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Exploring the evolution of global beef trade network patterns based on complex network analysis

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Introduction: The global beef trade, as a critical component of the meat trade, plays an important role in balancing beef supply and demand worldwide. However, research on the evolution of its network patterns remains relatively limited. This article aims to explore the evolution of global beef trade network patterns and provide insights into its implications for sustainable development.

Methods: Using complex network theory, this paper constructs weighted and unweighted global beef trade networks based on international trade data and conducts an in-depth analysis of the evolution of global beef trade patterns from 2013 to 2022 across the overall, individual, and clustering levels.

Results: The analysis reveals an increasing trend in connectivity, efficiency, and tightness within the global beef trade network. In the unweighted network, the core beef-importing countries are primarily concentrated in Germany, the United Arab Emirates, and the Netherlands. However, in the weighted network, the core importing countries shift to the United States, Japan, and China. Meanwhile, the core beef-exporting countries consistently remain Australia, Brazil, and New Zealand in both network types. Additionally, the analysis identifies clustering and regionalization characteristics within the global beef trade blocks.

Discussion: These findings highlight the evolving dynamics of global beef trade, emphasizing the roles of key countries and the structural shifts in the trade network. The study provides targeted recommendations for promoting sustainable development in the beef trade sector.

KEYWORDS

global beef, trade network, complex network, patterns, sustainable development

1 Introduction

The demand for meat has been increasing along with rising global residents' income and the improvements in dietary structure (Godfray et al., 2018). As a significant segment of the meat industry, beef has experienced growing global demand (Kibona et al., 2022). However, due to resource and environmental capacity constraints, many countries and regions are unable to meet beef production needs independently (Chen et al., 2022). Consequently, international trade has become a vital mechanism for balancing and stabilizing the supply and demand in the global beef market (Caro et al., 2014). In recent years, global beef trade has shown remarkable growth. Using import values as a key indicator, data from the UN Comtrade database indicate that the total import value of the global beef trade increased from USD 39.11 billion in 2013 to USD 66.11 billion in 2022, with an average annual growth rate of 6.01%. This growth highlights the expansion of the global beef trade market over the past decade. It can be said that global beef trade constitutes an essential part of international agricultural trade, and its evolution not only

affects food security and supply chain stability, but also has a link to global economic development and environmental sustainability.

Research on beef trade can be generally categorized into three areas. The first focuses on supply-demand dynamics, product structures and market competitiveness in the beef trade, utilizing statistical data to conduct comprehensive investigations at global or national levels (Reeves and Hayman, 1975; Anderson et al., 2002; Bindon and Jones, 2001; Fields et al., 2018). The second area investigates the impact of factors such as animal diseases, environmental regulations, and food safety on beef trade, mainly employing econometric models to analyze specific influencing factors (Darbandi et al., 2021; Webb et al., 2018; de Waroux et al., 2019; Wilson et al., 2003). The third area introduces advanced technological tools, such as machine learning, to forecast trends and patterns in beef trade by leveraging large datasets and complex algorithms (Batarseh et al., 2019; Jeong et al., 2024).

It is notable that the aforementioned studies have tended to emphasize the independence of individual countries' trade and cannot adequately capture the complex and interconnected relationships in global trade systems. Complex network analysis offers a robust framework for abstracting and simplifying real-world social systems, enabling a more precise investigation of interactions and influences between nodes (Strogatz, 2001; Pagani and Aiello, 2013; Costa et al., 2007). By representing trade relationships as networks, researchers can examine the structural characteristics of these networks, uncover relationships between countries, identify key players in trade, and reveal regional clustering and cooperation patterns. This approach offers a comprehensive understanding of the dynamic and intricate features of the global trade system (An et al., 2018; Hou et al., 2018; Wang et al., 2021). Consequently, complex network theory has gained widespread application as an effective analytical tool in international trade research (Li et al., 2003; Serrano and Boguñá, 2003; Fagiolo et al., 2009; Fan et al., 2014, 2021).

Despite the importance of the global beef trade in the international economy, systematic studies on the evolution of its network patterns remain relatively limited. For example, what are the trends in the evolution of the global beef network structure in recent years? Which countries or regions occupy central roles in the global beef trade network? Does the global beef trade network exhibit regional and clustering characteristics, and if so, how have these evolved? The answers to the above questions are particularly important for countries, especially major beef trading nations. Clarifying the relationships within the beef trade network can help nations adjust their industrial policies, thereby promoting the sustainable development of global beef trade.

To address these issues, this paper conducts an in-depth analysis of the relatively underexplored field of beef trade networks. First, topological structure indicators in complex networks are selected to analyze the overall structural characteristics of the global beef trade network. These indicators provide a quantitative basis for examining the network's topological features and dynamic evolution. Second, both unweighted and weighted centrality indicators are employed to comprehensively identify the countries and regions that play dominant roles in beef trade. Finally, block modeling analysis is applied to identify role similarities and grouping structures within the beef trade

network, providing deeper insights into trade relationships between countries. Therefore, this study not only enriches the application of complex network theory in agricultural trade research but also provides a reference framework for analyzing trade networks of other agricultural products.

2 Materials and methods

2.1 Complex network analysis indicators

2.1.1 Whole network analysis

Complex networks are characterized by a variety of metrics that reflect their overall characteristics. In this study, four key indicators—average distance, network density, network diameter and average clustering coefficient—are selected to explore the evolution of the overall characteristics of the global beef trade network (Hao et al., 2018; Bai et al., 2023).

1. Average Distance

Average distance measures the average shortest path length between any two nodes in the network. It is calculated using the following formula:

$$AD = \frac{1}{N(N-1)} \sum_{i \neq j} d(i, j) \quad (1)$$

where AD is the average distance, N is the total number of nodes, $d(i, j)$ is the shortest path length between node i and node j . It quantifies the average number of steps along the shortest paths required to connect any two nodes within the network. A larger average distance indicates poor connectivity and low efficiency, requiring more steps for nodes to reach each other.

2. Network Density

Network density quantifies the proportion of actual connections to all possible connections within the network. For a directed network, this metric is calculated as follows:

$$D = \frac{E}{N(N-1)} \quad (2)$$

where D , E and N represent the network density, actual number of edges, and the number of nodes, respectively. Network density reflects the extent of interconnectedness in trade networks, with higher densities indicating more integrated trade relationships.

3. Network Diameter

Network diameter represents the longest shortest path between any two nodes, and can be expressed as:

$$ND = \text{MAX}_{ij} d(i, j) \quad (3)$$

where ND is network diameter, $d(i, j)$ is the shortest path length between nodes i and j . The network diameter provides a measure of

the maximum distance within the network, indicating the longest direct trade connection in the network.

4. Average Clustering Coefficient

The clustering coefficient assesses the degree to which nodes in the network are clustered together. For a directed whole network, the average clustering coefficient is calculated as:

$$C = \frac{1}{N} \sum_{i=1}^N \frac{E_i}{k_i(k_i-1)} \quad (4)$$

where C is average clustering coefficient, N is the total number of nodes, E_i is the number of edges between the neighbors of node i , and k_i is the degree of node i . A higher average clustering coefficient indicates that countries tend to form tightly connected trading groups or clusters.

The changes in average distance and network diameter indicate the connectivity and efficiency of the global beef trade network, while network density and average clustering coefficient reflect the tightening and regionalization of the trade network. These structural indicators provide essential support for optimizing supply chain resilience, enhancing trade efficiency, and addressing unexpected external shocks.

2.1.2 Centrality analysis

Centrality is used to identify the most important or influential nodes in a network and serves as a critical structural metric. This article employs the commonly used degree centrality to measure node influence (Freeman, 1979). Degree centrality quantifies the number of direct connections a node has. In an undirected network, degree centrality refers to the total count of edges connected to a node. In directed networks, it is divided into in-degree (number of incoming edges) and out-degree (number of outgoing edges). The calculation formulas are as follows:

$$d_i = d_i^{out} + d_i^{in} \quad (5)$$

$$d_i^{out} = \sum_{j=1}^N a_{ij} \quad (6)$$

$$d_i^{in} = \sum_{j=1}^N a_{ji} \quad (7)$$

where d_i , d_i^{out} , d_i^{in} , N represent the degree centrality of node i , the out-degree centrality of node i , the in-degree centrality of node i , and the total number of nodes, respectively. a_{ij} is an element of the adjacency matrix, which indicates whether there is a directed edge from node i to node j (1 if yes, 0 if no), so is a_{ji} .

In weighted networks, it is essential it is essential to consider both the number of connections and the weights of those edges. This is measured using the node strength metric, which can be divided into out-strength and in-strength for directed networks. The calculation formulas are as follows:

$$s_i = s_i^{out} + s_i^{in} \quad (8)$$

$$s_i^{out} = \sum_{j=1}^N w_{ij} \quad (9)$$

$$s_i^{in} = \sum_{j=1}^N w_{ji} \quad (10)$$

where s_i , s_i^{out} , s_i^{in} , N represent strength of node i , out-strength of node i , in-strength of node i , and the total number of nodes, respectively. w_{ij} and w_{ji} stand for weight of the edge from node i to node j , and the weight of the edge from node j to node i .

The application of centrality indicators in the beef trade network identifies core countries or regions involved in beef trade and underscores their critical role in maintaining global trade stability. This analysis provides policymakers with valuable insights to identify dependencies and implement diversification strategies to mitigate supply chain risks.

2.1.3 Block modeling analysis

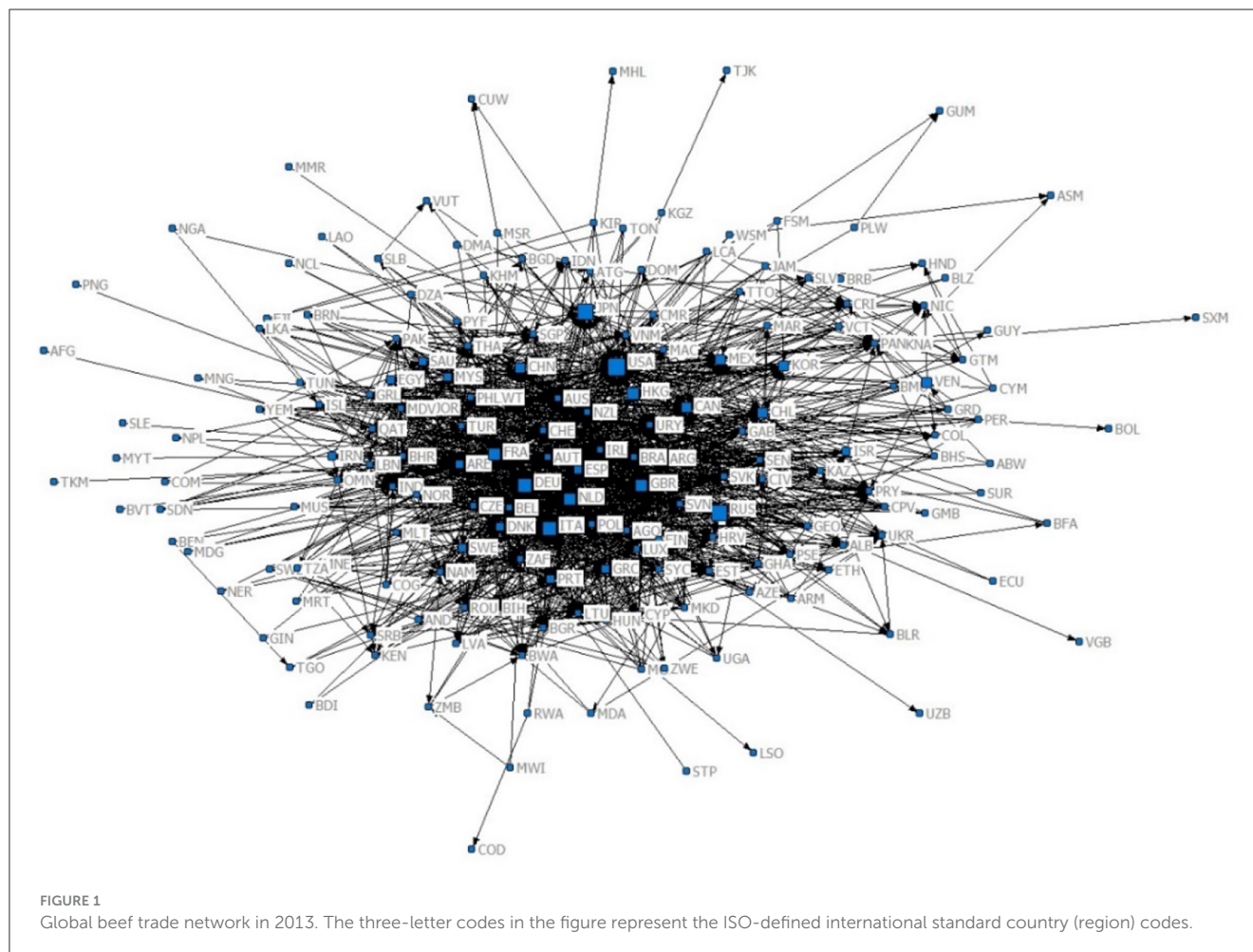
Block modeling analysis, introduced by White et al. (1976), is a method for studying network position models. As an effective tool, it can identify and understand structural patterns within complex networks. By grouping nodes with similar relationships into blocks, block modeling analysis could reveal the equivalence of roles within the network.

The application of block modeling analysis to the beef trade network identifies role distributions among regional clusters and peripheral countries. This approach facilitates the analysis of regional cooperation and the global competitive pattern, providing decision-makers with valuable insights to help peripheral countries better integrate into the global beef trade network.

In this article, we use the commonly employed CONCOR (CONvergence of iterated CORrelations) algorithm to iterate based on the correlation matrix between nodes until the correlation matrix converges (Breiger et al., 1975). The brief procedural steps are as follows: first, the number of blocks in the overall network is determined using the CONCOR algorithm. Subsequently, a density table and an image matrix between the blocks are derived. Finally, a simplified graph is presented, which more clearly illustrates the structure of each block within the entire network.

2.2 Data description

The HS codes used in this article to determine the classification of beef include HS0201 (fresh beef) and HS0202 (frozen beef). The data were sourced from UN Comtrade database (UN Comtrade Database, 2024). This study employs import value data to characterize trade relationships, as imports are potentially more accurate (Webb et al., 2018). Therefore, the global import trade value is calculated as the sum of the import values of fresh beef and frozen beef. The study covers a decade-long period from 2013 to 2022, with specific focus on the years 2013, 2017, and 2022. These years are selected to analyze the evolving trade network characteristics of beef-importing



countries. Additionally, the software used in this study is Ucinet 6 and Netdraw.

2.3 Global beef trade network construction

The global beef trade is a typically complex network. In this article, countries or regions are represented as nodes, and import relations as edges to construct a directed complex network of global beef trade. To better understand the global beef trade network, both unweighted and weighted networks are constructed.

In the unweighted network, the trade relations are represented by the adjacency matrix A , where each element a_{ij} indicates whether node i imports beef from node j (1 if it imports, 0 otherwise). In the weighted network, the trade relations are represented by the adjacency matrix W , where each element w_{ij} represents the value of beef trade imported by node i from node j .

It should be noted that the global beef trade network in this article only includes the countries and regions reported in the UN Comtrade database, resulting in minor variations in the number of nodes each year. However, these differences are minimal, and their impact on the comparability of complex network indicators can be reasonably disregarded in this study.

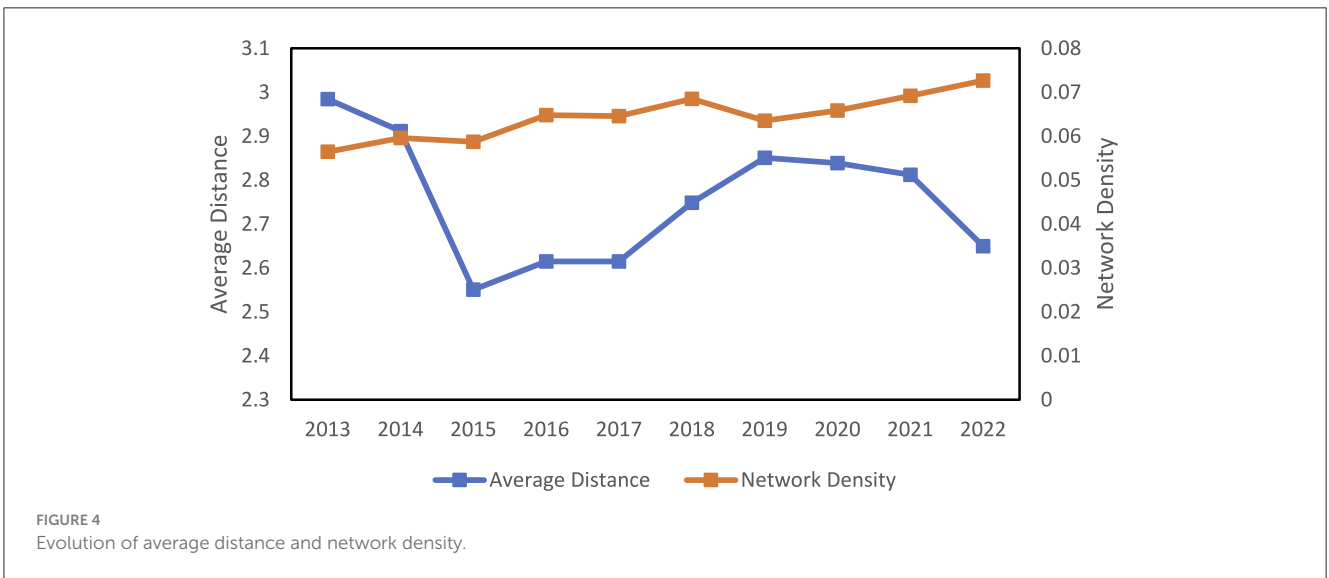
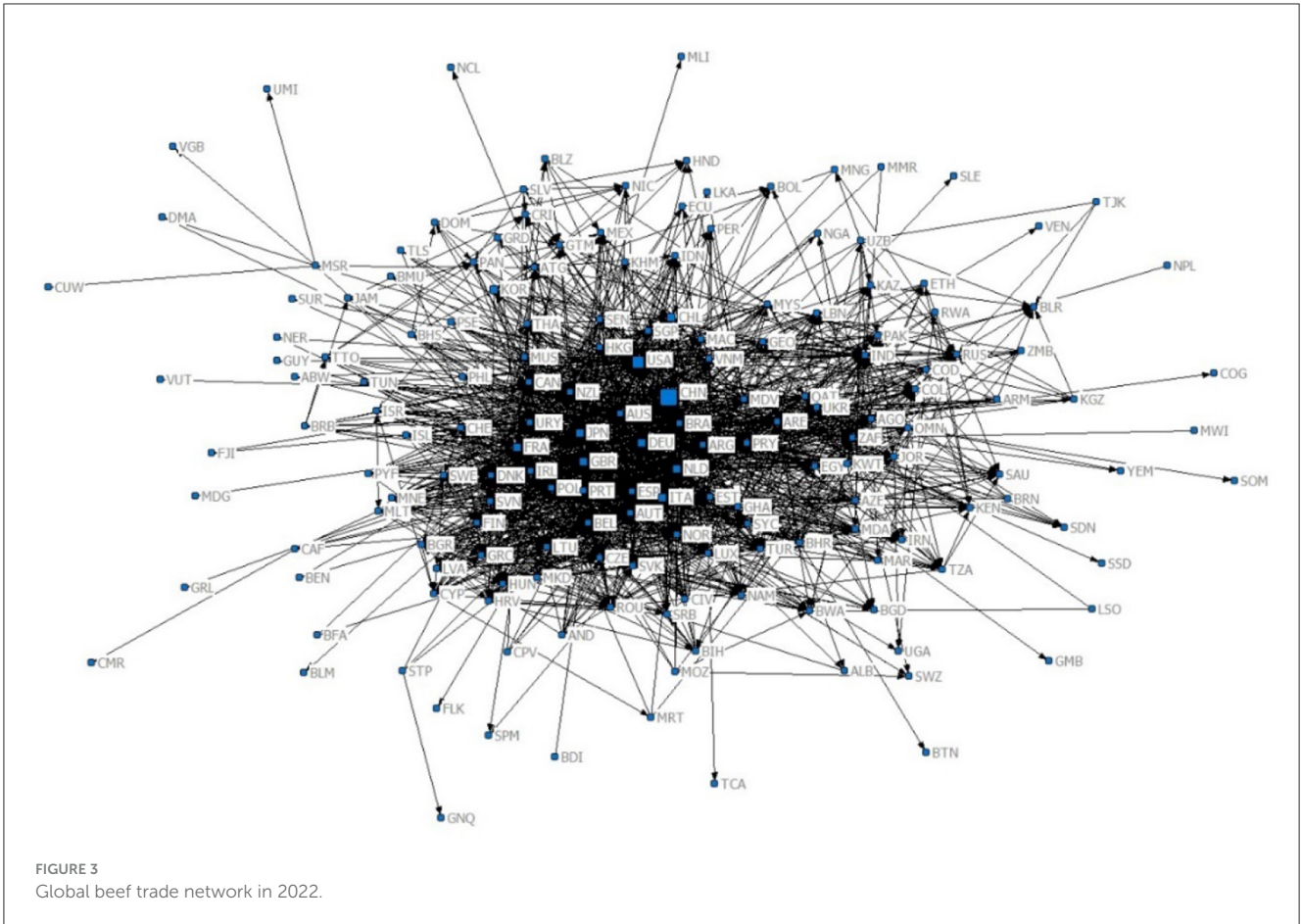
3 Results

3.1 Visualization of the beef trade network

To more intuitively examine the characteristics of the global beef trade network, this study utilizes Netdraw software to visualize the networks for the years 2013, 2017, and 2022 (Figures 1–3). The node size in the figures represents the out-degree centrality value, with larger nodes indicating higher out-degree centrality. Preliminary observations reveal certain changes in the beef trade networks over the years, particularly regarding the central positions of some countries or regions. However, more detailed analysis requires further examination using additional metrics.

3.2 Overall evolutionary characteristics of the global beef trade network

Understanding network connectivity and other structural characteristics is essential for analyzing the beef trade network. To simplify the analysis, this article employs an unweighted network that focuses solely on whether nodes are connected. The overall evolutionary characteristics of the global beef trade network are reflected using the four major topological indicators of the abovementioned complex networks.



variations in their rankings, showing that these countries or regions consistently serve as important beef import sources regardless of whether trade values are considered.

As shown in Table 2, compared to 2013, the rankings of the top 10 countries or regions for out-degree and in-degree in 2017 changed very little, remaining relatively stable. Specifically, for the out-degree indicator, beef-importing countries or regions were

still dominated by countries such as Germany, France, and the Netherlands. For the in-degree indicator, the main sources of beef imports continued to be led by the United States, Australia, and New Zealand, among others. In the weighted network, compared to 2013, the Russian Federation dropped out of the top 10 in terms of out-strength, while China surged from outside the top 10 in 2013 to third place, indicating a rapid increase in China's

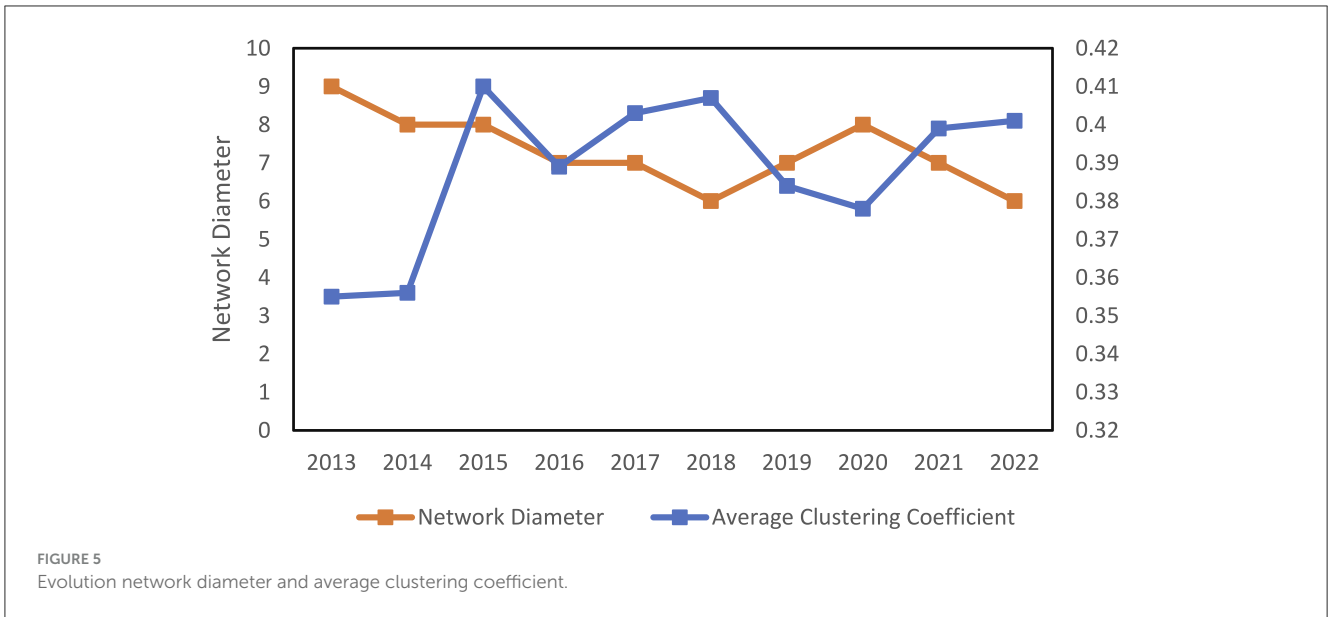


TABLE 1 The top 10 countries (regions) ranked by node centrality in 2013.

Country/region	Out-degree	Country/region	In-degree	Country/region	Out-strength	Country/region	In-strength
France	47	United States	100	United States	3550425344	Australia	5331096064
Germany	44	Australia	92	Russian Federation	2874125824	United States	4704177152
United Arab Emirates	41	New Zealand	81	Japan	2729087744	Brazil	4542610432
Netherlands	36	Brazil	76	Italy	2655511552	Netherlands	2580094976
Austria	34	Netherlands	75	Germany	2225403392	Ireland	2185708800
Spain	33	France	70	Netherlands	1969199360	Germany	1904731264
Angola	32	Italy	66	France	1869174528	New Zealand	1687826688
Hong Kong	31	Uruguay	62	Hong Kong	1632220416	India	1685328000
Italy	30	Germany	60	United Kingdom	1489831040	Uruguay	1378700032
Denmark/Luxembourg	30	Argentina	60	Republic of Korea	1395684736	France	1275534976

TABLE 2 The top 10 countries (regions) ranked by node centrality in 2017.

Country/region	Out-degree	Country/region	In-degree	Country/region	Out-strength	Country/region	In-strength
Germany	47	United States	105	United States	5022363136	Australia	5783886848
France	47	Brazil	86	Japan	3117799936	United States	5310192128
Netherlands	43	Netherlands	85	China	3065127936	Brazil	4835801600
United Arab Emirates	41	Australia	85	Germany	2264313600	Netherlands	2514087680
Hong Kong	41	France	76	Republic of Korea	2263236096	Ireland	2103994496
Italy	38	Italy	76	Italy	2166589952	New Zealand	1882374400
Denmark	37	New Zealand	75	Hong Kong	1986669312	India	1646242048
Spain	37	Spain	71	Netherlands	1864500480	Canada	1635460096
Austria	36	United Kingdom	68	United Kingdom	1381266944	Uruguay	1578598016
Luxembourg	34	Germany	65	France	1342759552	Poland	1500094848

TABLE 3 The top 10 countries (regions) ranked by node centrality in 2022.

Country/region	Out-degree	Country/region	In-degree	Country/region	Out-strength	Country/region	In-strength
Maldives	57	United States	94	China	17757921280	Brazil	11161127936
Germany	51	Brazil	82	United States	7899314688	United States	8692796416
United Arab Emirates	49	Netherlands	80	Republic of Korea	4238524928	Australia	7025408000
Austria	45	France	74	Japan	3740416768	Argentina	3995428864
Netherlands	43	Australia	70	Germany	2553453312	Canada	3222881280
United Kingdom	42	Argentina	67	Italy	2546027008	Netherlands	3069270784
Spain	39	Spain	66	Netherlands	2227252224	New Zealand	3034394368
Estonia	37	New Zealand	64	France	2047176576	Uruguay	3014063104
Italy	37	United Kingdom	60	United Kingdom	1533880832	Ireland	2694752000
Portugal/Slovenia	37	Italy	60	Chile	1482933504	India	2568632832

TABLE 4 The number of countries (regions) in each block.

Year	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Block 8
2013	32	11	25	22	44	27	18	8
2017	49	13	24	11	7	28	31	22
2022	26	34	30	30	18	25	6	4

import value and its rising import status. For in-strength, Germany and France dropped out of the top 10 rankings, while Canada and Poland entered the top 10, becoming important sources of beef imports.

From Table 3, it can be seen that for the unweighted network, a significant change in 2022 compared to 2013 and 2017 was that Maldives was ranked first with an out degree of 57. This indicates that the Maldives imported beef from 57 different countries or regions, highlighting a new feature of diversity in import sources. Meanwhile, the top ten in-degree rankings remained relatively stable. For the weighted network, in 2022 compared to 2013 and 2017, China ranked first in terms of out-strength, indicating that China became the largest beef importer globally. In terms of in-strength, Brazil has become the world's largest beef exporter. Additionally, it is noteworthy that the United States occupies a central position in beef trade regardless of imports and exports.

3.4 Block modeling analysis of the global beef trade network

Block modeling is an effective method for identifying the positional roles of nodes within a network. This study primarily focuses on analyzing the overall structure and connection relationships of the network. Therefore, an unweighted network is employed to explore its organizational structure. Based on the R-squared values, this article selects a max depth of splits of 3 and convergence criteria of 0.2, dividing the global beef trade network into 8 blocks. The number of countries or regions included in each block is summarized in Table 4.

In 2013, Block 1 included countries or regions such as the Bahamas and Panama. Many countries or regions within this block were located in the Caribbean and Central America, with many being small island nations. Block 2 comprised countries or regions such as the Democratic Republic of the Congo and Honduras, which were distributed across multiple continents. Most of these regions exhibited relatively small economies. Block 3 included countries or regions like Saudi Arabia and Yemen, which were primarily located in the Middle East, Africa, South Asia, and Southeast Asia. Block 4 encompassed countries or regions such as China, Indonesia, and Fiji, primarily distributed across Asia and Oceania. Block 5 was composed of countries or regions such as Finland and Poland, predominantly located in Europe with higher levels of economic development. Block 6 predominantly consisted of countries in Africa, such as Zimbabwe and Niger. Block 7 featured agriculturally advanced countries or regions such as the United States, New Zealand, Australia, and Brazil, which played significant roles in global agriculture and livestock industries. Block 8 comprised countries or regions such as Lesotho and Malawi, mainly located in Africa, where agriculture played a significant role in their economies.

The blocks in 2017 were formed by reorganizing the blocks from 2013. Specifically, Block 1 and Block 2 in 2017 were mainly composed of countries or regions from Blocks 3 and 4 in 2013. Block 3 in 2017 was primarily derived from countries or regions originally part of Blocks 1 and 4 in 2013. Block 4 mainly consisted of countries or regions from Blocks 1 and 2 in 2013. Block 5 was composed of countries or regions scattered across Blocks 3, 5, and 6 in 2013. Blocks 6, 7, and 8 were primarily formed from countries or regions originally in Blocks 7, 5, and 6 in 2013, respectively. Additionally, some blocks included newly added countries or regions.

TABLE 5 Density matrix of the global beef trade network.

Year	Block	1	2	3	4	5	6	7	8
2013	1	0.046	0.074	0.000	0.006	0.009	0.001	0.151	0.000
	2	0.003	0.000	0.000	0.004	0.000	0.000	0.020	0.000
	3	0.016	0.033	0.138	0.087	0.039	0.018	0.318	0.010
	4	0.013	0.033	0.020	0.041	0.025	0.000	0.268	0.017
	5	0.007	0.023	0.012	0.018	0.192	0.002	0.447	0.037
	6	0.008	0.007	0.016	0.027	0.037	0.013	0.265	0.014
	7	0.019	0.035	0.004	0.013	0.143	0.006	0.255	0.069
	8	0.000	0.000	0.000	0.034	0.003	0.014	0.035	0.000
2017	1	0.046	0.025	0.026	0.009	0.041	0.340	0.045	0.005
	2	0.033	0.013	0.006	0.000	0.011	0.080	0.017	0.021
	3	0.006	0.000	0.013	0.038	0.000	0.125	0.005	0.000
	4	0.000	0.000	0.015	0.164	0.000	0.049	0.000	0.000
	5	0.015	0.000	0.006	0.013	0.024	0.015	0.000	0.000
	6	0.012	0.005	0.019	0.029	0.020	0.347	0.174	0.005
	7	0.009	0.002	0.003	0.006	0.009	0.463	0.202	0.007
	8	0.022	0.007	0.008	0.004	0.019	0.208	0.021	0.013
2022	1	0.037	0.002	0.001	0.021	0.015	0.131	0.000	0.038
	2	0.011	0.070	0.018	0.082	0.170	0.216	0.000	0.000
	3	0.013	0.013	0.020	0.149	0.050	0.308	0.017	0.008
	4	0.019	0.008	0.029	0.470	0.024	0.460	0.000	0.000
	5	0.000	0.003	0.000	0.009	0.003	0.031	0.000	0.000
	6	0.006	0.004	0.007	0.169	0.016	0.202	0.020	0.000
	7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

In comparison to 2017, the changes in the blocks in 2022 were as follows: the main countries or regions in Block 1 originated from Block 1, Block 3, and Block 4 in 2017. Block 2 mainly included countries or regions from Block 1 and Block 2 in 2017. Block 3 was primarily composed of countries or regions from Block 1, Block 7, and Block 8 in 2017. Block 4 and Block 6 were mainly derived from Block 7 and Block 6 in 2017, respectively. The countries or regions in Block 5, Block 7, and Block 8 were scattered across various blocks from 2017.

To investigate the relationships between different blocks, this article presents the density matrix of the global beef trade network (Table 5). The values on the diagonal of the matrix indicate the degree of intra-block relationships, with higher values indicating tighter internal relationships within the block. The off-diagonal values represent the relationship degree between two blocks, with higher numbers indicating closer inter-block relationships. As shown in Table 5, there were significant differences in the degree of closeness both within and between each block.

To further clarify the relationships among the blocks, an image matrix is derived from the density matrix. Specifically, if the density matrix value is greater than the beef trade network density in the current year, it is assigned a value of 1 in the image matrix;

otherwise, it is 0. The image matrix for the 3 years is presented in Table 6.

In addition, a simplified diagram (Figure 6) visually depicts the inter-block relationships. The results showed that in 2013, Block 7 occupied a central position in the beef trade network, establishing close trade relationships with all other blocks except Block 2. Most of the blocks were oriented toward Block 7, indicating that Block 7 had become a major source of beef imports. Moreover, Block 7 exhibited significant internal characteristics, suggesting frequent beef trade activities among the countries within this block. The other seven blocks displayed independent or marginal roles, with close trade relationships established only between one or two other blocks. Blocks 3 and 5 also exhibited strong internal characteristics.

By 2017, the structure of the blocks had shifted to center around Block 6. The previous analysis showed that most of the countries or regions in Block 6 in 2017 originated from Block 7 in 2013. This indicated that the beef network group composed of countries like Brazil, the United States, and New Zealand played a key role in the global beef network, establishing close connections with multiple blocks (Blocks 1, 2, 3, 7, and 8). Additionally, Block 4 displayed internal characteristics, with frequent trade activities

occurring primarily within the block. Block 5 remained isolated, showing no significant beef trade relationships either with other blocks or internally.

TABLE 6 Image matrix of the global beef trade network.

Year	Block	1	2	3	4	5	6	7	8
2013	1	1	0	1	0	0	0	0	1
	2	0	0	0	0	0	0	0	0
	3	0	0	1	1	0	0	0	1
	4	0	0	0	0	0	0	1	0
	5	0	0	0	0	1	0	1	0
	6	0	0	0	0	0	0	1	0
	7	0	0	0	0	1	0	1	1
	8	0	0	0	0	0	0	0	0
2017	1	0	0	0	0	0	1	0	0
	2	0	0	0	0	0	1	0	0
	3	0	0	0	0	0	1	0	0
	4	0	0	0	1	0	0	0	0
	5	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	1	1	0
	7	0	0	0	0	0	1	1	0
	8	0	0	0	0	0	1	0	0
2022	1	0	0	0	0	0	1	0	0
	2	0	0	0	1	1	1	0	0
	3	0	0	0	1	0	1	0	0
	4	0	0	0	1	0	1	0	0
	5	0	0	0	0	0	0	0	0
	6	0	0	0	1	0	1	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0

The block modeling for 2022 exhibited a dual-core structure, with Block 4 (comprising countries such as Canada, China, and the United Kingdom) and Block 6 (comprising countries such as Brazil, the United States, and New Zealand) playing crucial bridging roles in the global beef trade network. The relationships among the other blocks were relatively loose, with Blocks 7 and 8 being particularly isolated and playing peripheral roles within the network.

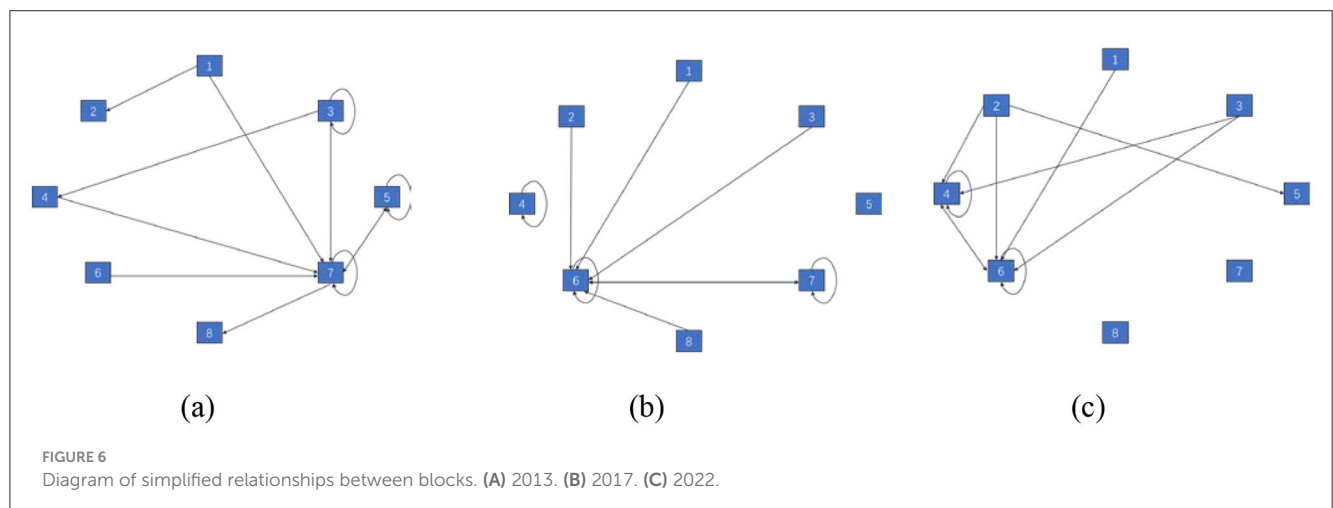
The evolution of the block modeling from 2013 to 2022 reveals that the global beef trade network has transitioned from full participation of all blocks in 2013, to a structure with one isolated block in 2017, and finally to a structure with two isolated blocks in 2022. This indicates an increasing trend toward regionalization and group formation in global beef trade.

4 Conclusion and discussion

The application of complex network theory in international trade effectively reveals both the global and local characteristics of trade network systems, highlighting the interdependencies among various trade entities. This approach represents a significant advancement over traditional economics, which typically focuses on the analysis of individual countries (Cai and Song, 2016; Qiang et al., 2020).

Using global beef trade data from 2013 to 2022, this article constructs a global beef trade network and conducts an in-depth analysis of its evolution from three levels: overall, individual, and clustering.

From an overall perspective, the structure of the global beef trade network has become increasingly complex. Specifically, although the average distance fluctuated between 2013 and 2022, it showed an overall downward trend, with significant decreases during the periods of 2013–2015 and 2019–2022, indicating that the network has become more tightly connected with improved overall connectivity. Network density showed a steady upward trend, reflecting the participation of more countries or regions in the trade network and the increasing closeness of trade relationships. The



network diameter decreased from 9 in 2013 to 6 in 2022, suggesting a gradual shortening of distances between the farthest nodes and reflecting enhanced tightness in the network. Furthermore, despite noticeable fluctuations, the average clustering coefficient showed an overall upward trend over the decade, indicating the formation of regional trade clusters and the strengthened localized trade relationships.

These changes in topological indicators reflect the combined influence of globalization, regional cooperation, trade policies, and social demand. Specifically, the increasing demand for beef in emerging markets has led major exporting countries to establish direct trade relationships with more partners. Simultaneously, advancements in modern logistics shortened trade paths, reducing average distance and network diameter while increasing network density. However, a phased increase in average distance during 2015–2019 may be related to global economic fluctuations and trade protectionism. For instance, Sino-US trade friction and adjustments in free trade policies by certain economies may have weakened some direct trade connections. Furthermore, the deepening of regional trade cooperation and the signing of several free trade agreements such as CPTPP and RCEP further strengthened regional ties, driving greater local network tightness. External shocks also had a significant impact on the network structure. For example, the COVID-19 pandemic in 2020 disrupted some trade relationships. However, as supply chains recovered, the network diameter rapidly shortened, demonstrating the resilience of the beef trade network.

From an individual perspective, this study uses degree centrality to measure the position and importance of countries or regions. In the unweighted network, which considers only the number of connections, the evolution of centrality in 2013, 2017 and 2022 showed that countries such as Germany, the United Arab Emirates, and the Netherlands ranked high in out-degree centrality. This highlights their role as key hubs for importing beef from a diverse range of trading partners. In contrast, countries with high in-degree rankings are concentrated in the United States, Australia, and Brazil, which have become significant sources of beef imports for many countries or regions. In the weighted network, which accounts for the value of import trade, significant changes occurred in the out-strength rankings. Countries such as the United States, Japan, and China demonstrate high out-strength centrality, highlighting their role as large-value importers, even though they maintain a limited number of trade partners. Notably, China's rapid expansion in beef imports over the decade has established it as the world's largest importer, significantly reshaping global trade patterns. This growth has been driven by the increasing demand for high-quality beef in China, supported by rising incomes and changes in dietary preferences. Meanwhile, countries such as Australia, Brazil, and New Zealand consistently rank high in in-strength centrality due to their abundant livestock resources and export-oriented production systems. These nations play a pivotal role in stabilizing the beef supply chain and meeting global demand.

From a clustering perspective, block modeling analysis for 2013, 2017, and 2022 reveals distinct trade blocks with varying levels of connectivity and influence. Blocks represented by countries such as Brazil, the United States, and New Zealand have consistently maintained central roles, reflecting their dominant

positions in beef production and trade. These countries are characterized by their strong export capacities and stable trade relationships, and form the backbone of global beef trade. Blocks formed by countries such as Canada, China, and the United Kingdom have also gained prominence over time. However, the growing number of isolated blocks reflects fragmented trade integration in certain regions, particularly in parts of Africa, where infrastructural and technological challenges limit participation in global trade. Consequently, the global beef trade network has evolved into a regionalized and clustered competitive structure.

The analysis of the global beef trade network reveals the evolution of trade patterns, enabling countries and regions to better understand their positions within the global beef trade and identify their competitive strengths and weaknesses. In addition, specific recommendations tailored to different countries and regions are essential for promoting the healthy and sustainable development of global beef trade. First, under the current trend of increasing connectivity in the beef trade network, core exporting countries such as Australia and Brazil should enhance cold chain logistics and infrastructure to ensure the stability of exports. Meanwhile, these countries could actively explore emerging international markets to improve supply chain resilience. Furthermore, with the rising demand for premium and environmentally friendly beef, major exporters must adopt sustainable technologies to reduce the environmental impact of production, aligning with global demand for green products. Second, for major importing countries such as China and Japan, efforts should focus on diversifying supply sources and strengthening regional cooperation to mitigate supply chain disruption risks. Additionally, these countries need to establish and enhance beef reserves to safeguard food security during supply chain interruptions. Third, for emerging and peripheral countries and regions, international technical assistance and infrastructure investments are essential to enhance their participation in the global beef trade network. Fourth, countries and regions within regional trade clusters should optimize internal trade policies to boost external market competitiveness, thereby improving overall network connectivity and resilience. The research in this article still has the limitation of not considering the impact of crises on the international beef trade network and their propagation processes, which will serve as a direction for future research.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

QW: Writing – original draft, Conceptualization, Formal analysis, Funding acquisition, Methodology. WX: Conceptualization, Formal analysis, Funding acquisition, Investigation, Writing – original draft. RC: Data curation, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships

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that could be construed as a potential conflict of interest.

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