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Factors influencing the global agricultural trade: A network analysis

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Abstract: In this study, a global agricultural trade network was constructed, and its topological characteristics from 1991 to 2021 were analysed. The influences of nine variables were empirically tested, including factor endowments and economic, geographical, and institutional factors. The research results show that the scale of trade networks is constantly expanding, and trade relations are becoming increasingly concentrated. Further, global agricultural trade patterns are gradually being reshaped. However, European economies and the United States still dominate the power of network control, with a clear 'core-edge' hierarchy. Among the factors influencing the global agricultural trade network, differences in arable land areas, agricultural product prices, geographical distances, and financial institutions have proven important. However, their influence varies. Compared to the differences in the endowments of other factors, the comparative advantage of agricultural trade in various nodes worldwide comes more from the arable land areas. The greater the difference in agricultural prices, the closer are the trade ties between nodes. Differences in geographical distance have proven conducive to establishing agricultural trade relations. Finally, the greater the difference in financial systems, the greater the likelihood that agricultural trade links will occur.

Keywords: agricultural products; Quadratic Assignment Procedure method; social networks

As a necessity for human survival, agricultural products play an increasingly prominent role in global and regional economic growth, and agricultural trade networks are gradually attracting attention. Economic growth, population expansion, and dietary shifts have led to profound changes in global and regional demand for agricultural products. The rapid growth of demand not only leads to the continuous evolution of the imbalance between supply and demand in global and regional food systems but also poses greater challenges to global sustainable development because of the uncoupled nature of its spatial distribution. Network analysis provides a comprehensive approach to quantifying the network structure of agricultural trade. Over the past two decades, network models based on statistical inference have been developed to explain network and temporal dependencies, as well as the drivers of network structure (Chung et al. 2020). Analysing trade

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networks, particularly agricultural trade networks, has become an important research topic in geography and economics. This study analyses the topological characteristics and evolutionary process of the global agricultural trade pattern to identify the position of countries in the world agricultural trade network and determine the main factors affecting global agricultural trade. This research is of great practical significance for accurately grasping the current situation of global agricultural trade, optimising the layout of agricultural trade, and better promoting agricultural trade development.

Social networks' first appeared in the 1930s. The use of the Internet to study international trade issues has long attracted the attention of scholars (Serrano and Boguna 2003). The structure and characteristics of international trade networks are particularly suitable for studying social network theories and methods (Schweitzer et al. 2009). However, traditional trade indicators do not fully reflect the complex trade relations between countries (Abeysinghe and Forbes 2005). Through a detailed description of the network topology, the social network analysis method compensates for the shortcomings of traditional trade indicators and scientifically integrates and analyses the characteristics of trade networks (Barabási and Albert 1999; Fair et al. 2017; Chung et al. 2020). Wilhite (2001), Blondel et al. (2008), and Ercsey-Ravasz et al. (2012) built trade network models to analyse trade patterns; Dupas et al. (2019) revealed changes in the topological structure and degree distribution of trade networks. Fagiolo et al. (2009) studied the topological characteristics of world trade networks using a weighted network approach. These studies suggest that the global trade network is gradually becoming more diversified and more complicated. Although the above studies explored the structural and topological characteristics of trade networks, little is known about the factors influencing the agricultural trade network.

In addition, some scholars have studied the factors driving international trade by other approaches. While geographical distance is an important factor affecting the trade between countries (Karagoz and Saray 2022), the shorter the geographical distance between economies, the greater the volume of trade (Anderson and Van Wincoop 2003). Land proximity also affects trade flow to some extent (Martinez-Zarzoso 2003; Serrano and Pinilla 2010). Besides geographical factors, the status of a country's agricultural resource endowment also determines the country's position in the international trade of agricultural products (Platte 1991; Clague and Desser 1998; Henderson et al. 2018). Furthermore, institutional factors and income distributions also affect cross-border trade to some extent (Cheptea 2007; Linders et al. 2005a), and countries with comparable income distributions trade more with each other (Martínez-Zarzoso and Vollmer 2016).

However, traditional methods such as ordinary least squares (OLS), mixed effects models (Chung et al. 2020), and exponential random graph models (ERGM) (Gutiérrez-Moya et al. 2020) are not appropriate for assessing dependencies, which can be highly intercorrelated. In addition, the use of traditional parameter estimation methods can lead to multicollinearity problems, increasing the standard deviation of parameter estimates and leading to the significance tests losing their meaning. One of the contributions of this study is that it uses the Quadratic Assignment Procedure (QAP) to explore the influencing factors of trade networks from both correlation analysis and regression analysis. Another contribution is filling the following gap in the global agricultural trade network. Previous studies have only focused on the network's structure and its topological characteristics, such as betweenness, centrality, and clusters. Few studies have quantified the dynamics of the agricultural trade network and the underlying forces that build the network, making it difficult to identify the driving forces that may lead to changes in the network over time. This study thus explores the impact of endowment differences, economic differences, institutional differences and geographical distance on agricultural trade by constructing an agricultural trade network from 1991 to 2021, which contributes to a better understanding of the factors influencing the global agricultural trade network.

MATERIAL AND METHODS

Network methods. A social network is defined as a group of actors and their connections, with two basic elements: 'nodes' and 'connections'. 'Nodes' are actors in social networks, which can be independent individuals or various social organisations, while 'connections' represent the connection between nodes. In the 1960s, sociologists and psychologists pioneered the use of social network analysis to explore interactive interpersonal relationships and group connections (Scott 2000). With the development of computer technology, social network analysis has evolved from the initial qualitative ideas to scientific and quantitative research methods. Economists began to focus on the characteristics of trade network structures, such as market networks, industry networks, and even world trade

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networks. Based on the network analysis approach, scholars have then started to explore issues related to the international trade dimension (Serrano and Boguna 2003; Garlaschelli and Loffredo 2004). A network where countries are abstracted as nodes and the existence of exports and imports between any two countries indicates the strength of ties and relationships between countries is called the world trade network. Considering the complexity of flows and relationships between countries that exchange agricultural products, complex network theory has been used as a suitable modelling tool. Based on the total agricultural trade between any two nodes worldwide from 1991 to 2021, this study constructs a weighted undirected symmetric matrix of global agricultural trade.

The Degree index, first proposed by Freeman (1979), refers to the number of nodes in a trade network (Dalin et al. 2012). The degree of node i is calculated as follows:

$$Degree_i = \sum_{j=1}^{n} I_{ij}, i \neq j \tag{1}$$

where: when the agricultural trade volume between nodes i and j is greater than 0, I_{ij} takes the value of 1, and 0 otherwise.

Network density reflects how closely the network's behaviour nodes are interconnected. *Density* is calculated as follows:

$$Density_i = \frac{M}{n \times (n-1)} \tag{2}$$

where: M – actual number of relationships between nodes due to agricultural trade; n – number of nodes in the trading network.

The reciprocity index is the ratio of the number of relationships in the network with two-way trade to the total number of relationships established in the network MD and is calculated as follows:

$$MD = \frac{M_m}{n} \tag{3}$$

where: M_m – number of relationships in a network with two-way trade.

The average clustering coefficient is the average of the local clustering coefficients of all nodes and is calculated as follows:

$$CE = \frac{1}{n} \sum_{i=1}^{n} \frac{J}{B \times (B-1)} \tag{4}$$

where: CE – clustering coefficient; J – number of other nodes connected to the node; B – number of edges connected between adjacent points of the node.

The average path length is the average of the shortest path edges between all pairs of node countries in the trade network and is calculated as follows:

$$APL = \frac{\sum_i d(i,j)}{n \times (n-1)}, i \neq j \tag{5}$$

where: APL – average path length; $d(i, j)$ – number of edges traversed by the shortest path between nodes i and j.

Intermediary centrality is an important indicator for determining key nodes in the network to reflect the path dependence and control degree of node countries on resources in the network, mainly through the index *BETWEENNESS.* In the global agricultural trade network, the intermediary indicator of node i is $BETWEENNESS_{i,}$ calculated as:

$$BETWEENNESS_{\mathrm{i}} = \sum_{i}^{n} \sum_{k}^{n} \frac{g_{ik}(j)}{g_{ik}}, (i \neq j \neq k) \tag{6}$$

where: $g_{ik}(j)$ – number of geodesics between nodes i and k passing through node j and g_{ik} is the number of geodesics between nodes i and k.

Structural hole is a gap in the flow of information or resources, emphasising the interdependence between the nodes of a network, being an index that measures the non-redundant relationship between two nodes in the network, which can usually be measured by the efficient scale. The larger the value of the efficient scale, the greater the freedom of the node's behaviour in the entire trade network, and the node is not easily restricted by the network. The efficient scale ES_i is calculated as follows:

$$ES_i = \sum_j \left(1 - \sum_q p_{iq} m_{jq}\right), q \neq i, j \tag{7}$$

where: j – all points connected to i and q denotes every third party except i or j; $p_{iq}m_{jq}$ – redundancy between point i and point j; p_{iq} – proportion of relationships in which i is invested in q; m_{jq} – marginal strength of the relationship from j to q, which is equal to the value taken by the relationship from j to q divided by the maximum value of the relationship from j to the other points.

In the Euclidean distance space, the algorithm of coreness is to find a vector C that satisfies the following conditions: the structure matrix formed by the

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product of C and C transpose has a high similarity to the original matrix, and vector C is normalised to become an actor core degree vector. The higher the coreness is, the closer it is to the centre. Coreness is a quantitative understanding of an actors' position in the network, and the strength of the association between two actors depends on their proximity to the core.

Estimation methods for the matrices. As is well known, the international division of labour and trade patterns of global agriculture are affected by many factors. Classical international trade theory of factor endowment, intra-industry trade, new economic geography theory, and new institutional economics theory are referred to when setting the research framework. First, according to the Hecksher-Ohlin (H-O) theory, because of the difference in regional factor endowments, there are differences in output between economies under the same technical level conditions, and the differences in output lead to the differences in commodity supply capacity; then, the commodity prices between the two economies are different, making it possible for trade between different economies to be analysed (Ohlin 1967). Second, the theory of demand similarity explains the roots of intra-industry trade from the perspective of demand. The more similar the demand structures of the two countries, the greater the potential volume of trade between them, while the main factor determining the structure of demand is the level of *per capita* income of countries (Kohlhagen 1977). Third, geographical location is an important factor affecting international trade. According to the new economic geography (Schmutzler 1999), the geographical proximity between two countries has an important impact on their participation in the international labour division, and the more neighbouring the country in terms of geographical distance, the easier it is to trade with each other. Finally, institutional factors influence a country's comparative advantage and foreign trade patterns by affecting productivity between economies; that is, the greater the institutional differences, the more disadvantageous they are to bilateral trade (Linders et al. 2005b).

Based on the above analysis, we posit the following hypotheses for the evolution of the global agricultural trade network:

H_1: The greater the difference in producer price of agricultural products between nodes, the closer the international division of labour and trade between them.

H_2: Trade is more likely to occur among nodes with greater gaps in factor endowments (including the amounts of arable land, labour, and agricultural capital inputs).

H_3: The greater the difference in GDP per capita between nodes, the looser the international division of labour and trade links between them.

H_4: Trade is more likely to occur among nodes that are geographically close and share a common border.

H_5: Trade relations are stronger between nodes that differ less in terms of institutional factors (trade or financial freedom).

In this study, the QAP method was used for analysis, and Ucinet 6.0 software and Netdraw visualisation software were used for data processing based on the NumPy and Pandas Library of Python 3.7 software. A matrix reflecting the network pattern of the global agricultural product trade market was constructed as the explanatory variable, and the mechanisms of the nine variables in the global agricultural trade network were empirically tested.

QAP is a method used for social network analysis and is useful for analysing dynamic datasets, especially paired datasets (Simpson 2001). The algorithm has three main steps. First, it calculates the Pearson correlation coefficient between the corresponding cells of two matrices. Second, it randomly and synchronously rearranges the rows and columns of a matrix and recalculates the correlation and other metrics. Finally, step two is repeated thousands of times to calculate the proportion of times that a random measure is greater than or equal to the observed measure calculated in step one. The QAP model is constructed as follows:

$$AT = \mathrm{f}\,(AE, EC, DIS, QTI) \tag{8}$$

where: AT – agricultural trade amount matrix; AE – agricultural factor endowment difference index system; EC – economic difference index system; DIS – distance indicator difference system; QTI – institutional quality difference index system; all variables are in matrix form.

The independent variables are the main factors affecting the relationship between global agricultural trade markets, including the agricultural factor endowment difference index system (AE), economic difference index system (EC), distance indicator difference system (DIS), and institutional quality difference index system (QTI). Among them, AE includes difference in arable land area (VLG), differences in the capital input of agriculture, forestry, fishing of general government (AIG) and differences in the number of people in the labour force (LPG). EC includes differences in the agricultural producer price in-

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dex (*APG*) and differences in the GDP per capita (*AGG*). *DIS* includes distance between nodes (*DIST)* and dummy variables for boundary (*BORD*), if there is a boundary between nodes, it takes the value of 1; otherwise, it is 0. *QTI* includes dummy variables for trade liberalisation (*FTG*), whose value ranges from 0 to 100, where the larger is the value, the higher is the degree of trade liberalisation, and dummy variables for financial liberalisation (*FFG*), whose value ranges from 0 to 100, where the larger is the value, the higher is the degree of financial liberalisation. The meaning, description, and treatment of the matrix of each explanatory variable are shown in Table 1.

Table 1. Description of variables

Variable			Description	Source
Dependent		*AT*	based on the total agricultural trade between any two nodes, a weighted undirected symmetric matrix of global agricultural trade is constructed (USD, 2014–2016 = 100).	UN Comtrade (2021)
Independent	*AE*	*VLG*	difference in arable land area (10^3 ha)	FAO (2021)
		LPG	differences in the number of people in the labour force (10^3)	World Bank (2021)
		AIG	differences in the capital input of agriculture, forestry, fishing of general government (10^6 USD, 2015 = 100)	FAO (2021)
	EC	*APG*	differences in the agricultural producer price index (2014–2016 = 100)	FAO (2021)
		AGG	differences in the GDP per capita (10^3 USD, 2015 = 100).	World Bank (2021)
	DIS	*DIST*	distance between nodes (km)	CEPII (2021)
		BORD	dummy variables; if there is a common boundary between nodes, it takes 1, and 0 otherwise.	CEPII (2021)
	QTI	*FTG*	dummy variables; the value ranges from 0 to 100, where the larger is the value, the higher is the degree of trade liberalisation.	Heritage Foundation (2021)
		FFG	dummy variables; the value ranges from 0 to 100, where the larger is the value, the higher is the degree of financial liberalisation.	World Bank (2021)

AE – agricultural factor endowment difference index system; *EC* – economic difference index system; *DIS* – distance indicator difference system; *QTI* – institutional quality difference index system
Source: Authors' own composition

Table 2. Continents and 103 nodes

Continents	Nodes
Asia (34)	China, Azerbaijan, Bangladesh, Brunei, Cambodia, Hong Kong, India, Indonesia, Iran, Iraq, Israel, Japan, Jordan, Kazakhstan, Kyrgyzstan, Laos, Lebanon, Malaysia, Mongolia, Myanmar, Nepal, Oman, Pakistan, Philippines, Saudi Arabia, Singapore, South Korea, Sri Lanka, Tajikistan, Thailand, Turkmenistan, Uzbekistan, Vietnam, Yemen
America (16)	Canada, United States, Argentina, Bolivia, Brazil, Chile, Cuba, Ecuador, Honduras, Jamaica, Mexico, Nicaragua, Peru, Uruguay, Colombia, Venezuela
Oceania (2)	Australia, New Zealand
Europe (35)	Albania, Austria, Belarus, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom
Africa (16)	Algeria, Angola, Botswana, Egypt, Ethiopia, Ghana, Gambia, Kenya, Liberia, Namibia, Tanzania, Niger, Nigeria, South Africa, Zambia, Zimbabwe

Source: Authors' own composition

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Considering the availability of the variable matrix data required for this study, 103 important nodes were screened as the research sample (Table 2).

RESULTS AND DISCUSSION

Global agricultural trade network. Social network analysis can express the intricate trade connections between various nodes in the form of networks. The overall characteristics of the agricultural trade network are shown in Table 3.

First, the scale of trade networks is constantly expanding, and trade relations are becoming increasingly concentrated. From 1991 to 2021, the number of nodes in the global agricultural trade network increased from 181 to 209, reaching a maximum of 211 nodes in 2006. Over the past 30 years, the scale of agricultural trade networks has expanded. Overall, the closeness of agricultural trade networks has improved, but it is still not close enough, meaning there is still room for further deepening global agricultural trade relations. Network density increased from 0.192 in 1991 to 0.371 in 2021, being highest at 0.409 in 2016, indicating that the trade relationship between economies gradually developed from a loose to a closer relationship. From the perspective of the reciprocity index, only 16.6% of the network relationships in 1991 were reciprocal, indicating that agricultural trade between nodes was mostly one-way. However, from 1991 to 1996, reciprocity significantly improved nearly fourfold over five years. Nevertheless, the reciprocity index remained above 54%, except in 1991. This finding shows that, since 1996, more than half of the node countries in the global agricultural trade network have had two-way agricultural trade relationships.

Secondly, trade networks have a distinctly 'small-world' character. From 1991 to 2021, the average path length was relatively stable. It did not exceed 2, meaning that the trade relationship between any two nodes required no more than two intermediary countries and that the accessibility of the trade network and the efficiency of trade transportation were relatively stable. Furthermore, although the average clustering coefficient fluctuated to a certain extent, it showed an increasing trend from 0.732 in 1991 to 0.809 in 2021, showing that in the development process of global economic integration, the connectivity of the agricultural trade network is strong, trade efficiency has improved, and the degree of agglomeration of agricultural trade links between trading partners is relatively high but not stable. Combined with the above calculation results, the global agricultural trade network shows a gradual tightening trend and trading partners tend to be stable, so that the momentum of trade network agglomeration is even more stable.

Third, although the trade pattern is gradually reshaping, European countries and the United States still have network control (Table 4). Overall, the top 10 nodes in terms of betweenness did not change significantly, indicating that the central positions of these nodes were relatively stable. With the exception of Japan, which ranked second in 2011, the top four nodes were the United States, Germany, France, and the Netherlands, thus showing that these four developed countries have the largest number of neighbouring nodes, high intermediary status and great importance and are the hub nodes. Although the control capacity of most developing nodes is weak, the importance of China, Brazil, and other countries has increased.

Fourth, the structural hole and core-edge analyses showed that European economies and the United States occupy the main power to control trade flows (Table 5). From 1991 to 2021, except for Thailand, the top structural hole indices are the United States, Germany and France, indicating that developed countries have a high degree of freedom of action and strong control over the trade network. Since 2001, the degree of nodes in a network in Asia and South America, such as China and India, has improved in an unstable situ-

Table 3. Statistics on the characteristics of global agricultural trade network

Indices	Year						
	1991	1996	2001	2006	2011	2016	2021
Degree	181	200	209	211	210	210	209
Density	0.192	0.265	0.333	0.358	0.386	0.409	0.371
Reciprocity	0.166	0.637	0.572	0.603	0.607	0.634	0.543
Average clustering coefficient	0.732	0.749	0.784	0.817	0.813	0.829	0.809
Average path length	1.496	1.568	1.570	1.548	1.519	1.486	1.439

Source: UN Comtrade Database (2021)

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Table 4. Node betweenness

1991		1996		2001		2006		2011		2016		2021	
Top 10 nodes	betweenness	top 10 nodes	betweenness	top 10 nodes	betweenness	top 10 nodes	betweenness	top 10 nodes	betweenness	top 10 nodes	betweenness	top 10 nodes	betweenness
Germany	1 125.500	USA	731.299	France	795.902	USA	797.200	USA	748.860	USA	600.177	Netherland	419.855
USA	1 153.080	Germany	611.544	USA	761.694	France	626.200	Japan	581.184	Netherland	542.687	USA	410.659
Japan	995.830	United Kingdom	592.499	Germany	696.300	China	624.100	Thailand	569.035	Japan	496.885	New Zealand	365.740
Spain	944.035	France	590.201	Netherlands	610.417	Germany	602.900	New Zealand	551.122	France	480.716	Brazil	359.908
Denmark	918.114	Netherlands	552.947	United Kingdom	595.575	Thailand	593.800	France	520.572	United Kingdom	471.899	Canada	350.075
Thailand	766.353	Belgium	469.189	Japan	593.466	United Kingdom	571.300	United Kingdom	498.864	Canada	470.752	United Kingdom	330.861
Canada	765.724	Thailand	458.531	Denmark	590.083	Japan	555.600	China	498.287	New Zealand	468.788	Thailand	315.939
New Zealand	724.978	Italy	455.633	Thailand	547.186	Netherlands	548.800	Germany	491.564	Germany	451.912	Germany	306.669
Switzerland	719.742	Canada	420.627	Australia	530.572	Canada	531.300	Canada	464.188	China	448.946	France	306.043
Australia	583.287	Spain	420.497	Belgium	528.068	New Zealand	526.100	Singapore	453.595	Thailand	429.796	Germany	303.062

Source: UN Comtrade Database (2021)

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Table 5. Structural holes of nodes

1991		1996		2001		2006		2011		2016		2021	
Top 10 nodes	efficient scale	top 10 nodes	efficient scale	top 10 nodes	efficient scale	top 10 nodes	efficient scale	top 10 nodes	efficient scale	top 10 nodes	efficient scale	top 10 nodes	efficient scale
Germany	155.920	USA	168.830	USA	181.570	USA	186.496	USA	183.253	USA	182.438	USA	183.200
USA	146.370	France	159.080	France	173.830	France	172.371	France	175.123	France	178.109	Netherlands	178.006
Spain	130.750	United Kingdom	158.250	Germany	167.770	Germany	170.995	New Zealand	169.773	Netherlands	177.052	United Kingdom	172.030
Denmark	130.640	Germany	156.590	United Kingdom	166.450	India	170.528	Thailand	169.690	Germany	172.980	UAE	170.080
Switzerland	119.710	Netherlands	153.310	Netherlands	160. 972	Netherlands	168.706	Germany	169.526	India	170.829	Turkey	169.620
Thailand	117.310	Thailand	146.620	Thailand	157.060	United Kingdom	165.828	Netherlands	168.010	United Kingdom	170.799	Germany	169.355
Japan	115.650	Denmark	145.020	Denmark	155.040	Thailand	165.613	India	166.789	Thailand	170.724	India	168.817
Portugal	110.800	Italy	144.980	Australia	154.720	Italy	164.279	United Kingdom	165.750	Poland	169.260	Thailand	167.306
Australia	102.920	Belgium	139.780	China	154.050	China	162.287	South Africa	165.621	New Zealand	168.302	France	166.833
Finland	102.520	Spain	138.770	India	152.130	Brazil	161.294	Italy	165.490	Italy	167.574	Brazil	165.875

Source: UN Comtrade Database (2021)

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ation, and South Africa, Turkey, and Brazil can occasionally enter the top 10 but rank lower.

Finally, the global agricultural trade network has a clear 'core-edge' hierarchy (Table 6). The higher the coreness of a node, the greater its control and influence. Core nodes play a leading and driving role in global agricultural trade relations. This study divides participation nodes into core, semi-marginal, and marginal nodes compared to the recent literature. Among them, nodes with a core degree higher than 0.1 are core nodes, those whose core degree is between 0.01 and 0.1 are semi-edge nodes, and those whose core degree is lower than 0.01 are edge nodes. From 1991 to 2021, the number of core nodes increased from 8 in 1991 to 12 in 2021, indicating that global agricultural trade relations are gradually deepening, with the United States still in an absolute core position. The status and control capacity of Europe is declining, while the status and control capacity of East Asia and South America are gradually improving.

QAP correlation analysis and results. Owing to space limitations, this study presents only the results for 1991, 1996, 2001, 2006, 2011, 2016, and 2021 (Table 7). There was a somewhat significant correlation between the agricultural trade matrix and the five factors of *VLG*, *APG*, *BORD*, *DIST* and *FTG*. However, there was no significant correlation between the agricultural trade matrix and the four variables of *AIG*, *LPG*, *AGG*, and *FFG*.

First, the difference in arable land area is an important condition for forming global agricultural trade networks. The relevant analysis shows that, since 2011, the difference in *VLG* has been statistically significant at the 5% level. Regarding the actual correlation coefficient, the greater the difference in arable land area between nodes, the closer the agricultural trade link. Second, agricultural price difference is an important factor in forming the global agricultural trade network structure. The results of the correlation analysis showed that, in 1996 and 2021, the *APG* achieved statistical significance at the 10% and 5% levels, respectively. From the actual correlation coefficient, the greater the difference in agricultural prices between nodes, the closer the agricultural trade link. Third, geographic difference is the basis for the evolution of the global agricultural trade network. *BORD* was statistically significant at the 1% level for all years. In 1991, 2016, and 2021, the *DIST* was statistically significant at the 5% level, while in the remaining years, it achieved significance at the 1% level. Therefore, when nodes have boundaries, the agricultural trade relationship is closer; the farther the geographical distance between nodes, the looser the agricultural trade links; and differences in trade institutions are important reasons for the evolution of the global agricultural trade pattern. Except for 1991, the *FTG* achieved significance at the 10% level, and although the correlation was negative, it showed that the greater the difference in trade institutions between nodes, the looser the trade links.

These results provide empirical evidence from the perspective of correlation analysis. However, QAP regression analysis is required to further reveal the impact of these factors.

QAP regression analysis and results. From 1991 to 2021, the adjusted goodness-of-fit value of the QAP showed an increasing trend, with the highest value recorded in 2011 (Table 8). According to the recent literature, the adjusted QAP goodness-of-fit value is lower than that of the traditional OLS model; therefore, the explanatory power of this model is ideal.

From the standardised regression coefficients perspective, *VLG*, *APG*, *DIST*, and *FFG* passed the significance test, providing strong empirical evidence. We can make the following observations by comparing the magnitude of the absolute values of the normalised regression coefficients.

First, the difference in arable land area will become an important source of comparative advantage in agricultural production in various countries worldwide, thus affecting the basic market pattern of global agricultural trade. Compared to the other two variables of factor endowments, the agricultural trade links between nodes with large differences in arable land area were closer. The results of the regression analysis showed that *VLG* was statistically significant at the 1% level for all years, while the standardised regression coefficient was positive and showed a significant upward trend. By contrast, both *AIG* and *LPG* had negative regression coefficients, with *AIG* achieving the 1% significance test only in 2021 and not being significant in the other years, whereas *LPG* failed the significance test in all years. The reason may be that agricultural subsidies account for the main part of capital input to agriculture but agricultural subsidies are mostly 'hidden' and not fully reflected in the statistics of agricultural capital input in the FAO database. Although the Organisation for Economic Co-operation and Development (OECD) and the World Bank have made great efforts to provide data on agricultural subsidies for each country, we did not use any of them in this study for various reasons. For example, the Producer Support Estimation (PSE) method developed by the

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Table 6. Coreness and core nodes

1991		1996		2001		2006		2011		2016		2021	
Core nodes	coreness	core nodes	coreness	core nodes	coreness	core nodes	coreness	core nodes	coreness	core nodes	coreness	core nodes	coreness
USA	0.653	USA	0.553	USA	0.588	USA	0.555	USA	0.542	USA	0.573	USA	0.550
Germany	0.517	Germany	0.349	Japan	0.324	Germany	0.354	China	0.346	China	0.408	China	0.506
Japan	0.386	Japan	0.336	Germany	0.316	France	0.289	Germany	0.315	Germany	0.286	Netherlands	0.237
Spain	0.196	France	0.332	France	0.282	Netherlands	0.279	Netherlands	0.277	Netherlands	0.258	Germany	0.235
Canada	0.189	Netherlands	0.281	Netherlands	0.243	China	0.249	France	0.247	France	0.202	Brazil	0.220
Denmark	0.147	Italy	0.213	Spain	0.202	Japan	0.228	Japan	0.196	Brazil	0.191	Spain	0.186
Thailand	0.115	United Kingdom	0.190	Italy	0.202	Italy	0.219	Brazil	0.192	Spain	0.189	France	0.178
Australia	0.102	Spain	0.177	United Kingdom	0.186	United Kingdom	0.216	Spain	0.181	Japan	0.162	Canada	0.144
–	–	Belgium	0.170	Canada	0.185	Belgium	0.184	Italy	0.180	Italy	0.156	Italy	0.141
–	–	Canada	0.144	Belgium	0.174	Canada	0.166	United Kingdom	0.159	United Kingdom	0.151	Japan	0.135
–	–	China	0.127	China	0.155	Brazil	0.143	Belgium	0.148	Canada	0.147	Mexico	0.117
–	–	Brazil	0.109	Brazil	0.112	Mexico	0.113	Canada	0.139	Argentina	0.117	United Kingdom	0.112
–	–	Denmark	0.102	Mexico	0.111	Argentina	0.112	Argentina	0.135	Mexico	0.116	–	–
–	–	–	–	Denmark	0.101	Denmark	0.104	Russia	0.113	Belgium	0.113	–	–
–	–	–	–	–	–	–	–	Thailand	0.105	–	–	–	–
–	–	–	–	–	–	–	–	Mexico	0.101	–	–	–	–

Source: UN Comtrade Database (2021)

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Table 7. Actual correlation coefficient

Variables	1991	1996	2001	2006	2011	2016	2021
VLG	0.0260	0.0243	0.0313	0.0439	0.0686**	0.0774**	0.0734**
LPG	–0.0071	–0.0110	–0.0086	–0.0015	–0.0003	0.0039	0.0070
AIG	–0.0119	–0.0196	–0.0181	–0.0199	–0.0181	–0.0225	–0.0186
APG	0.0140	0.0334*	0.0407	0.0579*	0.0728**	0.0818**	0.0775**
AGG	–0.0075	–0.0026	–0.0027	–0.0035	–0.0001	–0.0062	–0.0046
DIST	–0.0501**	–0.0804***	–0.0734***	–0.0747***	–0.0682***	–0.0603**	–0.0303*
BORD	0.0399**	0.0115***	0.1014***	0.1210***	0.1310***	0.1058***	0.0699***
FTG	–0.0221	–0.0360*	–0.0359*	–0.0405*	–0.0389*	–0.0405*	–0.0281*
FFG	0.0063	–0.0143	–0.0106	–0.0150	–0.0122	–0.0113	–0.0062

5 000 random displacements; *, **, ***significance at the 10%, 5%, and 1% levels, respectively; *VLG* –difference in arable land area; *LPG* – differences in the number of people in the labour force; *AIG* – differences in the capital input of agriculture, forestry, fishing of general government; *APG* – differences in the agricultural producer price index; *AGG* – differences in the GDP per capita; *DIST* – distance between nodes; *BORD* – dummy variables for boundary; *FTG* – dummy variables for trade liberalisation; *FFG* – dummy variables for financial liberalisation

Source: UN Comtrade Database (2021)

OECD to assess the combined effects of all agricultural policy measures currently covers only 26 economies, which is not sufficient to support our study.

Price difference is the main reason for the formation of the global agricultural trade network. In all years except 1991, the *APG* passed the 1% significance test. The standardised regression coefficient showed a fluctuation trend, indicating that price difference is one of the main factors influencing the global agricultural trade network. For example, although China is the fourth largest soybean producer worldwide, it is also the largest soybean importer. China's domestic agricultural production cost disadvantage has become the most direct cause of the rapid growth in soybean imports. Since their reform and opening up, China's soybean production costs have continued to rise due to factors such as rising labour costs, high prices of agricultural production materials, and increasingly land costs. Ac-

Table 8. QAP regression analysis results (10 506 observations)

Variables		1991	1996	2001	2006	2011	2016	2021
AE	*VLG*	0.0438***	0.0403***	0.0491***	0.0645***	0.0909***	0.0960***	0.1104***
	LPG	–0.0511	–0.0741	–0.0774	–0.0919	–0.1010	–0.0982	–0.0949
	AIG	–0.0194	–0.0182	–0.0185	–0.0209	–0.0190	–0.0232	–0.0192***
EC	*APG*	–0.0089	0.0196***	0.0153***	0.0222***	0.0233***	0.0306***	0.0368***
	AGG	–0.0005	–0.0196***	–0.0208	–0.0286	–0.0297	–0.0363	–0.0360
DIS	*DIST*	0.1322***	0.2003***	0.2245***	0.3100***	0.3533***	0.3636***	0.3770***
	BORD	1.2894	1.9980	2.1226	2.7503	3.0336	3.0553	3.0717
QTI	*FTG*	–0.0119	–0.1260	–0.0119	–0.0056	0.0009***	–0.0036	–0.0016
	FFG	0.0346***	0.0186***	0.0251***	0.0253***	0.0289***	0.0316***	0.0325***
Intercept		0	0	0	0	0	0	0
Adjusted R^2		0.0470	0.2100	0.2010	0.3140	0.3810	0.3110	0.2870

5 000 random exchanges; *, **, ***significance levels of 10%, 5%, and 1%, respectively; QAP – Quadratic Assignment Procedure; *AE* – agricultural factor endowment difference index system; *EC* – economic difference index system; *DIS* – distance indicator difference system; *QTI* – institutional quality difference index system; *VLG* –difference in arable land area; *LPG* – differences in the number of people in the labour force; *AIG* – differences in the capital input of agriculture, forestry, fishing of general government; *APG* – differences in the agricultural producer price index; *AGG* – differences in the GDP per capita; *DIST* – distance between nodes; *BORD* – dummy variables for boundary; *FTG* – dummy variables for trade liberalisation; *FFG* – dummy variables for financial liberalisation

Source: UN Comtrade Database (2021)

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cording to the data provided by the National Agricultural Product Cost-Benefit Data Compilation, from 1978 to 2015, the production cost per ha of oilseeds in China increased 294 times. As an international comparison, Chinese soybeans' cost and price competitiveness in the international market declined before 2005. Whether according to the production cost per ha or according to the production cost per unit of output, the production cost of Chinese soybeans was lower than that of the United States; however, after 2005, the growth rate of China's soybean production cost was significantly higher than that of the United States, resulting in the cost competitiveness of both sides beginning to reverse in 2011. According to the Brick Agricultural Database and Wind Database, a comparative analysis of daily soybean market price data from China, Brazil, Argentina, and the United States from January 2014 to May 2021 revealed that the average soybean prices in Brazil and Argentina were USD 3 375.806 and USD 3 332.876 respectively, lower than China's USD 3 462.952.

Geographical distance forms the basis for the evolution of global agricultural trade networks. Each node tends to follow the principle of proximity to conduct foreign trade activities, thereby saving transportation costs and reducing trade costs. The results of the regression analysis showed that the coefficient for *DIST* was positive, met the 1% significance test in all years, and showed a fluctuating upward trend. This finding indicates that geographical distance positively impacted the establishment of agricultural trade relations, which is not consistent with the theoretical expectations of the gravity model but can be explained at a practical level. The actual reason may be that, on the one hand, geographical distance originally affected the establishment of trade relations through the efficiency and frequency of bilateral trade links. However, with the development of communication technology, the hindering and weakening effects of geographical distance on international trade is diminishing day by day.

On the other hand, according to the gravity model, geographical distance mainly affects overall trade through the expansion margin; the greater the geographical distance, the greater the product differentiation and complementarity; therefore, the greater the chances for trade. Third, from 1991 to 2021, although the global agricultural trade pattern was gradually reshaped, Europe's status and control capacity showed a downward trend, while those of East Asia and South America gradually improved. Since 2001, the degree of nodes in a network in Asia and South America, such as China and India, have improved in less stable conditions, and South Africa, Turkey, and Brazil have occasionally entered the list of the top 10. This improvement explains why the role of geographical distance in agricultural trade relations has gradually weakened over time.

Finally, differences in financial systems are an important reason for the evolution of global agricultural trade networks. The smaller the financial institutional differences are, the easier it is to establish agricultural trade links between nodes. The results show a significant positive correlation between the *FFG* and bilateral agricultural trade relationships. Although this result is not consistent with the aforementioned theoretical assumptions, it provides a realistic basis. In 1991, the highest agricultural trade volume was mainly held by aquatic products/livestock products/corn/soybean trade between the United States and Japan, livestock trade between Germany and the Netherlands, livestock products/aquatic products trade between the United States and Canada, livestock trade between the United States and Australia, and livestock trade between Japan and Australia. However, in 2021, the highest agricultural trade volume was held by soybean/livestock trade between China and Brazil, soybean/corn trade between China and the United States, and fruit trade between the United States and Mexico. These results also echo the 'core-periphery' results of the global agricultural trade network.

CONCLUSION

This study used QAP to construct a matrix reflecting agricultural trade relations as the explanatory variable and empirically test the mechanism of agricultural factor endowment differences, economic differences, institutional differences, and geographical distance on the global agricultural product trade network. We can draw the following conclusions.

i) The scale of global agricultural trade networks is constantly expanding, and trade relations are becoming increasingly concentrated. The agricultural trade links between nodes gradually developed from a relatively loose state. Although the trade pattern has been gradually reshaping, the power of network control is still dominated by developed countries in Europe and the United States, with a clear 'core-edge' hierarchy. Ercsey-Ravasz et al. (2012), Dupas et al. (2019), and Gutiérrez-Moya et al. (2020) have reached similar conclusions. In recent years, the global agricultural trade network has become less vulnerable to attacks

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(Fair et al. 2017). However, due to the outbreak of the COVID-19 pandemic, the conflict between Russia and Ukraine, Sino-China trade frictions, and other events, there is still some uncertainty in the future of global agricultural trade as per Jafari et al. (2022). A clear piece of evidence is that recent indicators reflecting the scale and closeness of the global agricultural trade network, such as the number of nodes, network density, average reciprocity, average clustering coefficient, and average path length, have slightly decreased.

ii) There is a significant correlation between the agricultural trade relationship matrix of each node and the four factors of arable land area, agricultural product price, geographical distance, and financial freedom. As estimated by Torreggiani et al. (2018), the probability of country pairs belonging to the same food trade community depends more on geopolitical and economic factors than on the country's economic size and/or income.

The difference in arable land area is an important factor in forming global agricultural trade market patterns. The difference in arable land area affects the comparative advantage of each node in the global agricultural trade network and the basic pattern of the agricultural trade market. The QAP correlation and regression analysis results show that the greater the difference in arable land area between nodes, the closer the agricultural trade relationship and *vice versa*. These results are consistent with the factor endowment theory.

iii) Differences in agricultural prices are the main reason for forming a market pattern of agricultural trade for agricultural products. Regardless of using the actual correlation coefficient or standardised regression coefficient, the difference in agricultural prices shows a significant positive effect on the establishment of agricultural trade relations between nodes in all years, consistent with the usual theoretical expectations. China's soybean import trade is a typical example. Although China is the world's fourth-largest soybean producer, it is also the world's largest soybean importer. The production cost disadvantage of China's domestic agricultural products has become the most direct cause of the rapid growth of imports of bulk agricultural products such as soybeans. According to the Brick Agricultural Database and the Wind Database, a comparative analysis of daily soybean market price data from China, Brazil, Argentina, and the United States from January 2014 to May 2021 indicated that the average soybean prices in Brazil and Argentina were USD 3 375.806 and USD 3 332.876, respectively, both lower than China's USD 3 462.952. The policy significance of the substantial impact of agricultural prices on the international division of labour and trade relations in agriculture lies in the fact that the current need to focus on three trends may increase the uncertainty of agricultural prices. First, adverse weather affects crop sowing progress. For three consecutive years, La Niña has led to the drought and low temperatures in the southern hemisphere; as such, the sowing progress of corn and soybeans in Argentina and Brazilian corn has been slow. Second, the import supply chain faces more uncertainties. The water level of the Mississippi River in the United States has fallen, the railway strike crisis has reappeared, many sections of the Amazon River in Brazil have fallen to their lowest level, and the export capacity of major grain-producing countries has declined. Third, the risk of price fluctuations in the international market has increased. India's sugar export quota has fallen to only half of its original level, Russia has not yet decided to eliminate or adjust fertiliser export tariffs, and the price volatility of bulk agricultural products has intensified.

iv) Geographical location was the basis for the evolution of the global agricultural trade network. While the correlation and regression analysis results demonstrated the significance of the *DIST* variable, the actual correlation coefficient was negative, and the standardised regression coefficient was positive. The former shows that the agricultural trade links between nodes with a greater geographical distance are looser, whereas the latter are completely different. Although the latter is not in line with the usual theoretical expectations, it reflects the reality of today's global agricultural trade and can be reasonably explained. In addition, the correlation and regression analyses of the *BORD* yielded different conclusions. The results of the correlation analysis showed that the *BORD* passed the 1% significance test for all years. However, the regression analysis showed no statistical significance in all years. Based on the structural hole analysis and 'centre-edge' analysis results, from 1991 to 2021, although the global agricultural trade pattern has been gradually reshaped, regarding control capacity, Europe and Australia have shown a downward trend, while East Asia and South America have gradually improved. This situation is reflected in the fact that since 2001, the control abilities of China and India have improved despite the unstable situation. Moreover, although South Africa, Turkey, and Brazil can occasionally enter the top 10, they rank lower.

v) Institutional differences are important factors in the evolution of global agricultural trade networks.

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From the relevant analysis, except for 1991, *FTG* passed the 10% significance test, but the sign was negative. However, this conclusion was not verified by regression analysis. The results of the regression analysis show a significant positive correlation between the financial system difference and agricultural trade linkage; that is, the greater the differences in the financial system are, the more likely it is that agricultural trade links may occur. However, this is not in line with theoretical expectations, it is instead consistent with the reality of global agricultural trade by reflecting the deepening influence of the financial system on agricultural trade (Staugaitis and Vaznonis 2022). For example, in 1992, the highest agricultural trade volume occurred mainly between developed countries, such as the United States and Japan, Germany and the Netherlands, the United States and Canada, the United States and Australia, or between Japan and Australia. While China's top three agricultural trading partners were Brazil, the United States, and Thailand in 2022, the top three agricultural trading partners of the United States were Mexico, Canada, and China; Australia's top three agricultural trading partners were China, Vietnam, and Japan.

Based on previous research, this study has explored and researched work on the global agricultural network. However, due to the limitations of objective research conditions and subjective research capabilities, it inevitably has some shortcomings, mainly in the following aspects: data on the level of enterprises are not easy to obtain, and this study only conducted theoretical and empirical analysis from the national level and lacks corresponding micro foundation, fails to consider the diversification of enterprises in detail, which a direction that needs to be further expanded in future studies.

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