

Article

Identifying the Achilles' Heel: Using Complex Network Analysis to Pinpoint Systemic Vulnerabilities in the Global Food Supply Network

Xin Dai ¹, Xiaoyu Jiang ^{1,*}, Rui Han ¹, Zhong Li ¹ , Yongchao Ding ^{2,*} and Ye Liu ¹

¹ Agricultural Information Institute, Chinese Academy of Agricultural Sciences, Beijing 100081, China; daixin@caas.cn (X.D.); hanrui01@caas.cn (R.H.); lizhong@caas.cn (Z.L.); liuye01@caas.cn (Y.L.)

² Institute of Technology and Economy of Grain Industry, Academy of National Food and Strategic Reserves, Beijing 100037, China

* Correspondence: jiangxiaoyu@caas.cn (X.J.); dyc@ags.ac.cn (Y.D.)

Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and or methodology

- This study develops an integrated analytical framework combining complex network analysis and cascading failure simulation, providing a systematic methodology for quantifying systemic vulnerability and resilience in global staple food trade networks.
- It empirically demonstrates that network topology is a key factor of trade system resilience and reveals heterogeneous risk transmission mechanisms across crop varieties, enriching systems science research on agri-food supply chain risk.

What are the main findings and/or the implications of the main findings?

- All four staple food trade networks are far more vulnerable to targeted attacks than random attacks. Soybean networks suffer the most severe collapse, while wheat networks with dispersed nodes show stronger resilience, with cascading failures following a core-to-peripheral transmission path.
- The findings provide systematic evidence for enhancing supply chain resilience, offering practical references for global multilateral food-security governance.

Abstract

Systemic risk in the global staple food trade network has become a critical threat to global food security amid escalating geopolitical frictions and frequent extreme weather events. This study constructs directed weighted trade networks for wheat, rice, maize and soybean covering 196 economies, and applies a cascading failure model to compare cross-crop structural vulnerability. Simulation results reveal stark heterogeneous risk profiles: a shock originating from a top rice exporter in India spreads across two cascading rounds and impacts 25.5% of total network nodes, while a parallel shock from a top soybean exporter in Brazil triggers nine propagation rounds affecting 86.2% of nodes; by comparison, equivalent shocks to wheat and maize networks only affect 22.4% and 24.5% of nodes respectively. Under identical targeted attack conditions, rice and soybean networks suffer sharp connectivity deterioration after removing a small number of core exporter nodes, while wheat and maize networks retain relatively higher residual connectivity under the same attack intensity, reflecting that crop trade systems with higher supply concentration exhibit greater systemic vulnerability. This work adopts a single-

Academic Editor: Wen-Chyuan Chiang

Received: 21 August 2026

Revised: 23 September 2026

Accepted: 13 October 2026

Published: 16 October 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article

distributed under the terms and

conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)

[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

year static network framework; future research will extend to multi-year dynamic network tracking and incorporate adaptive supply-chain feedback mechanisms. Despite this boundary, the study fills the research gap in cross-crop systemic risk comparison, providing robust empirical evidence for differentiated global food supply-chain resilience governance.

Keywords: global food trade network; complex network analysis; cascading failure; network resilience

1. Introduction

With global population growth and increasing resource constraints, food security has increasingly become a core issue for human survival, social stability and global development [1–3]. Currently, the global food system is facing overlapping shocks from multiple compound crises [4–6]. The Global Report on Food Crisis (GRFC) 2026 estimates that about 266 million people in 47 food crisis countries and territories faced high levels of acute food insecurity in 2025 [7]. Sustained rigid demand driven by a global population exceeding 8 billion, production disturbances caused by extreme weather, supply chain disruptions triggered by geopolitical conflicts, and trade protectionism fueled by public health events jointly constitute systemic threats to global food security [8–15]. Globalization has promoted the high interconnection of food trade networks, forming a global resource allocation system [16]. While improving production efficiency and optimizing resource distribution, this system also makes local risks more likely to spread through trade links and evolve into global food security crises [17,18]. As core suppliers accounting for one-third of global wheat exports, the Russia–Ukraine conflict in 2022 severely disrupted the stability of global supply chains, especially for food-importing countries, through channels such as energy markets, transportation routes, supply and prices of agricultural production inputs, and food price inflation [19–22]. In March of the same year, the FAO Food Price Index rose to 159.7 points, the highest level since the index was launched in 1990. During the COVID-19 pandemic, many countries including Argentina, Kazakhstan, India, Indonesia and Malaysia imposed food-export restrictions, leading to a structural contraction in global food trade volume, highlighting the impact of fluctuations in key nodes on networks [23,24]. Against this background, accurately identifying the systemic vulnerabilities of the global food trade network has become a key prerequisite for ensuring global food security.

As an effective tool for characterizing the topological structure and correlation characteristics of systems, complex network analysis has been widely used in systemic risk assessment in trade, finance, energy and other fields. Driven by the global issue of food security, this method has gradually become a core tool for analyzing the global food trade system. Rich research results have been formed focusing on the diverse attributes and influencing factors of food trade networks. First, in terms of analysis of core network attributes, existing studies focus on the structural characteristics, dynamic evolution, systemic vulnerabilities of global food trade networks, and the competitive and cooperative relationships embedded among countries [25–28]. Scholars have taken China, the United States, Russia, the European Union and African countries as core research objects, systematically examining their role changes and network evolution paths in the global or regional grain trade network [29,30]. They have clearly pointed out that dynamic factors such as trade policy adjustments, network structure dependence, changes in interstate relations, and the spread of epidemics exert a significant impact on network stability [31,32], and more targeted response mechanisms need to be established [33].

Second, in the dimension of trade value and benefit evaluation, some studies break through the single perspective of supply security and extend to the investigation of multiple values of food trade. For example, some scholars focus on the social value of food trade and explore whether global food trade effectively fills the dietary nutrition gap of the world's poorest countries [34]. Other studies analyze the paradox of trade system development, examine the balance between resilience improvement and trade efficiency, and discuss whether resilience enhancement must come at the cost of efficiency [35], providing multiple considerations for optimizing food trade policies. Third, in vulnerability and risk-transmission research, scholars focus on the disturbance effects of various external shocks on global food trade networks, including global events such as COVID-19 and the Russia–Ukraine conflict [36,37] and long-term environmental challenges such as climate change [38,39]. Meanwhile, relevant studies have extended to internal risks of trade systems [40], assessing the cascading impacts that may be caused by disruptions to critical infrastructure [41]. Based on these analyses, researchers have generally confirmed that disruptions to food trade in key trading countries may trigger global supply chain reactions [42], and the stability of trade flows and diversity of trading partners are core elements enhancing the shock resistance of networks [43].

Overall, existing studies have introduced complex network analysis into the field of food trade, focusing on both the attributes of trade networks and their social value and risk resilience, enriching the dimensions of food trade research and providing important support for the understanding and governance of global food trade networks. However, most studies focus on a single food crop or a single external shock scenario, and have not formed a systematic comparative study on the transmission paths, impact intensity and mechanisms of different shocks such as geopolitical conflicts, climate disasters and policy changes, making it difficult to provide differentiated theoretical support for responding to different risks, which also points out the core direction for follow-up research. In this context, the following research questions are proposed: What topological and structural differences distinguish the wheat, rice, maize, and soybean trade networks? How does network resilience differ across crops under random and targeted attack scenarios? How do cascading failure transmission paths and impact scopes vary across the four crop systems when core supplier disruptions occur? Compared with existing research, the marginal contributions of this paper are as follows: First, rather than analyzing a single-crop trade network in isolation, this study applies a unified analytical framework to systematically compare the topological structure, core node roles, and connection patterns of wheat, rice, maize, and soybean trade networks covering 196 economies, quantifying how inherent crop-specific production concentration and trade-route characteristics shape heterogeneous network vulnerability. Second, full cascading failure dynamics are tracked in parallel across all four crop networks to uncover both shared patterns and heterogeneous differences in risk-transmission paths, pinpointing the critical hub nodes whose disruption would trigger the most severe cascading impacts for each staple food system.

The subsequent chapters of this paper are arranged as follows: Section 2 details the data sources, processing methods, and specific processes of network construction, topological index calculation and attack simulation. Section 3 presents the topological structural characteristics, key node identification results and robustness analysis under attack simulation of the four global staple food trade networks. Section 4 discusses the internal mechanisms, policy implications of the core research findings, and points out the research limitations and future directions. Section 5 summarizes the full research conclusions and proposes a systematic optimization path for safeguarding global food security.

2. Materials and Methods

2.1. Data Sources

The data of this study comes from the UN Comtrade Database, the most extensive and authoritative international trade statistics platform in the world, which collects detailed bilateral trade data of countries and regions worldwide with unified statistical calibre and complete time series, providing reliable data support for quantitative analysis of global food trade networks. Selecting 2024 as the research year, the research scope covers 196 countries to ensure the integrity and representativeness of the network. This study focuses on wheat, rice, corn, and soybeans, which are closely associated with national food security. For trade pairs where the source economy's reported export value and the destination economy's reported import value differ, we uniformly adopt the exporter-reported value as the official edge weight. For any bilateral trade pair with a missing export report from the source economy, we use the corresponding import record reported by the destination economy as a compensatory value. Where both import and export reports for a trade pair are missing, the bilateral flow is treated as zero trade and excluded from edge weight calculation.

2.2. Network Construction

Using information of reporting countries, partner countries and trade volumes, each country is regarded as a node, the food trade flow from country i to country j as a directed edge, and trade volume as the weight of the edge. Four independent directed weighted networks of wheat, rice, maize and soybean are constructed. The agricultural product trade network is expressed as $G^T = (V^T, E^T, W^T)$, where $V^T = \{v_1^T, v_2^T, v_3^T, \dots, v_n^T\}$ is the set of nodes, representing countries participating in agricultural trade. $E^T = \{e_{ij}^T | i, j = 0, 1, 2, \dots, n\}$ is the set of edges between nodes, and e_{ij}^T represents the trade relationship between node v_i^T and node v_j^T . $W^T = \{\omega_{ij}^T | i, j = 1, 2, \dots, n\}$ is the weight of edges, which is the agricultural trade volume between countries.

To fully characterize the status and function of nodes in the network, four core topological indicators are selected, with their definitions and calculation formulas shown in Table 1.

Table 1. Description of network indicators.

Network Indicator	Formula	Description
Degree Centrality	$C_d(v_i) = \frac{1}{2(N-1)} \left(\sum_{j=1}^N \omega_{ij} + \sum_{j=1}^N \omega_{ji} \right)$	Measures the connection breadth and basic importance of nodes
Betweenness Centrality	$C_b(v_i) = \sum_{\substack{s, t \in V \\ s \neq t \neq i}} \frac{\sigma_{st}(v_i)}{\sigma_{st}}$	Measures the “bridge” role of nodes in the shortest path of the network, reflecting their control over trade flows

Network Indicator	Formula	Description
Closeness Centrality	$C_c(v_i) = \frac{N-1}{\sum_{j=1, j \neq i}^N d(v_i, v_j)}$	Measures the average distance between a node and all other nodes, reflecting trade accessibility
Eigenvector Centrality	$C_e(v_i) = \lambda^{-1} \sum_{j=1}^N \omega_{ji} C_e(v_j)$	Measures the influence intensity of nodes, considering not only their own degree but also the importance of connected nodes

2.3. Network Attack Strategies

This study simulates real risk incentives of food supply chains through random and targeted attacks. Random attacks mainly simulate unpredictable shocks such as natural disasters (e.g., extreme drought in wheat-producing areas, floods in rice-growing areas) and public health emergencies. A notable feature of such risks is that they have no specific attack targets and exert random impacts on the four staple food supply chains. For example, wheat is widely planted globally, so random attacks cause relatively dispersed disturbances to its supply chain. While soybean-producing areas are concentrated in the United States, Brazil and Argentina, even random attacks may trigger local supply chain fluctuations if they affect core producing countries. In this study, random attacks are implemented by randomly selecting and removing a certain number of nodes, repeated 100 times to eliminate random errors and ensure result reliability.

Targeted attacks focus on targeted risks such as geopolitical conflicts, targeted sanctions and policy changes in core producing areas, which often directly impact key nodes of supply chains and exert devastating effects on the four staple-food trade networks. Considering the functional differences in core nodes in different staple-food trade networks, this study designs two sub-strategies. First, attack in descending order of out-degree centrality, targeting nodes with extensive export coverage (e.g., the United States and France in wheat trade, the United States and Brazil in maize trade), whose failure will directly cut off a large number of bilateral trade links. Second, attack in descending order of betweenness centrality, targeting “hub” nodes of trade flows (e.g., Ukraine in wheat trade, the Netherlands in maize trade), which are bridges connecting supply chains of different regions, and their failure will split the network into isolated blocks. This design is highly consistent with real risks. The impact of the 2022 Russia–Ukraine conflict on the wheat supply chain is essentially a targeted attack on nodes with high betweenness and degree centrality, while export restrictions imposed by India, Indonesia and other countries in rice trade are typical targeted risks on core nodes.

The network robustness assessment is to quantify the ability of supply chains to maintain operation under risk shocks. This study selects the relative size of the largest connected component (LCC) as the indicator. The relative size of the largest connected component reflects the scale of nodes that still maintain trade connectivity after disturbance. Specifically, this study calculates the largest weakly connected component: two nodes belong to the same component as long as there exists at least one directed trade path between them in either direction, which fits the practical characteristics of directed food-trade networks. The calculation formula is:

$$R_{LCC} = \frac{|LCC|}{N} \quad (1)$$

where $|LCC|$ is the number of nodes in the largest connected component of the network

after attack, $N = 196$ is the total number of nodes, and $R_{LCC} \in [0,1]$.

Weighted network efficiency further captures the quality and circulation capacity of actual trade flows. It measures the average weighted shortest-path efficiency across all node pairs, accounting for trade volume weights of edges. Its relative value E_{rel} is computed as the ratio of post-attack weighted network efficiency to the pre-attack baseline efficiency:

$$E_{rel} = \frac{E_{post}}{E_{pre}} \quad (2)$$

where E_{post} is weighted network efficiency after attack, E_{pre} is the initial weighted network efficiency of the intact network, and $E_{rel} \in [0,1]$.

R_{LCC} focuses on topological connectivity, whereas E_{rel} reflects losses in real-world trade circulation even when partial node connectivity persists. Joint application of these two metrics avoids one-sided evaluation relying merely on topological structure. The dynamic evolution of R_{LCC} and E_{rel} under different attack scenarios enables comprehensive comparison of resilience differences across four staple-food trade networks and provides quantitative support for policy formulation.

2.4. Cascading Failure Simulation

The cascading failure simulation restricts risk transmission triggered by import interruptions after key-node failure. This study adopts an import-dependence-threshold-based cascading-failure model. Different from classical load-redistribution overload cascading-failure frameworks, this model does not simulate the redistribution of purchasing demand toward alternative suppliers, nor does it incorporate supplier spare production capacity or overload effects generated by demand reallocation. Instead, it characterizes import volume losses caused directly by the failure of upstream trade partners, and threshold-driven cascading diffusion propagated through cross-country import-dependency linkages. When a key exporting country cannot fulfil its export commitments under risk events, its original importers suffer direct import interruptions. Each affected country accumulates import losses; once its total import loss exceeds the preset failure-tolerance threshold, the country turns abnormal, which may further pass shocks to its own trade partners and trigger broader supply-chain spillover.

The specific transmission process is described as follows: (1) All nodes on the network are set to normal. The initial load of country node i is defined as T_i , i.e., the total import and export trade volume of country i , and the initial load of edge e_{ij} is W_{ij} , i.e., the trade volume exported from country i to country j . (2) Assume node i is the initial propagation source (outbreak source) and set it to abnormal. Assume the export volume of country i decreases by α , an adjustable parameter ranging from 0 to 1. As a result, the weight W of all edges exported from country node i decreases by α , i.e., the weight of edges imported from node i becomes $(1 - \alpha)W$. (3) If the total change in import volume ΔW of any normal node j connected to the abnormal node exceeds β of the country's capacity T_j , node j also becomes abnormal. β is also an adjustable parameter ranging from 0 to 1. (4) Repeat step (3) until no new abnormal countries appear in the network, and the simulation ends (Figure 1).

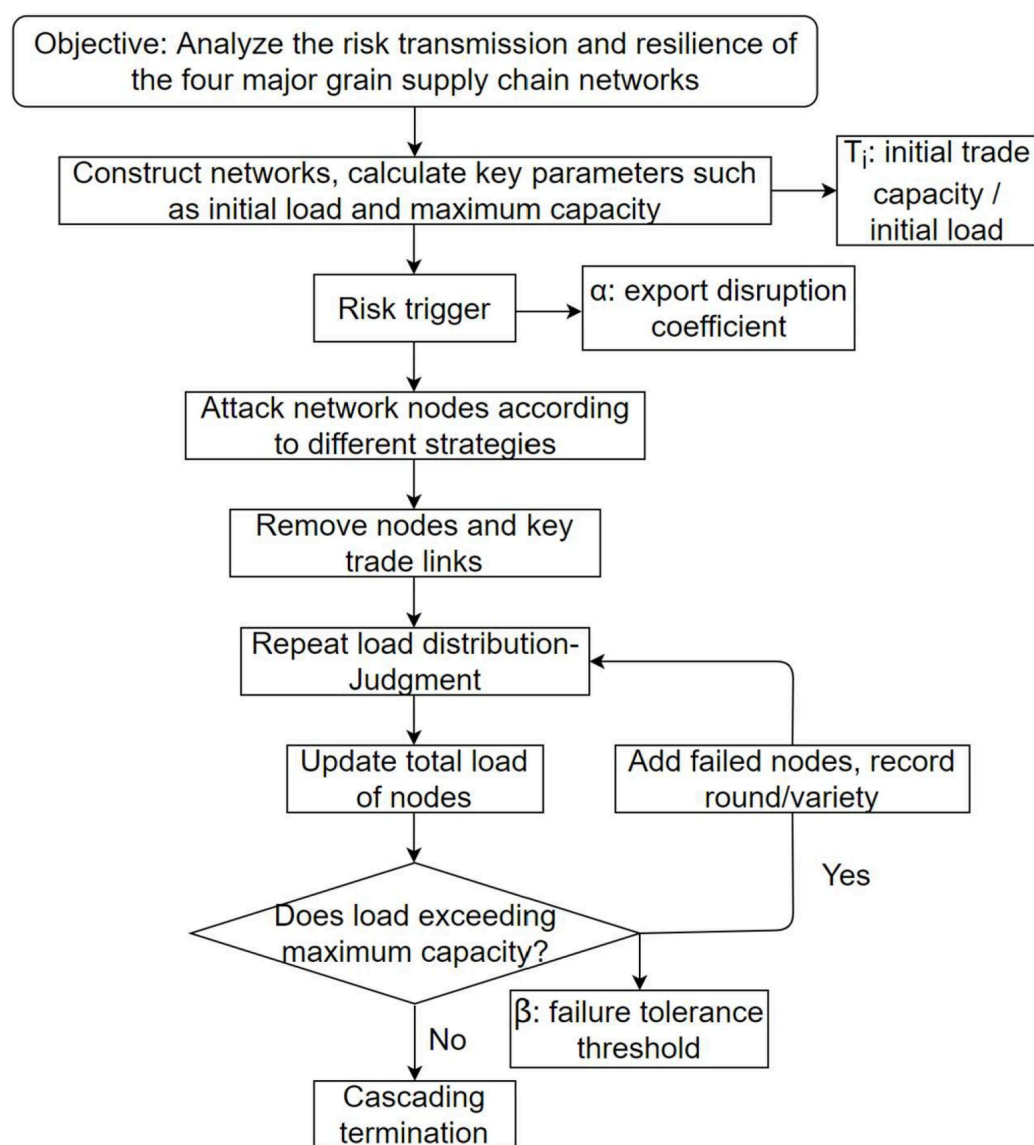


Figure 1. Cascading failure model algorithm.

In this model setting, total import-plus-export trade volume T_i is adopted to define node capacity threshold for each economy. For pure large importers such as China within the soybean trade network, total bilateral trade volume comprehensively reflects the overall exposure of a country to international staple-food trade, including its scale of import dependency and existing trade-partner portfolios. Although T_i does not separate import capacity from export capacity, this aggregated metric captures the overall magnitude of a country's food-trade-related economic and supply-chain footprint, serving as a practical proxy for the maximum trade disturbance that an economy can tolerate before supply-chain disruption propagates onward. Using only import volume would overlook indirect ripple effects transmitted through a country's re-export and cross-border redistribution linkages embedded within global food-trade networks.

In our cascading-failure experiments, we select the largest out-degree exporter within each crop-specific network as the initial shock source. This choice is motivated by real-world high-risk scenarios, in which major export-suppliers implement export bans or suffer large-scale production collapse, representing one of the most concerning systemic risk triggers for global staple-food security. Nevertheless, simulation outcomes are sensitive to the selection of shock-origin nodes. If alternative shock sources such as

large-scale importers or intermediate-hub transit countries are set as the initial failure point, the scope, number of propagation rounds, and spatial pattern of risk diffusion would change substantially. Shocks originating from critical transit-hub nodes may produce wider cross-regional contagion even with moderate export volume, while shocks originating from large pure-importer nodes would mainly generate domestic supply crises with limited outward cross-border cascading spillover onto third-party economies. Future research can conduct systematic sensitivity tests across diverse sets of potential initial-failure nodes to map the full spectrum of possible risk-propagation scenarios.

3. Results

3.1. Trade Flows of Four Major Food Crops

From the global trade data in 2024, the trade flows of the four major food crops show significant species-specific and regional concentration (Figure 2). The wheat trade features diversified exporters and dispersed importers. The Russian Federation, Canada, United States, Ukraine, Australia and France are the key exporters, with export quantities of 32.69 million tons, 25.55 million tons, 21.80 million tons, 20.66 million tons, 19.68 million tons and 15.07 million tons respectively. The import side is highly dispersed, with countries such as Egypt, Indonesia and some EU countries as major demanders, reflecting cross-regional dependence on global food security. Rice trade exports are concentrated in Cambodia, the United States, Brazil, India and Uruguay, and import demand is mainly concentrated in Asian countries such as the Philippines, Nepal and American countries such as Mexico, showing an overall regionalization-dominated feature. Asian exporters mostly supply neighbouring Asian countries, while American exporters such as the United States and Brazil form internal trade cycles in the Americas. Maize trade is dominated by the Americas, with the United States, Brazil and Argentina accounting for 66.33% of global maize exports with quantities of 62.59 million tons, 39.78 million tons and 32.06 million tons respectively. Major importers include China, Egypt, Mexico, Indonesia and other countries. Soybean trade exports are almost monopolized by the United States and Brazil, with export quantities of 98.81 million tons and 52.33 million tons respectively, accounting for 84.57% of global soybean exports. The import side is absolutely dominated by China, driving secondary demanders such as the United Kingdom and Japan.

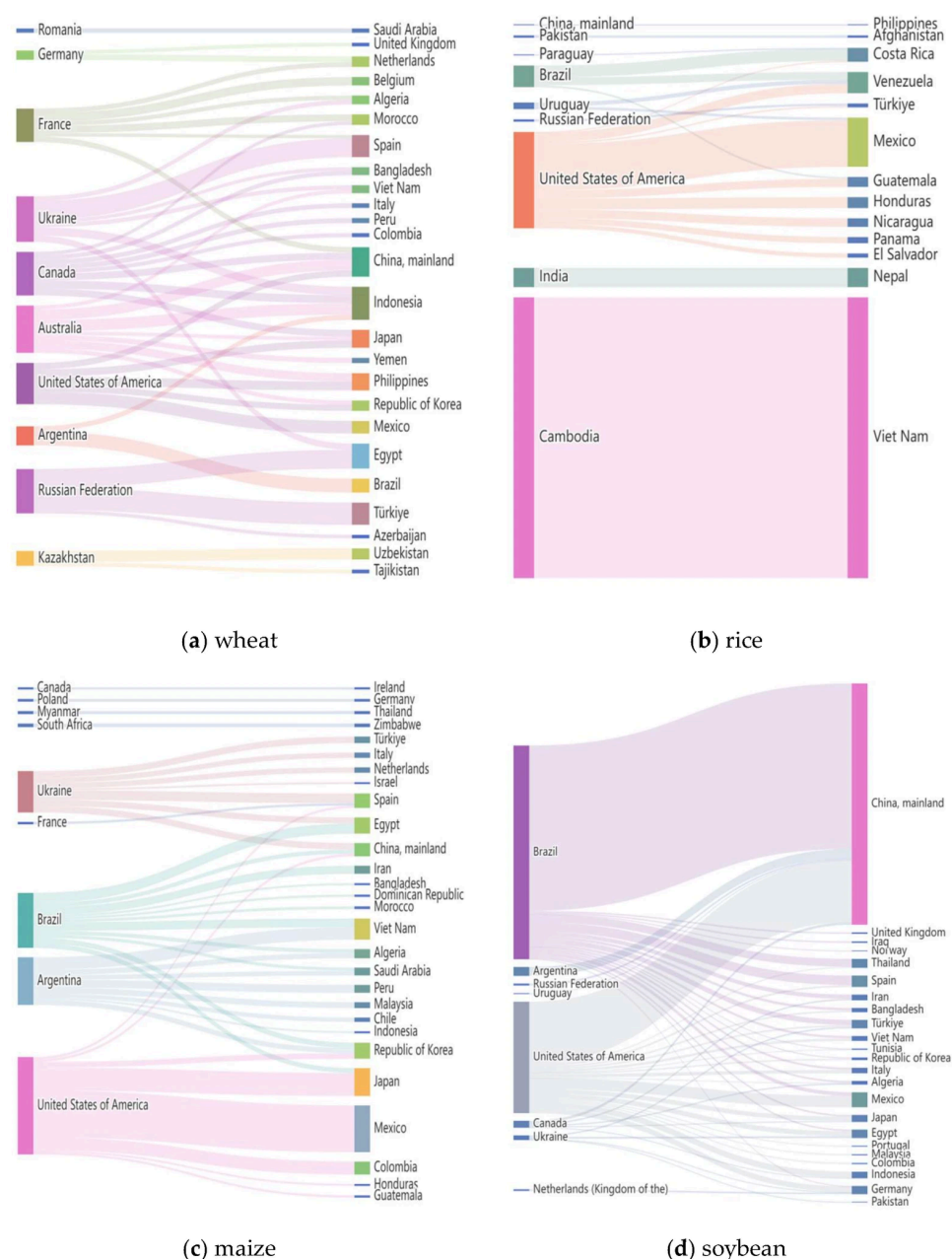


Figure 2. Global trade flows of four major crops in 2024. The figure shows the trade flows between the top 10 countries by export volume of the four major staple crops and their major importing countries.

3.2. Key Nodes Identification

For specific varieties, Canada, the United States and Ukraine have high degree centrality in the wheat trade network, reflecting the breadth of their trading partners. The United States and Germany record high betweenness centrality, indicating their function as core hub nodes in wheat trade flows. Key nodes in the rice trade network have significant regional attributes. India, Thailand and Pakistan rank high in degree centrality as core subjects of intra-regional trade, while the United States and Italy rank high in betweenness centrality, reflecting the existence of cross-regional hubs in the network. Key nodes in the maize trade network show American agglomeration characteristics. The United States and Brazil rank high in multiple indicators such as degree centrality, closeness centrality and eigenvector centrality, serving as core supply and circulation nodes for maize trade. In the soybean trade network, China, Brazil and the United States rank

high in degree centrality and eigenvector centrality, highlighting the core status of Brazil and the United States on the supply side and the network influence of China as a key consumer node (Table 2). Notably, for China, this high value originates overwhelmingly from massive inbound import links, instead of export capacity. China acts as a dominant consumption-side hub rather than a supply-side exporter within soybean trade. Degree centrality in this study adopts weighted total degree aggregating both in-degree and out-degree, so large-volume importers can achieve high overall degree centrality even with negligible export flows, which does not equate to strong export capacity or supply-side market power.

Table 2. Key nodes in global food trade networks.

Variety	Degree Centrality	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality
Wheat	Canada	Russian Federation	United States	United States
	United States	France	Germany	Canada
	Ukraine	Canada	South Africa	Australia
	Australia	Turkey	France	Indonesia
	France	Germany	Canada	China
Rice	India	India	United States	Vietnam
	Thailand	Thailand	India	Cambodia
	Pakistan	Turkey	Italy	India
	Vietnam	United States	France	Benin
	Cambodia	Italy	Thailand	Saudi Arabia
Maize	United States	United States	United States	United States
	Brazil	Brazil	France	Mexico
	Argentina	South Africa	Turkey	Japan
	Ukraine	France	South Africa	Colombia
	Mexico	Turkey	Brazil	Republic of Korea
Soybean	China	Benin	United States	China
	Brazil	Bolivia	France	Brazil
	United States	United States	Belgium	United States
	Argentina	Belgium	Germany	Argentina
	Paraguay	Brazil	South Africa	Spain

Note: This table lists the top 5 countries by centrality calculated using UCINET 6.7 software. Degree centrality adopts weighted total degree (sum of out-degree and in-degree), and all indicators are standardized to the range [0, 1]. For nodes with high degree centrality, core exporters (e.g., Canada, the United States, India, Brazil) derive their high values mainly from export-oriented out-degree links, while core importers (e.g., China) derive their high values mainly from import-oriented in-degree links. Nodes with high betweenness or closeness centrality mostly function as cross-regional trade hubs, with bidirectional import and export links serving as transit bridges.

3.3. Attack Simulation Results

First, focus on the comparison between targeted and random attacks in the same food trade network. Targeted attacks correspond to risks such as geopolitical conflicts and export restrictions, while random attacks correspond to natural risks such as extreme weather and sudden disasters. In our cascading-failure experiments, we adopt unified parameter settings of $\alpha = 1$ and $\beta = 0.4$ for all four staple-crop networks. The ex-

port-disruption coefficient $\alpha = 1$ represents a complete export suspension of the initial-failure exporter. This extreme scenario mirrors real-world high-risk episodes such as full-scale export bans implemented by major grain exporters amid geopolitical conflicts or total domestic production collapse. This setting allows us to evaluate the upper-bound worst-case systemic spillover risk for each crop network. For the failure-tolerance threshold $\beta = 0.4$, this value is grounded in empirical observations of global food market disturbances: short-term import volume reductions of 20–30% typically trigger moderate market fluctuations, while import shortfalls exceeding 40% generate substantial supply-side shocks capable of driving secondary cross-border cascading failures. Applying identical α and β across wheat, rice, maize and soybean eliminates confounding effects arising from crop-specific parameter differences. Consequently, cross-crop disparities in cascading-failure coverage and propagation rounds can be principally attributed to inherent topological heterogeneity of each trade network, instead of manually varied model parameters. Comprehensive sensitivity analysis across broader ranges of α , β , alternative node-capacity definitions and diverse initial shock-origin nodes remains a key priority for future research (see Section 4.3).

The targeted attack strategies operate through distinct mechanisms. Out-degree-based attacks prioritize nodes with the highest export volumes and widest trade reach, whose failure directly removes large-scale supply from the market and severs a large number of export links simultaneously. Betweenness-based attacks, by contrast, target nodes that function as critical intermediaries along cross-regional trade routes; their breakdown splits the network into disconnected regional clusters and disrupts trans-regional trade circulation, even if the attacked nodes are not top exporters. The targeted attack strategies operate through distinct mechanisms. Quantitatively, out-degree-targeted attacks produce sharp, immediate LCC deterioration by removing major supply sources, which directly cuts off mass export supply for importing economies. By comparison, betweenness-targeted attacks degrade network connectivity more gradually: they do not eliminate aggregate export volume of the whole system, but fragment global trade into isolated regional compartments. In some scenarios, networks retain higher residual LCC under betweenness-based attacks than under out-degree-based attacks at identical numbers of removed nodes, yet suffer severe blockage of inter-regional trade redistribution. Therefore, out-degree attacks mainly represent supply-collapse risks from major producing exporters, while betweenness attacks simulate failures of transit-hub and bridge economies, representing circulation-disruption risks rather than direct supply shortages.

Figure 3 illustrates the evolution of the relative size of the largest connected component (LCC) and relative weighted network efficiency of wheat, rice, maize and soybean trade networks under four attack scenarios, namely random attack, targeted attack by out-degree, out-degree centrality and betweenness centrality. Across all four commodity networks, targeted attacks based on node centrality trigger far more severe cascading failure than random node removal, manifested by faster declines in both LCC ratio and weighted network efficiency. The wheat trade network possesses the strongest robustness against random disturbance: its LCC ratio remains above 0.6 even after removing more than 30 nodes randomly, and network efficiency declines gradually. Nevertheless, targeted attacks rapidly break down network connectivity and trading efficiency, as the removal of a small number of core exporters collapses the whole system. The rice network exhibits the weakest robustness. Both LCC and network efficiency drop sharply once a small set of hub nodes are disrupted, indicating the rice trade system is highly concentrated and extremely sensitive to intentional shocks. The maize network shows moderate resilience. Random attacks slowly degrade network connectivity and efficiency, while targeted attacks produce abrupt system deterioration. The soybean net-

work is highly vulnerable to targeted attacks. A small number of failed core nodes induces a steep fall in LCC and network efficiency, revealing that soybean global trade heavily depends on a narrow group of dominant exporting economies.

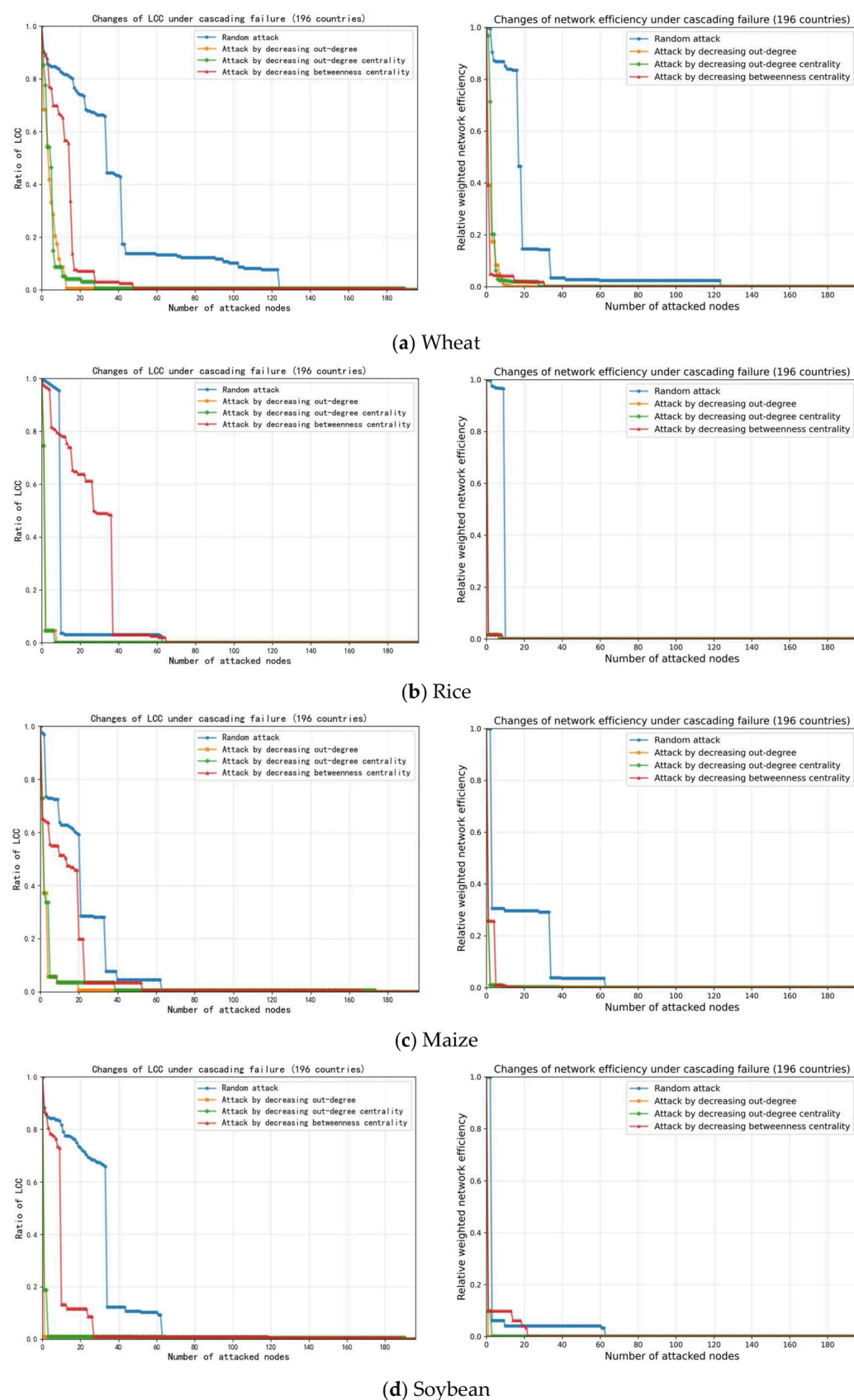


Figure 3. Attack simulation results of four networks.

Table 3 quantifies the association between node centrality and cascading-failure scale. Both Pearson and Spearman coefficients show consistent positive correlations: nodes with higher out-degree or weighted betweenness centrality tend to induce larger-scale cascading failures. At the network level, rice possesses the highest Freeman out-degree centralization value (0.737), indicating heavily concentrated export connections, which corresponds to its high systemic vulnerability observed in simulation.

Table 3. Correlation between node centrality and cascading-failure scale, together with network-level out-degree centralization for four staple-crop trade networks.

Crop	Out-Degree Centrality γ/ρ	Weighted Betweenness Centrality γ/ρ	Freeman Out-Degree Centralization
Wheat	0.606/0.742	0.557/0.769	0.404
Rice	0.610/0.615	0.595/0.664	0.737
Maize	0.588/0.717	0.583/0.733	0.486
Soybean	0.544/0.768	0.417/0.856	0.339

Note: For each pair, the first value is Pearson's linear correlation coefficient γ , the second value is Spearman's rank-order correlation coefficient ρ . All correlations are statistically significant ($p < 0.05$, $n = 196$). The response variable is the number of newly failed countries triggered when each node is set as the initial failure source. Freeman out-degree centralization quantifies the overall concentration of export linkages across the whole network. Higher values indicate exports are concentrated within fewer countries.

To further clarify the response differences in the four food trade networks to targeted attacks, this section takes the country with the largest out-degree in each variety network as the risk source to simulate the network collapse degree and cascading failure process when the country imposes an export ban. It focuses on both the failure node scale and collapse speed of different variety networks under targeted attacks, and analyzes the process differences such as the rounds and path characteristics of risk transmission, so as to clarify the vulnerability differentiation of the four food trade networks to risks from core supplier countries (Table 4).

Table 4. Quantitative comparison of cascading failure propagation across four staple food trade networks.

Staple Crop	Risk Source Country	Number of Propagation Rounds	Failed Nodes in the First Round	Total Affected Nodes	Share of Total Network Nodes (%)
Wheat	Canada	3	16	44	22.4
Rice	India	2	45	50	25.5
Maize	United States	4	29	48	24.5
Soybean	Brazil	9	28	169	86.2

When Canada, a major wheat-exporting node, is set as the initial failure source, the cascading-failure process unfolds in successive rounds Figure S1. In the first propagation round, 16 additional economies become abnormal, mainly covering Latin-American and South-Asian countries with direct import dependencies on Canadian wheat, bringing the cumulative number of failed nodes to 17. The second propagation round generates the largest wave of spillover, with another 23 newly failed nodes spanning East Asia, Southeast Asia, Latin America and Africa. Many of these economies rely indirectly on

wheat supplies through trade partners affected in the first round; cumulative failed nodes rise to 40 at this stage. The third round produces only four additional peripheral economies, and cascading diffusion gradually tapers off, ending with 44 total failed nodes. This layered propagation pattern reveals that risk originating from a key wheat exporter first strikes its direct trading partners, then spreads outward via indirect trade linkages to wider regions, before finally weakening when reaching peripheral network nodes.

When India, the top-out-degree rice-exporting node, is selected as the initial failure source, cascading risk exhibits fast-concentrated diffusion characteristics Figure S2. In the first propagation round, as many as 45 additional economies are driven into failure. These affected countries are mainly concentrated across South Asia, West Asia, North Africa and parts of sub-Saharan Africa, most of which maintain direct rice-import dependencies on India. By contrast, the second propagation round yields merely four newly failed southern African peripheral economies, bringing the total number of failed nodes to 50, after which risk propagation terminates. Such a propagation pattern demonstrates that shocks originating from India generate massive direct impacts on its extensive group of importing partners in the first round. Nevertheless, secondary cross-regional spillover is limited, and cascading diffusion rapidly subsides after the first-round shock.

Simulation results based on the cascading failure model of the maize trade network with the United States as the risk propagation source show that risks spread through four rounds and affect 48 nodes Figure S3. The 29 nodes failing in the first round are concentrated in North America and regions closely connected with the United States, achieving rapid initial risk diffusion relying on dense links of the North American maize trade core circle. The 14 nodes failing in the second round extend to Asia-Pacific and Oceania, as linkage transmission of direct trading partners outside the core circle. The five nodes failing in the third and fourth rounds are the extension of risks to island peripheral economies.

Simulation results based on the cascading failure model of the soybean trade network with Brazil as the risk-propagation source show that risks spread through nine rounds and eventually affect 169 nodes Figure S4. The 28 nodes failing in the first round are all core partners closely connected with Brazil, achieving large-scale initial risk diffusion relying on Brazil's extensive connections as a major global soybean supplier. The 23 nodes failing in the second round extend to Europe, America, Asia and Africa, forming cross-regional transmission. The 11 nodes failing in the third round involve core suppliers and peripheral nodes in Central Asia, with risks starting to penetrate into multi-level network layers. The 90 nodes failing in the fourth to sixth rounds further cover core and secondary nodes in Asia-Pacific, Latin America, Europe and other regions relying on trade links of previous nodes, marking the global diffusion stage of risks. The 16 nodes failing in the seventh to ninth rounds extend to middle-tier and outermost peripheral economies of the network.

4. Discussion

4.1. Further Analysis of Results

This study reveals the characteristics and resilience differences in the global trade networks of wheat, rice, maize and soybean through complex network analysis and cascading failure models. The wheat network has multi-polar exports and dispersed flows, the rice network is regionalization-dominated, the maize network is supplied by American countries, and soybean features American monopoly exports and China-led imports. In terms of key nodes distribution, wheat and maize have relatively dispersed

nodes, while rice and soybean have a higher concentration of core nodes. Attack simulation results show that four networks are significantly more vulnerable to targeted attacks than random attacks, with soybean and rice networks suffering the most severe collapse, while wheat and maize networks show stronger resilience. Cascading failures originating from key supplier countries follow a progressive transmission path from core trade associations through regional coverage to peripheral extension, and the number of failed nodes is positively correlated with the degree of network centralization.

The core driving mechanism of the above findings stems from the interaction of three factors, topological structural heterogeneity of networks, targeting of risk shocks and external environmental constraints. In terms of network structure, the multi-polarization of the export side of wheat and maize provides risk buffering, and rich alternative links make them more resilient to random shocks. By contrast, the regional trade dependence of rice and the supply monopoly of soybeans render key nodes the “Achilles’ heel” of the system, where targeted attacks can easily sever critical links and trigger cascading collapse. In terms of risk-transmission logic, targeted attacks concentrate on hub nodes with high degree and betweenness centrality, whose failure destroys the framework of network connectivity, while random attacks exert limited impacts on trade networks. In addition, the external environment further amplifies the impact of structural differences. Fragmentation of global trade rules exacerbates key node-dependence risks. Extreme weather caused by climate change makes local disturbances from random shocks more likely to escalate in centralized networks. The import concentration characteristics of large importers such as China further amplify the risk-transmission effect of key consumer nodes.

4.2. Policy Implications

At the global governance level, it is necessary to strengthen multilateral rule coordination to mitigate risks originating from highly concentrated core supply nodes. Our simulation demonstrates that targeted shocks to key export hubs trigger far-reaching cascading failures, particularly for rice and soybean networks characterized by high supplier concentration. The World Trade Organization should strengthen negotiations on issues such as public stockpiling and export restrictions to curb the export restrictions triggered by geopolitical conflicts. For example, the trade contraction caused by food export restrictions in many countries in 2022 requires rule constraints to balance national food security and global market stability. Meanwhile, relying on the background of re-globalization, it is necessary to promote climate-smart agricultural cooperation and digital innovation in trade logistics, help developing countries integrate into a more inclusive trade network, and reduce network marginality caused by technological gaps or resource constraints. Consistent with our node-identification results showing that peripheral economies suffer heavy secondary impacts during cascading diffusion, digital technology can be used to provide smallholder farmers with full-chain support from production to sales, reduce post-harvest losses, and improve their participation in regional trade, lowering their vulnerability as peripheral network nodes.

At the national level, it is necessary to find solutions to import concentration through diversification and industrial chain extension. Our results reveal that economies highly reliant on a small set of export suppliers face severe impacts once core suppliers are disrupted, as illustrated by the large-scale node failure triggered when major soybean or rice exporters cease exports. On the one hand, import-source diversification should be prioritized, especially for crops with highly concentrated global supply such as soybean and rice. On the other hand, the overseas agricultural industrial chain should be extended from simple imports to full-chain layout of overseas planting, processing

and transportation to enhance discourse power of industrial chains and address the vulnerability risk of key maritime routes. Meanwhile, import-dependent developing countries can cultivate new advantages in high-value-added exports such as back-end industrial chain products. Upgrading export structures can improve a country's position as an intermediate trade bridge within global food networks and reduce passive exposure to supply-side shocks originating from foreign core exporters.

At the technical-empowerment level, greening and digital intelligence are key paths to improve supply chain resilience. Our cascading-failure simulations confirm that risk spreads following a core-to-peripheral sequential path: disruptions originate from high-centrality supplier nodes, then diffuse through direct trading partners and finally reach peripheral importing economies. Traditional agricultural supply chains are highly affected by weather and have lower circulation efficiency. Smart agricultural technologies can be used to strengthen the risk resilience of the production side, and artificial intelligence and the Internet of Things can be used to realize precision farmland management, thereby reducing disturbances driven by random-attack-type such as extreme weather on crop yields. Meanwhile, a digital trade network should be built, and a cross-border food-trade-information-sharing platform established to break information islands, track real-time trade-flow dynamics, and implement early warnings for high-risk nodes identified in our centrality analysis. For example, electronic records can track agricultural input, output and sales to improve full-chain transparency and response efficiency, enabling timely intervention before risks propagate from core hubs to peripheral countries and slowing the cascading-failure chain reaction observed in our simulation.

At the regional cooperation level, tailor-made regional supply-resilience mechanisms should match the crop-specific network structures documented in this study. Our results show that rice trade exhibits strong regional-network features, while soybean, wheat and maize display distinct inter-continental trade architectures. Drawing on the experience of North America and the European Union, regional trade agreements should be used to reduce tariff and non-tariff barriers, strengthen intra-regional food trade connections, and form patterns combining intra-regional complementarity and cross-regional coordination. For rice, given its prominent regional-trade characteristics shown in our network topology analysis, Asia can build a regional emergency supply mechanism around rice trade, establishing reserve sharing and rapid deployment channels between key exporters such as India and Thailand and importers such as the Philippines and Nepal. By contrast, for maize and wheat with multi-polar, globally dispersed trade networks, regional cooperation should focus on complementing inter-continental supply channels rather than building closed regional self-sufficiency systems. African countries can strengthen regional economic community construction, raise the level of intra-regional trade, and reduce dependence on external core nodes, thereby forming a resilience support system within the global trade network.

4.3. Limitations

First, limitations related to input trade data apply to this analysis. Discrepancies may exist between export statistics reported by exporting countries in the UN Comtrade Database and corresponding import records from their trading partners. In addition, there are issues including missing bilateral-trade records and inconsistent national reporting cycles. Although standard harmonization rules have been applied for edge-weight assignment, residual measurement biases may still affect weighted-network construction and topological calculations. Furthermore, using a single-year cross-section prevents us from capturing multi-year structural evolution of trade flows, gradual supply-chain diversification adjustments, or long-term route reconfiguration triggered by

geopolitical crises and climate-related production shocks. Therefore, the identified vulnerability patterns represent only a temporal snapshot of 2024 and may not fully reflect persistent long-run characteristics of global staple-food trade systems. Future research should adopt multi-year panel trade datasets together with enhanced multi-step data-harmonization workflows. Cross-validation against supplementary agricultural production and trade datasets can help filter unreliable bilateral observations, supporting robust dynamic tracking of network topology, node criticality and systemic resilience over time.

Second, the cascading-failure simulation excludes multiple real-world adaptive buffering mechanisms that mitigate risk propagation. On the market side, four independent single-commodity directed-weighted networks are built without explicit cross-crop substitution effects. Importing nations can in practice offset supply shortfalls for one staple by increasing imports of alternative grain varieties. On the institutional-policy side, the model omits practical mitigating instruments including national public grain reserves, emergency tariff adjustments and cross-border emergency stock-sharing arrangements. Collectively, market-driven substitution behaviours and institutional stock buffers absorb supply-side disturbances and slow cascading risk diffusion. Since these adaptive responses are not activated within our modelling setup, simulation outputs tend to over-estimate the geographical scope, number of propagation rounds and overall damage magnitude of real-world supply-chain crises. Future work should develop an integrated multi-crop network framework embedding cross-crop substitution logic, alongside stylised simplified representations of grain reserve buffers and emergency policy interventions, to generate more realistic systemic risk-propagation outcomes.

Third, the cascading-failure modelling is subject to parameter-sensitivity constraints. Node-capacity thresholds defined by total import-plus-export trade volume T_i , the export-disruption coefficient α , and the failure-tolerance coefficient β are determined based on theoretical reasoning and prior literature, while exhaustive sensitivity testing across alternative parameter combinations and diverse shock-origin nodes has not been completed in this study. In the present simulation, we adopt α , representing the extreme scenario of full export suspension from the initial shock source; however, partial export-reduction scenarios with lower α values are not explored. As a result, simulated cascading damage is partly conditional on selected parameter values and initial failure sources. Future analyses should conduct comprehensive sensitivity examinations covering alternative node-capacity definitions, plausible ranges of α and tolerance-threshold parameters β , and multiple candidate shock-origin nodes (major exporters, large importers, cross-regional transit hubs), so as to characterize the full range of plausible risk-transmission scenarios.

Finally, the adopted robustness metric, the relative size of the largest connected component (LCC), only quantifies topological network connectivity after disturbance. It cannot capture actual trade-volume losses, economic welfare impairment or the severity of physical food-supply shortages. A network may maintain relatively high LCC values while experiencing sharp bilateral trade-flow contraction, which this purely topological indicator fails to detect. Future studies are advised to deploy complementary volume-weighted robustness indicators together with LCC, combining topological and volumetric perspectives for a more comprehensive evaluation of food-supply-chain resilience.

5. Conclusions

This study constructs directed-weighted trade networks for four major staple foods (wheat, rice, maize, and soybean) and applies complex-network metrics alongside cascading-failure simulations to identify systemic vulnerabilities within global food-trade

systems.

Theoretically, this work advances cross-crop comparative research on food-trade network resilience. It empirically confirms that network topological characteristics constitute a core driver of systemic risk: supply concentration at key nodes elevates network vulnerability to targeted shocks, whereas dispersed multi-polar trade structures confer stronger shock resistance. Distinct risk-transmission patterns are verified across crop systems: cascading failures triggered by major-supplier disruptions universally follow a core-to-peripheral propagation path, while propagation scale and rounds are jointly shaped by export concentration and regional trade linkages. These findings enrich quantitative evidence linking network topology to agri-food supply-chain systemic risk.

Practically, heterogeneous vulnerability profiles demand-differentiated food-security governance. For soybean and rice with highly concentrated supply-consumption nodes, priority should be given to import-source diversification and emergency cooperation among core suppliers. For rice characterized by prominent regional trade features, building intra-regional reserve-sharing and rapid-deployment mechanisms can mitigate regional risk spillovers. For wheat and maize with relatively decentralized export patterns, existing diversified trade partnerships should be consolidated to maintain inherent network resilience. At the multilateral level, stricter governance over disruptive export-restriction measures and enhanced digital early-warning for high-risk trade nodes help contain cross-border risk contagion.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/systems14101313/s1>, Figure S1: Risk transmission path of wheat trade with Canada as risk propagation source; Figure S2: Risk transmission path of rice trade with India as risk propagation source; Figure S3: Risk transmission path of maize trade with the United States as risk propagation source; Figure S4: Risk transmission path of soybean trade with Brazil as risk propagation source.

Author Contributions: Conceptualization, X.D. and X.J.; methodology, X.J. and Y.D.; software, X.J.; validation, X.D., Z.L. and R.H.; formal analysis, Y.L.; data curation, Y.D.; writing—original draft preparation, X.J.; writing—review and editing, X.D., R.H. and Z.L.; visualization, Y.L.; supervision, X.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Central Public-interest Scientific Institution Basal Research Fund of CAAS, grant number JBYW-AII-2026-32, JBYW-AII-2026-74&CAASTIP-2026-08-06.

Data Availability Statement: The raw data analyzed in this research are publicly available in the UN Comtrade Database, accessible at <https://comtradeplus.un.org>. The researchers of this article accessed this website on 29 October 2025.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Qazi, A. Exploring global food security from a Bayesian network perspective on food availability. *Environ. Dev. Sustain.* **2025**, *352*, 351. [Google Scholar] [CrossRef]
2. Manono, B.O.; Gichana, Z. Agriculture-livestock-forestry nexus: Pathways to enhanced incomes, soil health, food security and climate change mitigation in Sub-Saharan Africa. *Earth* **2025**, *6*, 74. [Google Scholar] [CrossRef]
3. Luqman, M.; Mahmood, F.; Al-Ansari, T. Supporting sustainable global food security through a novel decentralised offshore floating greenhouse. *Energy Conv. Manag.* **2023**, *277*, 116577. [Google Scholar] [CrossRef]

4. Gupta, B.; Zurek, M.; Woodhill, J.; Ingram, J.S.I. Advancing the next-generation of global food system scenarios: A critical review of existing narratives. *Front. Sustain. Food Syst.* **2025**, *9*, 1620374. [Google Scholar] [CrossRef]
5. Li, S.; Zhang, Z.; Xu, J.; Han, J.; Zhuang, H.; Cui, X.; Cai, H.; Xiao, C.; Yang, S.; Tao, F. Global food security under a sustainability perspective: Assessment, challenges, and strategies. *Geogr. Sustain.* **2026**, *7*, 100495. [Google Scholar] [CrossRef]
6. Smyth, S.J.; Webb, S.R.; Phillips, P.W.B. The role of public-private partnerships in improving global food security. *Glob. Food Secur.* **2021**, *31*, 100588. [Google Scholar] [CrossRef]
7. FAO; WFP; GNAFC. *2026 Global Report on Food Crises-Joint Analysis for Better Decisions*; FAO & WFP: Rome, Italy, 2026. [Google Scholar]
8. Lee, C.C.; Zeng, M.; Luo, K. How does climate change affect food security? Evidence from China. *Environ. Impact Assess. Rev.* **2024**, *104*, 107324. [Google Scholar] [CrossRef]
9. Abay, K.A.; Breisinger, C.; Glauber, J.; Kurdi, S.; Laborde, D.; Siddig, K. The Russia-Ukraine war: Implications for global and regional food security and potential policy responses. *Glob. Food Secur.* **2023**, *36*, 100675. [Google Scholar] [CrossRef]
10. Tian, X.; Engel, B.A.; Qian, H.; Hua, E.; Sun, S.; Wang, Y. Will reaching the maximum achievable yield potential meet future global food demand? *J. Clean. Prod.* **2021**, *294*, 126285. [Google Scholar] [CrossRef]
11. Alam, M.F.B.; Tushar, S.R.; Ahmed, T.; Karmaker, C.L.; Bari, A.B.M.M.; de Jesus Pacheco, D.A.; Nayyar, A.; Islam, A.R.M.T. Analysis of the enablers to deal with the ripple effect in food grain supply chains under disruption: Implications for food security and sustainability. *Int. J. Prod. Econ.* **2024**, *270*, 109179. [Google Scholar] [CrossRef]
12. Wei, C.; Xiao, Y.; Li, L.; Huang, G.; Liu, J.; Xue, D. After pandemic: Resilience of grain trade network from a port perspective on developed and developing countries. *Resour. Conserv. Recycl.* **2025**, *215*, 108119. [Google Scholar] [CrossRef]
13. Naja, F.; Hazim, K.; Alameddine, M. Food security amid the US Iran war: A food system analysis and a framework for coordinated multilevel action. *Glob. Food Secur.* **2026**, *49*, 100919. [Google Scholar] [CrossRef]
14. Hopewell, K.; Margulis, M.E. Global trade rules threaten food security amid climate shocks. *Earth Syst. Gov.* **2023**, *18*, 100198. [Google Scholar] [CrossRef]
15. Saboori, B.; Radmehr, R.; Zhang, Y.Y.; Zekri, S. A new face of food security: A global perspective of the COVID-19 pandemic. *Prog. Disaster Sci.* **2022**, *16*, 100252. [Google Scholar] [CrossRef] [PubMed]
16. Guo, J.; Mao, K.; Yuan, Z.; Qin, Z.; Xu, T.; Bateni, S.M.; Zhao, Y.; Ye, C. Global food security assessment during 1961–2019. *Sustainability* **2021**, *13*, 14005. [Google Scholar] [CrossRef]
17. Terdoo, F.; Feola, G. The vulnerability of rice value chains in Sub-Saharan Africa: A review. *Climate* **2016**, *4*, 47. [Google Scholar] [CrossRef]
18. Domenech, J.; Lubroth, J.; Eddi, C.; Martin, V.; Roger, F. Regional and international approaches on prevention and control of animal transboundary and emerging diseases. *Ann. N. Y. Acad. Sci.* **2006**, *1081*, 90–107. [Google Scholar] [CrossRef] [PubMed]
19. Hatab, A.A. Africa's food security under the shadow of the Russia-Ukraine conflict. *Strateg. Rev. South. Afr.* **2022**, *44*, 37–46. [Google Scholar] [CrossRef]
20. Ben Hassen, T.; El Bilali, H. Impacts of the Russia-Ukraine war on global food security: Towards more sustainable and resilient food systems? *Foods* **2022**, *11*, 2301. [Google Scholar] [CrossRef] [PubMed]
21. Neik, T.X.; Siddique, K.H.M.; Mayes, S.; Edwards, D.; Batley, J.; Mabhaudhi, T.; Song, B.K.; Massawe, F. Diversifying agrifood systems to ensure global food security following the Russia-Ukraine crisis. *Front. Sustain. Food Syst.* **2023**, *7*, 1124640. [Google Scholar] [CrossRef]
22. Shandrivska, O.; Fihun, N.; Nycz-Wojtan, S.; Krykavskyy, V. The Ukrainian wheat market in the system of global food security: Wartime impact research. *Econ. Agrar. Recur. Nat.* **2026**, *26*, 260102. [Google Scholar] [CrossRef]
23. Falkendal, T.; Otto, C.; Schewe, J.; Jägermeyr, J.; Konar, M.; Kumm, M.; Watkins, B.; Puma, M.J. Grain export restrictions during COVID-19 risk food insecurity in many low-and middle-income countries. *Nat. Food* **2021**, *2*, 11–14. [Google Scholar] [CrossRef] [PubMed]
24. Yıldırım, C.; Önen, H.G. Vulnerabilities of the neoliberal global food system: The Russia-Ukraine war and COVID-19. *J. Agrar. Change* **2024**, *24*, e12601. [Google Scholar] [CrossRef]
25. Ji, G.; Zhong, H.; Feukam Nzudie, H.L.; Wang, P.; Tian, P. The structure, dynamics, and vulnerability of the global food trade network. *J. Clean. Prod.* **2024**, *434*, 140439. [Google Scholar] [CrossRef]
26. Dong, C.; Yin, Q.; Lane, K.J.; Yan, Z.; Shi, T.; Liu, Y.; Bell, M.L. Competition and transmission evolution of global food trade: A case study of wheat. *Physica A* **2018**, *509*, 998–1008. [Google Scholar] [CrossRef]

27. Wang, J.; Dai, C. Evolution of global food trade patterns and its implications for food security based on complex network analysis. *Foods* **2021**, *10*, 2657. [Google Scholar] [CrossRef] [PubMed]
28. Feng, X.; Ye, H.; Wang, C.; Seco, L. The impact of US-China trade war on China's centrality in the world trade network. *China Agric. Econ. Rev.* **2026**. [Google Scholar] [CrossRef]
29. Hu, W.; Xie, D.; Le, Y.; Fu, N.; Zhang, J.; Yin, S.; Deng, Y. Evolution of food trade networks from a comparative perspective: An examination of China, the United States, Russia, the European Union, and African countries. *Foods* **2024**, *13*, 2897. [Google Scholar] [CrossRef] [PubMed]
30. Liu, Y.; Wu, X.; Zhao, L.; Wang, W.; Wang, M. Evolutionary dynamics of agricultural trade in Central Asia under the Belt and Road Initiative. *China Agric. Econ. Rev.* **2025**, *17*, 527–550. [Google Scholar] [CrossRef]
31. Cao, J.; Lei, Q. Global agricultural trade network characteristics and its influencing factors. *Hum. Soc. Sci. Commun.* **2025**, *12*, 1230. [Google Scholar] [CrossRef]
32. Ma, Y.J.; Jiang, Z.Q.; Zhou, W.X. Determinants of the international crop trade dynamics: New insights from a network structure dependence perspective. *Empir. Econ.* **2025**, *69*, 77–128. [Google Scholar] [CrossRef]
33. Wang, X.; Ma, L.; Yan, S.; Chen, X.; Growe, A. Trade for food security: The stability of global agricultural trade networks. *Foods* **2023**, *12*, 271. [Google Scholar] [CrossRef] [PubMed]
34. Geyik, O.; Hadjikakou, M.; Karapinar, B.; Bryan, B.A. Does global food trade close the dietary nutrient gap for the world's poorest nations? *Glob. Food Secur.* **2021**, *28*, 100490. [Google Scholar] [CrossRef]
35. Karakoc, D.B.; Konar, M. A complex network framework for the efficiency and resilience trade-off in global food trade. *Environ. Res. Lett.* **2021**, *16*, 105003. [Google Scholar] [CrossRef]
36. Xu, H.; Niu, N.; Li, D.; Wang, C. A dynamic evolutionary analysis of the vulnerability of global food trade networks. *Sustainability* **2024**, *16*, 3998. [Google Scholar] [CrossRef]
37. Hedlund, J.; Carlsen, H.; Croft, S.; West, C.; Bodin, Ö.; Stokeld, E.; Jägermeyr, J.; Müller, C. Impacts of climate change on global food trade networks. *Environ. Res. Lett.* **2022**, *17*, 124040. [Google Scholar] [CrossRef]
38. Zhang, Y.T.; Li, M.Y.; Zhou, W.X. Impact of the Russia-Ukraine conflict on international staple agrifood trade networks. *Foods* **2024**, *13*, 2134. [Google Scholar] [CrossRef] [PubMed]
39. Keys, P.W.; Barnes, E.A.; Diffenbaugh, N.S.; Hertel, T.W.; Baldos, U.L.C.; Hedlund, J. Exposure to compound climate hazards transmitted via global agricultural trade networks. *Environ. Res. Lett.* **2025**, *20*, 044039. [Google Scholar] [CrossRef]
40. Jin, Y.; Zhang, A.; Liu, B. Risk contagion among renewable energy, fossil energy and agricultural commodity markets: Insights from dynamic networks. *Econ. Anal. Policy* **2025**, *87*, 1361–1378. [Google Scholar] [CrossRef]
41. Wellesley, L.; Preston, F.; Lehne, J.; Bailey, R. Chokepoints in global food trade: Assessing the risk. *Res. Transp. Bus. Manag.* **2017**, *25*, 15–28. [Google Scholar] [CrossRef]
42. Pandit, A.; Karakoc, D.B.; Konar, M. Spatially detailed agricultural and food trade between China and the United States. *Environ. Res. Lett.* **2023**, *18*, 084031. [Google Scholar] [CrossRef]
43. Li, X.; Wang, H.; Kharrazi, A.; Fath, B.D.; Liu, G.; Liu, G.; Xiao, Y.; Lai, X. A network analysis of external shocks on the dynamics and resilience of the global staple food trade. *Food Secur.* **2024**, *16*, 845–865. [Google Scholar] [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.