Conclusion

The study shows that China's agricultural trade network with SCO member countries shows a significant trend of multipolarity and regional integration. The density of the network continues to rise, reaching 0.6294 in 2024, and the intermediate central potential decreases year by year to 27.42% in 2024, indicating that the control of traditional core countries such as Russia is weakening, and the status of emerging nodes such as India and Kazakhstan is improving. Empirical analysis shows that China's GDP elasticity coefficient of 0.384 and SCO countries' GDP elasticity coefficient of 0.378 indicate that economic scale is the core driving force for trade growth, while the negative effect of geographic distance β=-0.843 highlights the constraints of logistics costs on trade. The common language, β=0.804, does not pass the significance test, but its potential cultural bonding role deserves attention. The spatial autocorrelation test shows that countries such as Russia and India are characterized by “high and high agglomeration”, while the small Central Asian countries are mostly in “high and low agglomeration” zones, reflecting the heterogeneity of geo-economic patterns.

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